UGP - IPOs on SME Board

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DECLARATION

We hereby declare that the work presented in this project report, entitled **“IPOs on SME Board”**, is the result of our own independent effort and original research. Wherever ideas, data, or content have been sourced from published or unpublished materials, appropriate references have been provided. To the best of our knowledge, this report does not contain any material copied or reproduced from the work of others without due acknowledgment.

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Signature

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Thank You.

Your sincerely

Shubham Kumar Maurya

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Supervisor Signature

Abstract

Small and Medium Enterprises (SMEs) in India leverage dedicated stock exchange platforms like NSE Emerge and BSE SME to access public capital. However, concerns persist about market manipulation, particularly during a surge in September IPOs, driven by regulatory deadlines. This study investigates anomalies in SME IPOs listed between 2012 and 2023, focusing on September listings, to identify patterns indicative of manipulation. We analyzed daily return volatility and apply the Fama-French three-factor model with both self-calculated and externally sourced factors to detect abnormal price behavior.

Key findings reveal companies exhibiting post-listing volatility exceeding expected thresholds, alongside firms flagged for significant deviations from expected return. Notably, a subset of companies emerged as common outliers, displaying both high volatility and abnormal returns. The Fama-French model demonstrated limited explanatory power in the Indian context, underscoring the need for market-specific risk factors.

The study highlights regulatory vulnerabilities in SME IPOs, particularly around September deadlines, and advocates for enhanced scrutiny of flagged entities. Future research should integrate IPO-specific factors, time-varying market dynamics, and qualitative data to strengthen anomaly detection. This work contributes to understanding market inefficiencies in emerging economies and offers a framework for regulators to mitigate manipulative practices in SME listings.

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Chapter 1

Introduction

1.1 Background

Small and Medium Enterprises (SMEs) play a crucial role in India's economic growth by fostering entrepreneurship, employment, and innovation. To enable SMEs to raise capital from public markets, the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) introduced dedicated SME platforms—NSE Emerge and BSE SME—in 2012. These platforms were designed to simplify listing requirements and facilitate access to equity funding for smaller enterprises.

However, over the years, concerns have emerged regarding the integrity of some SME Initial Public Offerings (IPOs). Market insiders and regulators have noted that certain SME IPOs may be used as instruments for price manipulation, especially in the month of September. In fact, in September 2023 alone, a record 37 SME IPOs raised over INR 1,000 crore—marking the highest monthly fundraising since the inception of SME listings. The Securities and Exchange Board of India (SEBI) imposed Additional Surveillance Measures (ASM) and Trade-to-Trade (T2T) settlement requirements on SME stocks to curb suspected manipulative practices.

Industry sources reveal a well-coordinated mechanism behind such IPO rigging. A single operator, often commanding a network of over 50 smaller operatives—particularly active in Mumbai and Ahmedabad—can manipulate an SME IPO with just a few thousand applications. Promoters, operators, and retail investors may engage in informal agreements wherein applications are pre-sold for a fixed or contingent fee. This enables promoters to artificially inflate subscription figures, leading to exaggerated listing gains, which are subsequently offloaded onto retail investors. Meanwhile, select institutional investors may purchase these overpriced stocks to offset tax liabilities elsewhere in their portfolios.

The surge in IPO filings every September is linked to compliance deadlines. If an SME misses the September 30 cutoff, it must update its IPO prospectus with additional financial disclosures for the half-year period, requiring filings with the Ministry of Corporate Affairs (MCA), the exchanges, and SEBI. To avoid such regulatory scrutiny, many firms expedite their IPO process before September 30, even securing exchange approvals within days.

These market dynamics raise critical questions about the true quality and transparency of SME IPOs, particularly those rushed before the regulatory deadline. The potential misuse of SME platforms for manipulation undermines investor confidence and warrants closer scrutiny.

1.2 Objective

The primary objective of this study is to investigate the phenomenon of an abnormal surge in SME IPOs during the month of September, while defining the scope of analysis within this context. Specifically, the study aims to:

- Analyze trends in SME IPO listings since 2012, focusing on anomalies observed in the month of September.
- Understand the regulatory processes and listing guidelines for SME IPOs on NSE and BSE.
- Examine potential mechanisms of IPO rigging, including application pre-selling and coordinated operator networks.
- Apply statistical and machine learning techniques to identify patterns indicative of manipulation, using publicly available data, regulatory filings, and market reports.
- Focus the analysis on SME IPOs listed on NSE Emerge and BSE SME from 2012 to 2023, emphasizing September listings while laying groundwork for broader investigations into IPO performance, calendar anomalies, and price behavior in future studies.

Chapter 2

Literature Review and Methodology

2.1 Fundamental Concepts

2.1.1 Initial Public Offerings: SEBI and DRHP Documents

An Initial Public Offering (IPO) marks the first time a company offers its shares to the public. In India, the Securities and Exchange Board of India (SEBI) regulates the IPO process to ensure transparency, fairness, and investor protection. A key document in this process is the Draft Red Herring Prospectus (DRHP), which serves as a preliminary disclosure before the final prospectus is filed. The DRHP contains:

- Details about the company's business model and operations.
- Financial statements and auditor reports.
- Risk factors and use of IPO proceeds.
- Information about promoters, directors, and shareholding patterns.
- Legal proceedings involving the company.

SEBI reviews the DRHP to ensure compliance with regulations before approving the public offering.

2.1.2 Underpricing of an IPO: Role of Investment Bankers

IPO underpricing refers to the phenomenon where the offer price is set below the first-day closing price, leading to abnormal initial returns. Investment bankers play a critical role in setting the offer price, balancing between:

1. **Maximizing Issuer Proceeds**: Higher offer price increases funds raised by the company.
2. **Ensuring Successful Subscription**: Lower offer price attracts more investor demand and reduces subscription risk.

Investment bankers may intentionally underprice to create excess demand, ensure listing gains, and maintain relationships with institutional investors. However, excessive underpricing transfers wealth from the issuer to initial investors.

2.1.3 Underwriting Process of an IPO

The underwriting process involves investment banks or syndicates committing to sell the offered shares, either by:

- **Firm Commitment**: Underwriter purchases all shares and resells to investors, assuming price and demand risk.
- **Best Efforts**: Underwriter agrees to sell as much as possible without guarantee, with no obligation to purchase unsold shares.

The underwriter performs due diligence, assists in pricing, markets the IPO to potential investors, and stabilizes the market post-listing through price support mechanisms.

2.1.4 Underwriter Reputation and IPO Performance

Underwriter reputation acts as a signal of IPO quality to investors. High-reputation underwriters:

1. Attract more institutional investors.
2. Provide certification that the issuer's disclosures are credible.
3. Are associated with lower information asymmetry and reduced adverse selection.

Empirical evidence suggests IPOs managed by reputable underwriters experience less severe underpricing but better aftermarket liquidity and analyst coverage.

2.1.5 Measures of Underwriter Reputation

Underwriter reputation is typically measured using proxies such as:

- **Market Share**: Share of IPO proceeds or number of deals managed in a given period.
- **League Table Rankings**: Rankings published by financial data providers based on underwriting activity.
- **Carter-Manaster Rankings**: A scale based on underwriter prominence in IPO tombstone advertisements.

Higher-reputation underwriters are often able to command higher fees, attract prestigious clients, and achieve better IPO outcomes.

2.1.6 Definition of Small and Medium Enterprises (SMEs)

Small and Medium Enterprises (SMEs) are defined based on investment and turnover thresholds. According to the MSME Development Act (2006) in India, an enterprise is categorized as:

- **Micro**: Investment in plant and machinery or equipment does not exceed 1 crore and turnover does not exceed INR 5 crore.
- **Small**: Investment does not exceed 10 crore and turnover does not exceed 50 crore.
- **Medium**: Investment does not exceed 50 crore and turnover does not exceed 250 crore.

2.1.7 Classification Criteria

The classification of MSMEs is based on a dual criterion of:

1. **Investment in Plant and Machinery or Equipment**
2. **Annual Turnover**

Enterprises must satisfy both conditions to qualify under each category.

2.1.8 Statistics on MSMEs Over the Years

The number of registered and unregistered MSMEs in India has grown steadily. Recent reports indicate:

- Approximately 63 million MSMEs operating across India.
- MSMEs contribute nearly 30% to India's GDP.
- Over 11 crore people are employed by MSMEs.

2.1.9 Financing Challenges for SMEs

SMEs face several barriers in accessing formal financing channels:

1. **Collateral Requirements**: SMEs often lack tangible assets to pledge.
2. **High Cost of Credit**: Higher perceived risk leads to costlier loans.
3. **Limited Credit History**: Absence of credit records impedes creditworthiness evaluation.
4. **Informal Operations**: Many SMEs operate without formal accounting, discouraging institutional lenders.

2.1.10 Government Steps to Alleviate Financing Troubles

The government has implemented multiple initiatives to improve SME access to finance:

- **Credit Guarantee Fund Trust for Micro and Small Enterprises (CGTMSE)**: Facilitates collateral-free loans.
- **Priority Sector Lending Mandate**: Banks are mandated to allocate a portion of lending to MSMEs.
- **MUDRA Scheme**: Provides refinancing support to micro-units.
- **Startup India and Stand-Up India**: Supports innovative and first-time entrepreneurs.

2.1.11 Financing Modes and Associated Statistics

SMEs typically raise funds through debt or equity financing:

1. **Debt Financing**: Predominantly from banks, NBFCs, and informal lenders.
2. **Equity Financing**: Through venture capital, angel investors, or public offerings.

Recent data shows:

- Debt accounts for over 90% of MSME external financing.
- SME IPOs have seen steady growth post-2012, with more than 350 companies listed on SME exchanges.

2.1.12 Process and Guidelines for Listing on SME Boards

The Securities and Exchange Board of India (SEBI) and stock exchanges have established criteria for SME listings:

1. Post-issue paid-up capital should not exceed 25 crore.
2. At least 50 allottees are required for IPO eligibility.
3. SMEs must enter into an agreement with depositories for dematerialized shares.
4. Mandatory market-making for 3 years post-listing to ensure liquidity.
5. Relaxed disclosure and compliance norms compared to the main board.

2.1.13 Success Stories of SMEs Availing IPO Financing

Several SMEs have leveraged IPO financing for expansion and visibility. Examples include:

- **Insolation Energy Limited**: Raised INR 22 crore through IPO in 2022 and expanded solar module production capacity.
- **Rachana Infrastructure Ltd**: Utilized IPO proceeds to bid for larger infrastructure projects.
- **Focus Lighting and Fixtures**: Achieved significant post-IPO growth, driven by retail store contracts.

> "A growing number of SMEs are using IPO financing not only as a funding mechanism but as a branding exercise to attract customers, vendors, and future investors." (Economic Times, 2023)

2.2 Brown and Warner (1985): "Using daily stock returns: The case of event studies"

The 1985 paper by **Stephen J. Brown** and **Jerold B. Warner**, titled *"Using Daily Stock Returns: The Case of Event Studies"*, is a foundational work in event study methodology, particularly in the context of daily stock returns.

2.2.1 Key Contributions and Findings

1. **Event Study Methodology Validation**

   The paper examines whether daily stock returns provide reliable insights into market reactions to corporate events (e.g., earnings announcements, mergers). It finds that event studies using daily data can be effective, despite concerns about non-synchronous trading and biases.

2. **Market Model vs. Mean-Adjusted Returns**

   It compares different models for measuring abnormal returns:

   - **Market Model**: Uses regression against the market return.
   - **Mean-Adjusted Returns**: Uses the historical average return of the stock.

   The study shows that the Market Model is not significantly superior to the simpler Mean-Adjusted Returns method in most cases.

3. **Statistical Properties and Test Statistics**

   The paper evaluates the performance of test statistics, including:

   - **Standard parametric tests** (e.g., t-tests for abnormal returns).
   - **Non-parametric tests** (useful for cases with non-normal returns).

   It finds that traditional test statistics remain valid and powerful when applied to daily stock return data.

4. **Implications for Market Efficiency**

   The results support the idea that stock prices adjust quickly to new information, reinforcing the Efficient Market Hypothesis (EMH). However, event studies must control for confounding effects, as daily data can be noisy.

2.2.2 Practical Implications

Event studies can be reliably conducted using daily stock returns. Simpler statistical models (like the Mean-Adjusted model) can perform just as well as complex ones. Researchers must be mindful of biases in daily data, such as thin trading and microstructure effects. This study remains a benchmark for event study methodology and continues to influence empirical finance research.

2.2.3 Key Formulas

- **Abnormal Return (AR) calculation:**

$$AR_{it} = R_{it} - E(R_{it})$$

  where:

$$\begin{aligned} AR_{it} &= \text{Abnormal return for stock } i \text{ on day } t \\ R_{it} &= \text{Actual return for stock } i \text{ on day } t \\ E(R_{it}) &= \text{Expected return for stock } i \text{ on day } t \end{aligned}$$

- **Market Model:**

$$E(R_{it}) = \alpha_i + \beta_i R_{mt}$$

- **Mean-Adjusted Model:**

$$E(R_{it}) = \bar{R}_i$$

- **Cumulative Abnormal Return (CAR):**

$$CAR_i = \sum_{t=T_1}^{T_2} AR_{it}$$

- **Average Abnormal Return (AAR):**

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it}$$

- **Cumulative Average Abnormal Return (CAAR):**

$$CAAR = \sum_{t=T_1}^{T_2} AAR_t$$

2.3 Fama and French (1993): "Common risk factors in the returns on stocks and bonds"

2.3.1 Purpose of the Paper

The paper investigates whether certain common risk factors can explain the cross-section of average stock and bond returns. CAPM, which only considers market risk, failed to explain persistent anomalies like the size effect (small firms outperform large ones) and the value effect (high book-to-market stocks outperform growth stocks). Fama and French addressed this by introducing two additional factors.

2.3.2 The Three Factors in the Model

The model incorporates the following factors:

1. **Market Risk Premium (Market Return − Risk-Free Rate)** : Captures the traditional market exposure as in CAPM.
2. **Size Premium (SMB: Small Minus Big)** : Represents the excess return of small-cap stocks over large-cap stocks. This captures the size effect, where smaller firms tend to yield higher returns, possibly due to higher risk or under-coverage.
3. **Value Premium (HML: High Minus Low)** : Represents the excess return of value stocks (high book-to-market) over growth stocks (low book-to-market). This reflects the value effect, where distressed or undervalued firms offer better long-term performance.

2.3.3 Key Model Equation

The three-factor model estimates expected returns using the regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_m(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \epsilon_{it}$$

where:

- R_{it}: Return on asset i at time t
- R_{ft}: Risk-free rate at time t

- R_{mt}: Market return at time t
- SMB_t: Size factor at time t
- HML_t: Value factor at time t
- α_i: Intercept (abnormal return)
- ϵ_{it}: Error term

2.3.4 Key Results

- The three-factor model explains a substantial portion of the cross-sectional variation in average stock returns.
- CAPM is rejected because it cannot capture the size and value effects.
- The factors SMB and HML are significant and consistent over time, improving model performance.
- The same factors explain some variation in bond returns, particularly related to default and term risks.

2.3.5 Construction of Factors

- SMB is constructed by taking the difference in returns between a portfolio of small stocks and a portfolio of large stocks, controlling for value and growth characteristics.
- HML is constructed by taking the difference in returns between a portfolio of high book-to-market (value) stocks and low book-to-market (growth) stocks, controlling for size.

2.3.6 Impact and Legacy

The Fama-French three-factor model became a cornerstone of modern empirical asset pricing and portfolio management. It provided a more robust explanation of returns than CAPM and inspired further factor models, such as the Fama-French Five-Factor Model (2015). It is used by academics, practitioners, and asset managers to evaluate portfolio performance, measure risk-adjusted returns, and construct factor-based strategies.

2.4 Lyon Barber (1997, 1999) – Key Insights on Long-Term Event Studies

Papers: "Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics" (1997, JBFA) and "Firm Size, Book-to-Market Ratio, and Security Returns: A Holdout Sample of Financial Firms" (1999, JFQA) Together, these papers laid the methodological foundation for event studies that seek to measure long-term abnormal stock returns. Barber and Lyon focus especially on the empirical challenges in detecting long-run performance and propose improvements over earlier methods like Buy-and-Hold Abnormal Returns (BHARs).

2.4.1 Theoretical Motivation

Barber and Lyon address a fundamental issue in event studies: How can we reliably estimate long-run abnormal returns after corporate events (e.g., mergers, SEOs, repurchases), when the event might signal either mispricing or changes in risk? They argue that traditional long-horizon methods (like BHARs and cumulative abnormal returns or CARs) often fail basic statistical requirements, producing biased and misleading inferences.

2.4.2 Core Problems Identified

- Benchmark misspecification: Using a broad market index can lead to biased estimates if event firms differ in characteristics like size or book-to-market.
- Compounding and skewness: Long-run BHARs and CARs are non-normally distributed, making t-tests unreliable.
- Cross-sectional dependence: Many event firms move together, violating the assumption of independence across observations.
- Rebalancing bias: Holding strategies that assume constant investment or periodic rebalancing may not reflect investor experience.

2.4.3 Proposed Solutions (1997 Paper)

A. Use of Matched-Firm and Matched-Portfolio Benchmarks : Instead of using the market or CAPM, they propose matching event firms to non-event firms that are similar in size and book-to-market ratio. This improves the accuracy of abnormal return estimation.

B. Buy-and-Hold Abnormal Returns (BHAR) :

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{jt})$$

where:

$$\begin{aligned} R_{it} &= \text{Return of firm } i \text{ in month } t \\ R_{jt} &= \text{Return of matched benchmark firm or portfolio in month } t \\ T &= \text{Investment horizon (e.g., 36 or 60 months)} \end{aligned}$$

This contrasts with cumulative abnormal returns (CARs), which sum excess returns linearly and do not reflect compounding.

C. Average BHAR for Sample of Firms

$$\overline{BHAR} = \frac{1}{N}\sum_{i=1}^{N} BHAR_i$$

This average is used to assess whether the event group significantly over- or under-performed relative to the benchmark group.

D. Test Statistic (t-test on BHAR)

$$t = \frac{\overline{BHAR}}{StandardError(BHAR)}$$

They caution, however, that this t-statistic may still be misleading due to skewed return distributions.

2.4.4 Key Contribution: Specification vs Power Trade-Off

Barber and Lyon highlight the trade-off between:

- Specification (correct inference under the null): Matching firm size/book-to-market improves specification.
- Power (ability to detect true effects): BHARs are powerful but biased if not matched properly.

Their solution is to improve benchmark selection and test designs to balance specification and power in long-run return studies.

2.4.5 Insights from the 1999 Paper (Financial Firms)

In this follow-up, they apply their methodology to financial firms, which were often excluded in earlier studies due to regulatory/accounting differences.

Key findings:

- Their matched-firm BHAR approach still works well for financial firms.
- They show that firm size and book-to-market also explain long-run returns in the financial sector, confirming the broader relevance of these variables.

This supports the external validity of their 1997 approach.

2.4.6 Comparison to Other Approaches

Method	**Main Issue**	**Barber & Lyon Solution**
BHAR (unmatched)	Misspecification, skewness	Use matched firm/portfolio
CAR	Misses compounding	Use BHAR for realism
Fama-French regressions	Need time-series data	Use when appropriate, but BHAR is more intu

2.4.7 Implications for Researchers and Practitioners

- Improved accuracy in estimating long-run abnormal returns
- Matched-firm BHAR became the dominant approach in empirical finance for many years
- Warns against overreliance on statistically significant BHARs unless properly benchmarked

Buy-and-Hold Abnormal Return (BHAR):

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{jt})$$

Average BHAR:

$$\overline{BHAR} = \frac{1}{N}\sum_{i=1}^{N} BHAR_i$$

t-test for significance:

$$t = \frac{\overline{BHAR}}{s/\sqrt{N}} \quad \text{(use with caution)}$$

Where:

- R_{it}: Return of firm i in month t
- R_{jt}: Return of matched benchmark firm or portfolio in month t
- T: Investment horizon (e.g., 36 or 60 months)
- N: Number of firms
- s: Sample standard deviation of the BHARs

2.5 Mitchell & Stafford (2000): "Managerial Decisions and Long-Term Stock Price Performance"

2.5.1 Objective of the Study

Mitchell and Stafford evaluate how well long-run abnormal stock returns—following corporate events like mergers, equity issues, and repurchases—are measured. They specifically examine the reliability of Buy-and-Hold Abnormal Returns (BHARs) and propose an alternative: the Calendar-Time Portfolio Approach.

Their key message is that traditional BHAR-based methods are biased and produce overstated statistical significance. The calendar-time regressions using monthly portfolio returns offer more robust and reliable inferences.

2.5.2 Problems with BHARs

BHARs have been widely used to evaluate post-event performance. The authors critique them for three main reasons:

1. **Skewness**: BHARs are positively skewed, leading to misleading averages and t-statistics.
2. **Cross-Sectional Dependence**: Returns across firms are correlated, violating independence assumptions.
3. **Survivorship and Rebalancing Biases**: Arise from compounding returns over time and changing event-firm sets.

2.5.3 Alternative Approach: Calendar-Time Portfolio Method

Instead of evaluating each firm in isolation, Mitchell & Stafford construct monthly portfolios of all firms experiencing a given event. These portfolios are held over time and rebalanced as new firms enter.

2.5.4 Key Model Equation (Calendar-Time Portfolio Regression)

$$R_{pt} - R_{ft} = \alpha + \beta_m(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \epsilon_t$$

where:

$$\begin{aligned}
R_{pt} &= \text{Return on event portfolio in month } t \\
R_{ft} &= \text{Risk-free rate in month } t \\
R_{mt} &= \text{Market return in month } t \\
SMB_t &= \text{Return on small-minus-big portfolio (size factor)} \\
HML_t &= \text{Return on high-minus-low book-to-market portfolio (value factor)} \\
\alpha &= \text{Average abnormal return (main variable of interest)} \\
\epsilon_t &= \text{Error term}
\end{aligned}$$

2.5.5 Key Formulae and Metrics

Buy-and-Hold Abnormal Return (BHAR) — used and critiqued

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{bt})$$

where:

$$\begin{aligned} R_{it} &= \text{Return of firm } i \text{ at time } t \\ R_{bt} &= \text{Return of benchmark (market or matched firm)} \\ T &= \text{Holding period} \end{aligned}$$

Average BHAR across firms

$$A\text{-}BHAR = \frac{1}{N}\sum_{i=1}^{N} BHAR_i$$

T-test on BHAR (biased due to skewness)

$$t = \frac{A\text{-}BHAR}{Standard\ Error(BHAR)}$$

Calendar-Time Abnormal Return

$$\alpha = \text{Intercept from the monthly Fama-French regression}$$

If $\alpha \neq 0$, then long-run abnormal returns exist post-event.

2.5.6 Key Findings

- BHAR-based methods produce exaggerated abnormal returns due to their statistical flaws.
- Calendar-time regressions provide smaller, more realistic estimates of abnormal performance.
- Long-run abnormal returns around events like SEOs, mergers, and repurchases largely disappear when evaluated using calendar-time methods.
- The evidence suggests market efficiency is more consistent with calendar-time results.

2.5.7 Implications

The paper challenges prior findings of large post-event anomalies and questions the robustness of BHAR-based conclusions.

Practitioners and academics should prefer the calendar-time approach when evaluating long-run returns to reduce bias and improve inference reliability.

2.5.8 Contribution and Legacy

This paper helped shift the methodological standard in event studies from BHARs to calendar-time regressions.

It supports Fama-French-style asset pricing frameworks in evaluating long-term performance and anomaly studies.

2.6 Fama & French (2015): "A Five-Factor Asset Pricing Model"

2.6.1 Objective of the Study

Fama and French (2015) extend their renowned three-factor model (1993) by adding two new factors—profitability and investment—to better explain average stock returns. Their goal is to address the model's failure in capturing anomalies related to profitability and investment patterns in firm returns.

The five-factor model aims to improve pricing accuracy over the three-factor model by explicitly accounting for variations in profitability and investment, building on the theoretical foundations of the dividend discount model and corporate finance.

2.6.2 The Five Factors

The model adds two factors to the original three-factor framework:

1. **Market Risk Premium (MKT)**: $R_m - R_f$ — excess return of the market over the risk-free rate.

2. **Size (SMB)**: Small minus big — return difference between small and large firms.
3. **Value (HML)**: High minus low — return difference between high and low book-to-market firms.
4. **Profitability (RMW)**: Robust minus weak — return difference between firms with robust and weak operating profitability.
5. **Investment (CMA)**: Conservative minus aggressive — return difference between firms investing conservatively and aggressively.

2.6.3 Key Model Equation

The five-factor model estimates expected returns using the regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_m(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \beta_r RMW_t + \beta_c CMA_t + \epsilon_{it}$$

where:

- R_{it}: Return on asset i at time t
- R_{ft}: Risk-free rate at time t
- R_{mt}: Market return at time t
- SMB_t: Size factor at time t
- HML_t: Value factor at time t
- RMW_t: Profitability factor at time t
- CMA_t: Investment factor at time t
- α_i: Intercept (abnormal return)
- ϵ_{it}: Error term

2.6.4 Rationale for Additional Factors

The authors justify the inclusion of profitability and investment factors based on corporate finance theory:

- Firms with **higher profitability** are theoretically expected to generate higher expected returns.
- Firms that **invest aggressively** are predicted to have lower future returns under the investment-return relation.

By adding these factors, the model better aligns with observed cross-sectional return patterns and economic intuition.

2.6.5 Key Findings

1. The five-factor model explains **more variation in average returns** than the three-factor model, particularly for portfolios sorted on profitability and investment.
2. The inclusion of RMW and CMA makes the value factor HML redundant for certain portfolios; its explanatory power weakens.
3. Despite improvements, the model fails to explain returns for portfolios with **low investment and low profitability** (small-growth anomalies persist).

2.6.6 Evaluation of the Model

The authors test the model across:

- **U.S. stocks (1963–2013)**
- **25 and 100 portfolios sorted by size, value, profitability, and investment**

Metrics:

- **Intercept (α) significance**: Closer to zero $\rightarrow$ better pricing
- R^2: Proportion of variation explained

The average absolute intercepts in the five-factor model are lower than in the three-factor model, suggesting **improved pricing accuracy**, though anomalies remain for subsets of stocks.

2.6.7 Implications

The study implies that:

- Future asset pricing models need to account for profitability and investment effects.
- Practitioners should consider multifactor exposures in portfolio construction and performance evaluation.
- The weak performance of HML in the five-factor context questions its continued inclusion as a standalone factor.

2.6.8 Contribution and Legacy

Fama and French's (2015) five-factor model expanded the standard asset pricing framework, influencing empirical finance, portfolio management, and academic research. It reinforced the empirical role of investment and profitability patterns, sparking debates about factor redundancy and anomalies.

2.7 Market Valuation and Acquisition Quality: Empirical Evidence

2.7.1 Objective of the Study

The study examines how market-wide valuation levels affect the quality and outcomes of corporate acquisitions. It investigates whether acquisitions made during high-valuation periods differ in performance from those made during low-valuation periods, both at announcement and over the long run. The key aim is to assess whether managerial decisions are influenced by market misvaluation or fundamental considerations.

2.7.2 Problems with High-Valuation Acquisitions

Acquisitions in high-valuation markets are critiqued for several potential issues:

1. **Overpayment Risk**: Elevated market valuations may inflate target prices, leading acquirers to overpay.
2. **Herding Behavior**: Managers may follow prevailing market optimism rather than base decisions on intrinsic firm value.
3. **Poor Long-Term Synergies**: Deals driven by market sentiment may lack true strategic fit, resulting in weak long-term performance.

2.7.3 Methodology: Calendar-Time Portfolio and Event-Study Approach

The study employs both short-term event-study methods and long-term calendar-time portfolio regressions to evaluate acquisition performance:

- **Event-Study**: Measures abnormal returns around the acquisition announcement date.
- **Calendar-Time Regression**:

$$R_{pt} - R_{ft} = \alpha + \beta_m(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \epsilon_t$$

  where:

$$\begin{aligned} R_{pt} &= \text{Return on acquirer portfolio at time } t \\ R_{ft} &= \text{Risk-free rate at time } t \\ R_{mt} &= \text{Market return at time } t \\ SMB_t &= \text{Small-minus-Big factor return at } t \\ HML_t &= \text{High-minus-Low factor return at } t \\ \alpha &= \text{Abnormal return (main parameter of interest)} \end{aligned}$$

2.7.4 Key Findings

1. **Announcement Returns**: Acquisitions during high-valuation markets show higher announcement abnormal returns.
2. **Long-Term Underperformance**: These acquisitions exhibit negative abnormal returns in the years following the deal.
3. **Valuation Timing Effect**: The underperformance is more pronounced when acquirers use stock financing, suggesting reliance on overvalued equity.

2.7.5 Implications

- Market valuation levels systematically affect acquisition quality.
- Investors should interpret high announcement returns during high-valuation markets cautiously.
- Managers may exploit temporarily overvalued equity to finance acquisitions, but such deals may erode shareholder value over time.

2.7.6 Contribution and Legacy

The study provides empirical evidence that high market valuations create incentives for lower-quality acquisitions. It reinforces skepticism about mergers during market booms and supports calendar-time regression as a robust method to evaluate long-term acquisition performance while adjusting for market factors.

Chapter 3

Data

3.1 Data and Data Pre-processing

3.1.1 Data Source

The primary dataset for this project was compiled from **CMIE Prowess dx** for daily stock trading data for companies listed on the **National Stock Exchange (NSE) of India**, covering the period from **January 1996 to February 2025**. The dataset included daily records for both IPOs and existing listed companies. For each company, the dataset contains the following columns:

Column Name	**Description**
`co_code`	Unique company code
`company_name`	Name of the company
`co_stkdate`	Trading date
`nse_opening_price`	Opening price on the trading day
`nse_high_price`	Highest price on the trading day
`nse_low_price`	Lowest price on the trading day
`nse_closing_price`	Closing price on the trading day
`nse_returns`	Daily returns (calculated or reported)
`nse_traded_qty`	Quantity of shares traded
`equity_bv_on_stkdate`	Book value of equity on the trading date

Table 3.1: Dataset columns and their descriptions

In addition to price and trading data, the project also incorporated **Factor Data from the Fama-French and Momentum Factors: Data Library for the Indian Market by IIMA - Indian Institute of Management Ahmedabad**. This external dataset provided the following variables:

- Market Premium (%)
- SMB (Small Minus Big)
- HML (High Minus Low)
- WML (Winners Minus Losers)

These factor coefficients were used to contextualize market-wide risk and return characteristics during the IPO listing periods.

3.1.2 Data Filtering and Preparation

The following key steps were performed during data preparation:

- **Mean value imputation:** Instead of removing rows with missing values, we imputed missing entries with mean values. This approach provided better performance in preliminary Ordinary Least Squares (OLS) regression tests compared to simple deletion of incomplete rows.
- **Standardization of date format:** All dates in the dataset were reformatted to **DD-MM-YYYY** to ensure consistency and compatibility across data sources.
- **Addition of listing and trading dates:** We manually added the **listing date for each company** along with their respective **first trading day**, creating a reliable reference point for further analysis.
- **Grouping by year of listing:** The companies were **segregated and grouped according to their year of listing**, enabling year-wise comparisons and trend analysis.

These preprocessing steps ensured a clean, structured dataset suitable for better statistical modeling and exploratory analysis.

Chapter 4

Analysis

This chapter presents a detailed analysis of the daily stock price and return data for IPO-listed companies on the NSE between 1996 and February 2025. The analysis focuses on examining stock returns, volatility patterns, and short-term post-listing price behaviors. The operations performed are outlined below, grouped by their analytical objective, with relevant formulas included.

4.1 Daily Price and Return Analysis

4.1.1 Daily High-Low Percentage

Calculated the percentage difference between the daily high and low prices for each stock:

$$\text{High-Low \%} = \frac{\text{High Price} - \text{Low Price}}{\text{Low Price}} \times 100$$

This identifies intra-day price volatility.

4.1.2 Daily Return with Stock Price

Plotted daily returns alongside closing stock prices for the recent 3 years, using:

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

where:

- R_t: Return on day t
- P_t: Closing price on day t

4.1.3 Days with Return $> \pm 15\%$

Flagged all trading days where:

$$|R_t| > 0.15$$

These instances were highlighted in return plots to indicate abnormally high positive or negative returns.

4.2 Rolling Standard Deviation Analysis (Recent 3 Years)

Computed rolling standard deviation (volatility) of returns using different window sizes w:

$$\sigma_t^{(w)} = \sqrt{\frac{1}{w}\sum_{i=0}^{w-1}(R_{t-i} - \bar{R})^2}$$

where:

- $\sigma_t^{(w)}$: Standard deviation at day t with window w
- $\bar{R}$: Mean return over the window

Windows applied:

- $w = 30$ days
- $w = 2$ days
- $w = 1$ day

4.3 Return and Volatility Analysis After Listing

Conducted focused return and volatility analysis for specific days after IPO listing.

4.3.1 Daily Return with Stock Price After Listing

Returns and prices were plotted after:

- 1 day
- 2 days
- 3 days
- 7 days
- 10 days
- 15 days
- 60 days

Each plot tracks how stock prices and returns evolved in the early trading days.

$$R_t^{(\text{post-IPO})} = \frac{P_t - P_{t-1}}{P_{t-1}}, \quad t = \text{Days since listing}$$

4.3.2 Rolling Standard Deviation After Listing

Rolling standard deviation was calculated after:

- 1 day
- 3 days
- 5 days
- 7 days
- 15 days
- 30 days
- 45 days
- 60 days

Each computed with varying rolling windows w:

- $w = 3$ days
- $w = 5$ days
- $w = 7$ days
- $w = 10$ days
- $w = 15$ days

These were plotted to observe how volatility stabilizes (or remains high) post-IPO.

4.4 Abnormal Volatility Flagging Post-IPO

Companies were flagged for **abnormally high volatility** based on thresholds after 60 days post-listing:

$$\sigma_t^{(w)} > 0.10, \quad t \geq 60$$

(volatility > 10% after 60 days)

$$\sigma_t^{(w)} > 0.075, \quad t \geq 60$$

(volatility > 7.5% after 60 days)

These flags identified stocks exhibiting persistent volatility beyond initial listing volatility.

4.5 Fama-French Factor Calculation

After return and volatility analysis, factor exposures were computed based on the *Fama and French (1993)* three-factor model and Carhart momentum factor. Unlike using pre-published factor returns, the factors were computed directly from the raw stock data:

$$R_i - R_f = \alpha + \beta(R_m - R_f) + s \cdot SMB + h \cdot HML + m \cdot WML + \epsilon$$

where:

- R_i: Return of stock i
- R_f: Risk-free rate
- R_m: Market return
- SMB: Small minus Big factor
- HML: High minus Low factor
- WML: Winners minus Losers (momentum factor)

Each factor was constructed by sorting companies based on market cap, book-to-market ratio, and past returns, then forming portfolio-based return spreads.

4.5.1 Construction of Fama-French Factors and Exploratory Predictive Modeling

In this study, the Fama and French (1993) three-factor model was implemented by directly calculating the factors from stock-level data obtained from the NSE via the Prowess Database, covering the period from November 7, 1994 to December 31, 2024. This approach ensured that factor returns were fully derived from the same dataset used for stock returns, maintaining consistency and market specificity.

The following steps were undertaken to construct the factors:

- **Market Capitalization (MC)** for each stock was computed as:

  $$MC_{i,t} = P_{i,t} \times Q_{i,t}$$

  where $P_{i,t}$ is the closing price and $Q_{i,t}$ is the traded quantity for stock i on day t.

- For each day, stocks were classified as **Small** or **Big** by comparing their market capitalization to the daily median market capitalization:

  $$\text{Size}_{i,t} = \begin{cases} \text{Small} & \text{if } MC_{i,t} \leq \text{Median}(MC_t) \\ \text{Big} & \text{otherwise} \end{cases}$$

- The **SMB (Small Minus Big)** factor was then calculated as the difference in average daily returns between small and big stocks:

  $$SMB_t = \overline{R}_{Small,t} - \overline{R}_{Big,t}$$

- The **Book-to-Market Ratio (BM)** for each stock was calculated as:

$$BM_{i,t} = \frac{BV_{i,t}}{MC_{i,t}}$$

where $BV_{i,t}$ is the book value of equity.

- For each day, stocks were categorized into **High B/M** and **Low B/M** portfolios based on the median daily BM_t:

$$BM\_Group_{i,t} = \begin{cases} High & \text{if } BM_{i,t} > \text{Median}(BM_t) \\ Low & \text{otherwise} \end{cases}$$

- The **HML (High Minus Low)** factor was calculated as the difference in average daily returns between high and low B/M stocks:

$$HML_t = \overline{R}_{High,t} - \overline{R}_{Low,t}$$

- The **market return** was computed daily as the average return across all stocks:

$$R_{m,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} R_{i,t}$$

where N_t is the number of stocks traded on day t.

- The **risk-free rate** was estimated daily by assuming an annual risk-free rate of 6% (referencing the Clearing Corporation of India Limited), converted to a daily rate:

$$R_{f,t} = (1 + 0.06)^{1/252} - 1$$

With these self-constructed factors, the expected return for each stock was estimated using the Fama-French three-factor model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + \epsilon_{i,t}$$

where $\beta_{i,M}$, s_i, and h_i represent sensitivities to the market, SMB, and HML factors, respectively.

While the core analysis employed **Ordinary Least Squares (OLS)** regression to estimate the model coefficients and expected returns, additional machine learning models were explored as an extension to assess if they could provide better predictive accuracy. These alternative methods were applied as a comparison to the traditional Fama-French model, but they do not follow its theoretical framework. The models tested included:

- **Random Forest Regression**
- **XGBoost Regression**
- **GridSearchCV** for hyperparameter tuning and model optimization

It is important to note that these machine learning approaches do not inherently follow the theoretical structure of the Fama-French model; rather, they were implemented as exploratory tools to assess whether alternative non-linear or ensemble methods could provide better predictions of stock returns compared to the linear factor model.

Expected daily returns for each company were estimated using both OLS and the machine learning methods, and saved into a CSV file for further analysis. A comparison plot of **expected versus actual daily returns** was generated for each company to visually assess the performance of different modeling approaches.

Factor	Correlation with Expected Return
Expected Return	1.00
Excess Market Return	0.33
SMB (Small Minus Big)	-0.19
HML (High Minus Low)	-0.28

Table 4.1: Correlation between Expected Return and Fama-French Factors

4.5.2 Summary of Operations Performed

- Daily high-low % for recent 3 years
- Daily return + price for recent 3 years
- Flag days with $|R_t| > 15\%$
- Rolling standard deviation (1d, 2d, 30d windows) recent 3 years
- Return + price after 1,2,3,7,10,15 days post-listing
- Rolling std after 1,3,5,7,15,30,45,60 days post-listing
- Volatility flagging $> 10\%$, $> 7.5\%$ after 60 days
- Rolling vol windows: 3d, 5d, 7d, 10d, 15d after 60 days

- Fama-French and Momentum factor calculations from raw data

4.6 Utilizing the Fama-French and Momentum Factors: Data Library for the Indian Market

In addition to constructing factor portfolios directly from the raw stock data, the analysis also incorporated factor data obtained from the **Fama-French and Momentum Factors: Data Library for the Indian Market by IIMA**. This external dataset provided pre-calculated factor returns for the Indian equity market, including market excess return (MKT), size premium (SMB), value premium (HML), and momentum factor (WML). Utilizing this dataset allowed for benchmarking and cross-validation of the internally constructed factors.

With these externally sourced factor returns, the Fama-French three-factor model was re-estimated, along with the Carhart four-factor extension, to calculate the expected return for each IPO-listed company. The model was specified as:

$$E[R_i] = R_f + \beta(R_m - R_f) + s \cdot SMB + h \cdot HML + m \cdot WML$$

where R_f represents the risk-free rate, and β, s, h, m denote the factor loadings estimated via time-series regression using the external factor returns. This dual approach—using both internally derived and externally sourced factor data—enabled a more robust estimation of factor exposures and expected returns, while also aligning the analysis with established academic benchmarks specific to the Indian market.

Factor	Correlation with Expected Return
Expected Return	1.00
Excess Market Return	0.46
SMB (Small Minus Big)	0.24
HML (High Minus Low)	0.26
WML (Winners Minus Losers)	0.12

Table 4.2: Correlation between Expected Return and Fama-French Factors

This completes the **Analysis** chapter summarizing and explaining all operations performed in the project.

All the Scripts and Results of the analysis can be accessed from here: https://drive.google.com/drive/folders/13PnBiJMLVok1MafZBFCzIFNwJjBM7vyV?usp=sharing

Chapter 5

Conclusion and Future Work

5.1 Conclusion and Outcome Method 1: Daily Return Volatility Analysis

In this analysis, the focus was on identifying companies exhibiting **abnormally high volatility** post-listing, using **standard deviation of daily returns** as the volatility measure. For this, we specifically looked for companies whose volatility exceeded **10%** during the **60 days** after their listing on the National Stock Exchange (NSE), using **rolling windows of 3, 5, 7, and 10 days**.

The volatility for each company was calculated using the rolling window method, which allowed us to capture short-term fluctuations in the stock's daily return over different periods. Companies that showed sustained high volatility, above the 10% threshold, were flagged as suspected for further investigation.

The outcome of this analysis identified a list of **suspected companies**, indicating that their stock prices exhibited highly volatile behavior post-listing. This could suggest either speculative trading, market inefficiencies, or other factors influencing the stock price in an unstable manner. The identified companies are as follows:

1. ADANI WILMAR LTD.
2. DEV INFORMATION TECHNOLOGY LTD.
3. GLAND PHARMA LTD.
4. TEAMLEASE SERVICES LTD.

5. MITCON CONSULTANCY & ENGG. SERVICES LTD.
6. NAZARA TECHNOLOGIES LTD.
7. R K SWAMY LTD.
8. SHRI RAM SWITCHGEARS LTD.
9. TRANSWIND INFRASTRUCTURES LTD.
10. ZODIAC ENERGY LTD.
11. RAIL VIKAS NIGAM LTD.
12. ECOS (INDIA) MOBILITY & HOSPITALITY LTD.
13. ONE 97 COMMUNICATIONS LTD.
14. BARBEQUE-NATION HOSPITALITY LTD.
15. AURANGABAD DISTILLERY LTD.
16. A U SMALL FINANCE BANK LTD.
17. JANA SMALL FINANCE BANK LTD.
18. P B FINTECH LTD.
19. ZOMATO LTD.
20. OLA ELECTRIC MOBILITY LTD.
21. ELECTRONICS MART INDIA LTD.
22. BRAND CONCEPTS LTD.
23. MOKSH ORNAMENTS LTD.
24. LATENT VIEW ANALYTICS LTD.
25. SUPRIYA LIFESCIENCE LTD.
26. A M I ORGANICS LTD.
27. GLOBE INTERNATIONAL CARRIERS LTD.
28. NANDANI CREATION LTD.
29. ART NIRMAN LTD.
30. ICE MAKE REFRIGERATION LTD.

31. JET FREIGHT LOGISTICS LTD.
32. IDEAFORGE TECHNOLOGY LTD.
33. UJJIVAN SMALL FINANCE BANK LTD.
34. ACCORD SYNERGY LTD.
35. MADHYA PRADESH TODAY MEDIA LTD.
36. RELIABLE DATA SERVICES LTD.
37. SILLY MONKS ENTERTAINMENT LTD.
38. ANI INTEGRATED SERVICES LTD.
39. MINDPOOL TECHNOLOGIES LTD.
40. LE TRAVENUES TECHNOLOGY LTD.
41. TARA CHAND INFRALOGISTIC SOLUTIONS LTD.

Table 5.1: Maximum Volatility of Suspected Companies over the Different Rolling Windows

Code	Company Name	Max Vol (3-day)	Max Vol (5-day)
5709	ADANI WILMAR LTD.	0.123 290 038	0.111 499 525
58843	DEV INFORMATION TECHNOLOGY LTD.	0.142 407 621	0.110 516 184
82107	GLAND PHARMA LTD.	0.091 125 357	0.066 875 537
98501	TEAMLEASE SERVICES LTD.	0.096 620 638	0.069 872 326
146980	MITCON CONSULTANCY & ENGG. SERVICES LTD.	0.140 817 965	0.102 781 503
156763	NAZARA TECHNOLOGIES LTD.	0.111 832 345	0.079 869 825
186645	R K SWAMY LTD.	0.123 565 596	0.091 873 069
224917	SHRI RAM SWITCHGEARS LTD.	0.149 733 114	0.113 637 470
253095	TRANSWIND INFRASTRUCTURES LTD.	0.144 315 456	0.103 761 193
275567	ZODIAC ENERGY LTD.	0.110 904 348	0.083 172 826
329799	RAIL VIKAS NIGAM LTD.	0.089 364 541	0.106 964 811
358481	ECOS (INDIA) MOBILITY & HOSPITALITY LTD.	0.158 237 680	0.112 491 684
368872	ONE 97 COMMUNICATIONS LTD.	0.157 195 280	0.113 868 694
375044	BARBEQUE-NATION HOSPITALITY LTD.	0.127 259 752	0.109 442 545
380323	AURANGABAD DISTILLERY LTD.	0.108 317 433	0.121 318 798
380713	A U SMALL FINANCE BANK LTD.	0.137 225 962	0.098 761 378

Code	Company Name	Max Vol (3-day)	Max Vol (5-day)
397686	JANA SMALL FINANCE BANK LTD.	0.093 839 642	0.068 784 748
402730	P B FINTECH LTD.	0.104 090 655	0.088 554 047
412105	ZOMATO LTD.	0.089 270 223	0.079 348 639
415517	BRAND CONCEPTS LTD.	0.152 467 435	0.133 086 812
459845	MOKSH ORNAMENTS LTD.	0.132 429 414	0.112 461 024
478127	LATENT VIEW ANALYTICS LTD.	0.145 302 637	0.126 038 872
497496	TARA CHAND INFRALOGISTIC SOLUTIONS LTD.	0.093 617 696	0.074 231 502
499291	SUPRIYA LIFESCIENCE LTD.	0.125 103 725	0.101 514 274
528025	A M I ORGANICS LTD.	0.132 560 618	0.109 188 705
533881	GLOBE INTERNATIONAL CARRIERS LTD.	0.142 418 134	0.103 887 291
547344	NANDANI CREATION LTD.	0.119 709 997	0.121 657 385
547454	ART NIRMAN LTD.	0.181 731 170	0.133 080 776
549540	ICE MAKE REFRIGERATION LTD.	0.115 893 174	0.110 190 221
550858	JET FREIGHT LOGISTICS LTD.	0.119 406 089	0.099 842 511
552508	IDEAFORGE TECHNOLOGY LTD.	0.097 548 563	0.071 035 618
555551	UJJIVAN SMALL FINANCE BANK LTD.	0.098 243 805	0.071 161 730
565063	ACCORD SYNERGY LTD.	0.181 552 693	0.133 508 828
571292	MADHYA PRADESH TODAY MEDIA LTD.	0.144 197 029	0.114 791 309
571694	RELIABLE DATA SERVICES LTD.	0.159 877 618	0.138 037 123
571695	SILLY MONKS ENTERTAINMENT LTD.	0.091 493 635	0.088 051 832
575190	ANI INTEGRATED SERVICES LTD.	0.115 785 954	0.122 683 636
585974	MINDPOOL TECHNOLOGIES LTD.	0.207 872 117	0.172 717 489
590793	OLA ELECTRIC MOBILITY LTD.	0.130 441 584	0.109 834 037
606183	LE TRAVENUES TECHNOLOGY LTD.	0.104 000 349	0.076 651 720
611996	ELECTRONICS MART INDIA LTD.	0.105 048 996	0.088 583 294

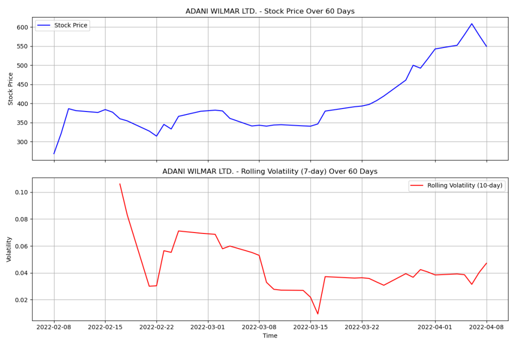

Figure 5.1: Adani Wilmar Ltd

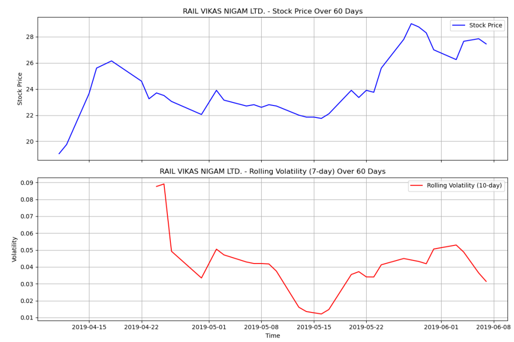

Figure 5.2: Rail Vikas Nigam Ltd

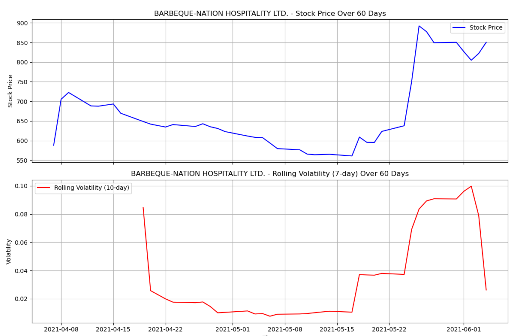

Figure 5.3: Barbeque Nation

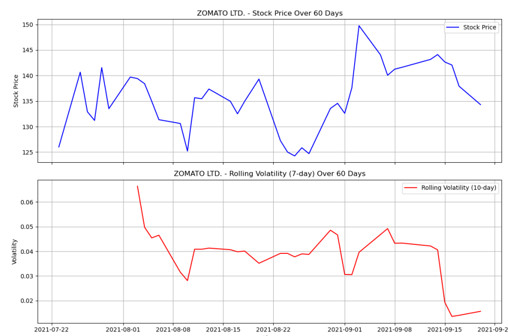

Figure 5.4: Zomato Ltd

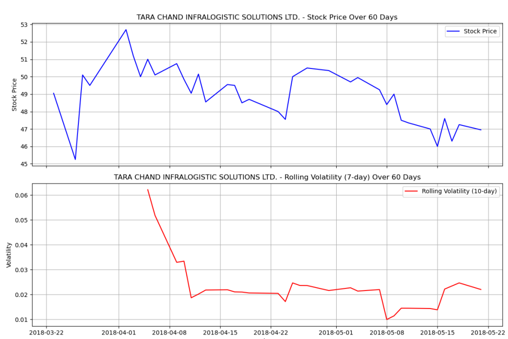

Figure 5.5: Tara chand Infralogistics

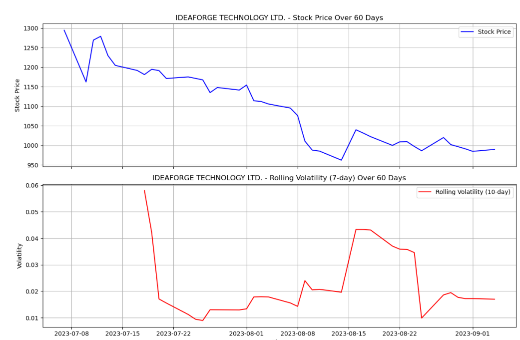

Figure 5.6: Ideaforge Technology

These companies were marked for further research and analysis to determine if the high volatility was due to market inefficiencies or if it signaled any underlying issues such as speculative trading, manipulation, or other factors that may require regulatory scrutiny.

The **volatility plots** for these companies were created, showing how their daily stock price fluctuated over time, especially post-listing. Additionally, the comparison between the four rolling windows (3, 5, 7, and 10 days) helped assess how volatility was distributed across these different time horizons.

5.2 Conclusion and Outcome Method 2: Fama-French Model with Self-Calculated Factors

In this method, the Fama-French three-factor model was applied using factors (Excess Market Return, SMB, HML) calculated directly from NSE daily stock trading data between 1994 and 2024. The factors were computed based on daily market capitalisation, book-to-market ratios, and stock returns, ensuring they were focused on the Indian market. The expected returns were then estimated using Ordinary Least Squares (OLS) regression.

However, the correlation analysis between the expected return and the Fama-French factors revealed weak relationships:

- Excess Market Return: +0.33
- SMB: –0.19
- HML: –0.28

These low correlations indicate that the factors do not strongly explain the variation in expected returns for the companies in the dataset. This suggests that the classic Fama-French model, while theoretically valid, exhibits **limited predictive power in the Indian market context** with self-calculated factors.

Overall, while the model framework was successfully implemented, the weak explanatory power of the factors limits its practical use for accurately estimating expected returns in this setting. This finding highlights the need to explore additional factors (such as momentum) or alternative models better suited for emerging markets.

5.3 Conclusion and Outcome Method 3: Fama-French Model with Available Data from IIM Ahmedabad

In the third method, the Fama-French three-factor model was applied using publicly available data from the Fama-French and Momentum Factors: Data Library for the Indian market by IIMA - Indian Institute of Management Ahmedabad. The four primary factors—Excess Market Return, SMB, HML and WML were obtained directly from the external dataset, ensuring they represent better market dynamics.

The expected return for each company was calculated using **Ordinary Least Squares (OLS) Regression**.

Upon performing a correlation analysis between the expected return and the factors, it was observed that the relationships were stronger than those in the previous method (self-calculated factors). Specifically, the correlation coefficients were:

- Excess Market Return: 0.46
- SMB (Small Minus Big): 0.24
- HML (High Minus Low): 0.26
- WML (Winners Minus Losers): 0.12

While these correlations suggest a better fit compared to the self-calculated factors, they still remain relatively weak, indicating that the chosen factors do not fully capture the variability in expected returns for the Indian market. The market returns, SMB, HML and WML factors show limited predictive power in explaining the stock price movements, which might be due to the unique characteristics of the Indian stock market or the selected time frame.

Furthermore, to identify companies with potential anomalies in returns, abnormal returns were flagged based on their residuals. Residuals were calculated by subtracting the expected returns from the actual returns for each company. A Z-score was then computed for each residual to identify outliers. If the absolute value of the Z-score exceeded a threshold of 7, the company was flagged as exhibiting abnormal returns. This approach helped in marking companies with unusually high or low deviations from their expected returns, indicating potential market irregularities or further analysis needs.

The Z-score for each residual was calculated using the following formula:

$$Z_i = \frac{(\text{Residual}_i - \mu_{\text{Residual}_i})}{\sigma_{\text{Residual}_i}}$$

Where:

- Residual_i is the difference between the actual return and the expected return for company i,
- μ_{Residual_i} is the mean of residuals for company i,
- $\sigma_{\text{Residual}_i}$ is the standard deviation of residuals for company i.

Companies with an absolute Z-score greater than 7 were flagged as having abnormal returns, indicating possible irregularities in their stock price movements.

The following companies were identified as having abnormal returns:

1. MUSIC BROADCAST LTD.
2. PRINCE PIPES & FITTINGS LTD.
3. HAPPIEST MINDS TECHNOLOGIES LTD.
4. MATRIMONY.COM LTD.
5. EQUITAS SMALL FINANCE BANK LTD.
6. L & T TECHNOLOGY SERVICES LTD.
7. ZOTA HEALTH CARE LTD.
8. SURYODAY SMALL FINANCE BANK LTD.
9. A M I ORGANICS LTD.
10. DODLA DAIRY LTD.
11. RAIL VIKAS NIGAM LTD.
12. LATENT VIEW ANALYTICS LTD.
13. M A S FINANCIAL SERVICES LTD.
14. GODREJ AGROVET LTD.
15. AMBER ENTERPRISES INDIA LTD.

16. CHEMCON SPECIALITY CHEMICALS LTD.
17. FIVE-STAR BUSINESS FINANCE LTD.
18. HERANBA INDUSTRIES LTD.
19. T C N S CLOTHING CO. LTD. [MERGED]
20. MEDPLUS HEALTH SERVICES LTD.
21. TAMILNAD MERCANTILE BANK LTD.
22. INDIA PESTICIDES LTD.
23. COCHIN SHIPYARD LTD.
24. HOUSING & URBAN DEVP. CORPN. LTD.
25. VENUS PIPES & TUBES LTD.
26. POLYCAB INDIA LTD.
27. I R M ENERGY LTD.
28. CAMPUS ACTIVEWEAR LTD.
29. CENTRAL DEPOSITORY SERVICES (INDIA) LTD.
30. FUSION MICRO FINANCE LTD.
31. KAPSTON SERVICES LTD.
32. EXXARO TILES LTD.
33. C M S INFO SYSTEMS LTD.
34. MAHANAGAR GAS LTD.
35. EMKAY TAPS & CUTTING TOOLS LTD.
36. YES BANK LTD.
37. INFIBEAM AVENUES LTD.
38. BANDHAN BANK LTD.
39. EQUITAS HOLDINGS LTD. [MERGED]
40. I I F L FINANCE LTD.
41. ENDURANCE TECHNOLOGIES LTD.

42. GENERAL INSURANCE CORPN. OF INDIA
43. MISHRA DHATU NIGAM LTD.
44. UJJIVAN SMALL FINANCE BANK LTD.
45. LAURUS LABS LTD.
46. HINDUSTAN AERONAUTICS LTD.
47. FINE ORGANIC INDS. LTD.
48. ADVANCED ENZYME TECHNOLOGIES LTD.
49. THYROCARE TECHNOLOGIES LTD.
50. SHRENIK LTD.
51. P N B HOUSING FINANCE LTD.
52. PARAS DEFENCE & SPACE TECHNOLOGIES LTD.
53. METRO BRANDS LTD.
54. G N A AXLES LTD.
55. SIRCA PAINTS INDIA LTD.
56. I R B INVIT FUND
57. I C I C I PRUDENTIAL LIFE INSURANCE CO. LTD.
58. SINTERCOM INDIA LTD.
59. S B I CARDS & PAYMENT SERVICES LTD.
60. BOHRA INDUSTRIES LTD.

In conclusion, although the use of external Fama-French data represents an improvement over the self-calculated factors, the predictive accuracy remains suboptimal. This highlights the limitations of the Fama-French three-factor model in the Indian market, where other factors, such as liquidity, profitability, or market-specific risk factors, might play a more significant role in determining expected returns. Additionally, flagging abnormal returns using residual analysis provided valuable insights into potential outliers for further investigation.

5.4 Common Companies Identified in Both Analyses

After performing both the volatility-based analysis and the Fama-French model analysis, four companies were identified as common in both categories, indicating that they exhibited both high volatility and abnormal returns. These companies are:

1. A M I ORGANICS LTD.
2. RAIL VIKAS NIGAM LTD.
3. LATENT VIEW ANALYTICS LTD.
4. UJJIVAN SMALL FINANCE BANK LTD.

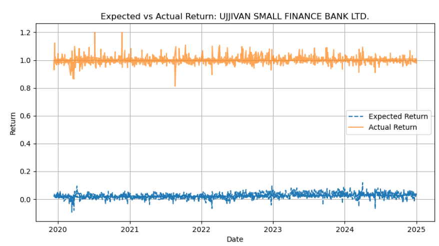

Figure 5.7: Ujjivan Finance

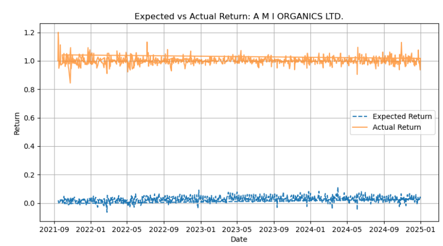

Figure 5.8: AMI Organics

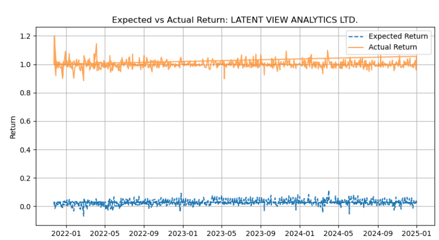

Figure 5.9: Latent View Analytics

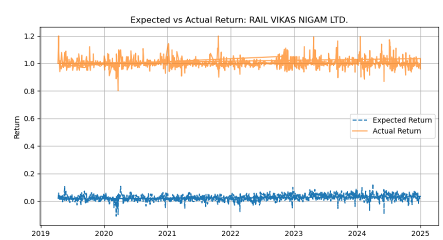

Figure 5.10: Rail Vikas Nigam

These companies were marked for further research and analysis to determine if the high volatility was due to market inefficiencies or if it signaled any underlying issues such as speculative trading, manipulation, or other factors that may require regulatory scrutiny.

These companies were flagged in the **volatility-based** analysis for having daily return volatility exceeding 10% during the first 60 days after their listing on the NSE, using rolling windows of 3, 5, 7, and 10 days. Additionally, in the **Fama-French model analysis**, their actual returns were found to deviate significantly from the expected returns, with Z-scores indicating abnormal returns.

The identification of these companies in both analyses suggests that they may exhibit characteristics of higher risk or market instability. The overlapping results from both methods highlight the potential for further investigation into their market behavior and financial performance.

5.5 Conclusion and Future Work

5.5.1 Conclusion

The study employed a multi-method approach—combining volatility analysis and the Fama-French three-factor model (with both self-calculated and external factors)—to identify companies exhibiting unusual market behavior during the post-listing period on the NSE.

From the volatility-based analysis, several companies demonstrated daily return volatilities exceeding 10% within the first 60 days of listing, signaling heightened price fluctuations. Separately, the Fama-French model (using both internally computed and IIM Ahmedabad-provided factors) identified multiple companies whose actual returns deviated significantly from expected returns, as indicated by residual Z-scores exceeding ± 7, flagging them for abnormal return behavior.

Crucially, four companies AMI Organics Ltd., Rail Vikas Nigam Ltd., Latent View Analytics Ltd., and Ujjivan Small Finance Bank Ltd.—emerged as common outliers in both analyses. These companies not only exhibited high short-term volatility but also produced abnormal returns relative to market expectations, suggesting possible market inefficiencies, speculative activity, or other irregularities.

This overlap reinforces the need for targeted regulatory scrutiny and deeper financial investigation into these firms, particularly regarding trading behaviour and post-listing dynamics. Moreover, the limited explanatory power of the Fama-French factors in this Indian market context points toward the necessity of incorporating additional factors—such as momentum, liquidity, or profitability metrics—for more accurate modeling of stock returns in emerging markets.

5.5.2 Future Work

Future research can enhance this analysis through several key directions:

1. **Incorporating Time-Varying Market Factors:** Rather than using single market factors, we can group companies by month and obtain corresponding monthly market risk-free rates from Treasury bills and regulatory sources. Applying the Fama-French model with more precise factors may improve the accuracy and explanatory power of abnormal return estimates.

2. **Focusing on the Initial Post-Listing Period:** Over time, stock prices tend to stabilize unless influenced by significant financial or regulatory events such as government budgets or policy changes. Therefore, emphasizing the analysis on the early post-listing days when price volatility and information asymmetry are highest may yield more meaningful insights into market anomalies.

3. **Segregating IPOs from the Broader Market:** Currently, the dataset includes all companies listed on the NSE. Future work should explicitly isolate IPO stocks from the broader pool to focus the analysis on firms newly entering the market, as their return dynamics differ substantially from mature firms.

4. **IPO-Specific Factor Data Collection:** Standard Fama-French factors are typically derived from the entire stock universe and may not directly reflect conditions specific to IPOs. Therefore, a key challenge and opportunity lies in constructing or estimating factor values tailored for IPO firms, which may require additional data collection.

5. **Toward Conclusive Identification of Anomalies:** By systematically integrating a broader set of market-influencing factors including market variables, regulatory events, and firm-specific news future analyses may progress from identifying statistical anomalies to establishing stronger causal links. This could enable more conclusive identification of companies exhibiting abnormal or suspicious price behaviour during critical periods.

Additionally, applying other techniques such as event studies or machine learning-based anomaly detection could further uncover subtle or nonlinear patterns in IPO return dynamics. Qualitative investigations, including the review of regulatory filings or contemporaneous news reports, may complement quantitative models by providing contextual validation of abnormal return signals.

Chapter 6

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