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Investor Demand Through Oversubscription: A Quantile Regression and Machine Learning Evidence from Emerging Market

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Abstract

This study investigates the oversubscription in public issues of Small and Medium Enterprises in India, across different quantiles. This study further explores the non-linearity in factors through machine learning. Utilising data from 1014 IPOs during the period 2012 to 2024 listed on SME exchanges of NSE and BSE, this study applies OLS regression, quantile regression and a Random Forest model. SHapley Additive exPlanations values are computed to validate and extend econometric findings. Underpricing, listing delay and hot markets are the prominent factors affecting oversubscription. The Random Forest model outperforms OLS, revealing non-linear effects of predictors. This study offers crucial insights enabling policymakers and regulators to refine disclosure regulations and strengthening investor protection measures, while firms can efficiently structure their offerings and attract significant investor interest.

Keywords: IPO oversubscription; underpricing; quantile regression; machine learning; signalling theory

1. Introduction

The ninth goal of the 2030 Agenda set by the United Nations focuses on developing robust infrastructure, encouraging inclusivity and sustainable industrial growth, and fostering innovation. An estimated US \$5.7 trillion financial shortfall exists in emerging economies regarding access to finance ([International Finance Corporation & World Bank, 2025](#)). Growing firms require adequate funds to project their expansion prospects ([Nlemvo & Bouslama, 2025](#)). Conventionally, small businesses have relied on debt finance for operations, often linked with a high risk of lending ([Dore et al., 2024](#); [Mahmud & Akin, 2019](#); [Moyi, 2019](#)). Public grants help smaller units achieve financial sustainability and survive in times of crisis ([Boccaletti et al., 2025](#)).

In emerging economies like India, Small and Medium Enterprises (SMEs) serve a crucial role in employment and economic development. However, persistent challenges exist in the sector, including bankruptcy, complex loan processes, high interest rates, limited market competitiveness, and irregular loan repayments ([Athaide & Pradhan, 2020](#)). NSE and BSE Stock exchanges cater to growth-oriented SMEs, offer flexible listing requirements, and drive innovation and equitable access to capital markets ([L. Gupta & Anand, 2020](#); [Verma et al., 2021](#)). Small companies can get listed through the IPO route ([Darmadi & Gunawan, 2013](#); [Tripathi et al., 2017](#)). [Vong \(2006\)](#) stated that the market reaction towards



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IPO is first captured through its subscription rate. According to [Kaur and Singh \(2019\)](#), large firms that float IPOs on stock exchanges are well-known and recognisable to naïve investors. Such investors view the firm size as an indicator of strength. Consequently, these entities enjoy economic advantages by functioning on a broader scale ([Ghalke et al., 2022](#); [V. Gupta et al., 2020](#); [Sandhu & Guhathakurta, 2020](#); [Sahoo, 2017](#)).

Prior studies have studied the aftermarket performance of IPOs globally ([Alsabah, 2025](#); [Aghamolla & Thakor, 2022](#); [Albada et al., 2025a](#); [Albada et al., 2025b](#); [Agrawal, 2024](#); [Ahmed et al., 2024](#); [Deng & Liu, 2024](#); [Joo & Lee, 2022](#); [Kim & Shin, 2024](#); [Ong et al., 2025](#); [Ong et al., 2020](#); [Peng et al., 2022](#); [Suresha et al., 2023](#); [M. Zhang & Du, 2025](#)). [Chatterjee et al. \(2024\)](#) found though a bibliometric analysis of Indian IPO research from 2002 to 2021 that the majority of research has focused on post-IPO performance.

Although substantial evidence is available on large IPOs, much less is known about the drivers of investor demand for SME IPOs ([Joshi et al., 2023](#)). It is essential to address this gap, considering that SME exchanges in India have grown vastly since their inception in 2012. Figure 1 shows the trend of IPOs on SME platforms during the period 2012 to 2024, revealing a positive outlook for the Indian capital market as it validates investors' interest in small-sized entities. It reflects CEO confidence in choosing to go public rather than relying on debt financing ([Boccaletti et al., 2025](#)). The issues are predominantly focussed on attracting retail investors to fund the SMEs, which is supported by the strong regulatory framework of the Securities Exchange Board of India (SEBI). Given the relaxed listing environment on SME exchanges due to their size, the factors that influence demand for SME securities differ from those affecting mainboard companies. This study addresses the gap by examining drivers of investor demand for SME IPOs in India. It also explores possible non-linear relationships between variables using machine learning methods like Random Forest (RF) and Shapley, which traditional regression models do not reveal. This study is rooted in signalling theory ([Spence, 1973](#)), the winner's curse hypothesis ([Rock, 1986](#)), and hot market theory ([Ritter, 1984](#)), which collectively explain the proposed relationships between the variables and IPO oversubscription. The research adds to the limited literature on oversubscription in small firm IPOs. The findings are crucial for small-business CEOs planning to go public, as they can help align their strategies for better resource allocation and a smoother capital-raising process. For policymakers, the results offer new insights into the changing dynamics of India's capital markets. The rest of this paper is organised as follows: Section 2 reviews the existing literature on IPOs and develops the hypotheses, Section 3 explains the data and research methods, Section 4 presents the empirical results, and Section 5 discusses the key findings; Section 6 explains the implications, and Section 7 draws conclusions.

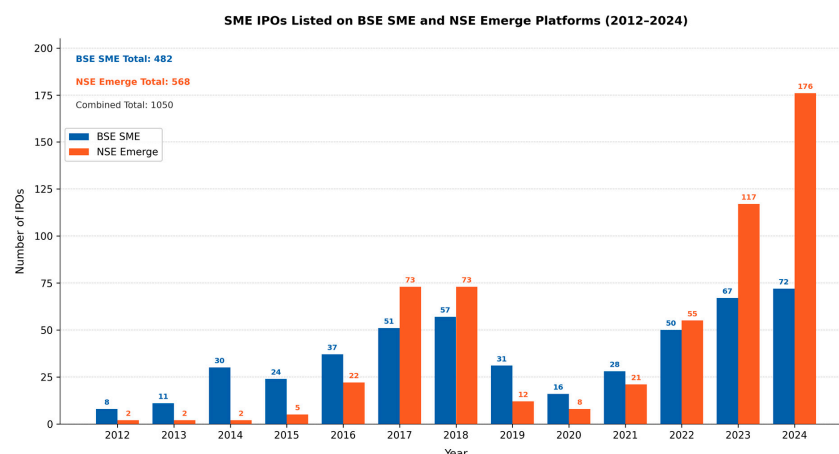


Figure 1. SME IPOs listed on BSE SME and NSE Emerge platforms, 2012–2024. Source(s): Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) official records.

2. Literature Review and Hypotheses Development

2.1. IPO Subscription: Theoretical Framework

A widely popular theory in IPO studies is the signalling theory put forth by [Spence \(1973\)](#). Signalling theory posits that one party communicates non-observable qualities to the other party ([Connelly et al., 2011](#); [Yang et al., 2025](#)). Investor decisions largely depend on such signals ([Arora & Singh, 2020](#)). Well-informed investors make rational choices, subscribing to good-quality IPOs, leading to high oversubscription ([Rock, 1986](#)). Conversely, the uninformed investors, lacking sufficient knowledge, follow the herding behaviour ([Welch, 1989](#)). Firms with strong financial indicators expect a higher subscription ([Vong, 2006](#)). Information asymmetry is the central condition underlying these theoretical frameworks, where oversubscription serves as a signal of perceived value.

Oversubscription ratio (OSR) is an ex ante proxy for investor confidence and demand ([Mehmood et al., 2020](#); [Low & Yong, 2011](#); [Rahim et al., 2013](#)). Retail subscription rates are robust predictors of IPO aftermarket volatility compared to institutional subscription rates ([Sahoo, 2015](#)). Turning to empirical evidence, [Mehmood et al. \(2025\)](#) investigate the influence of institution frameworks at the country level, finding that institutional quality and regulatory transparency positively affect IPO returns by increasing investor confidence and market efficiency. [Ong et al. \(2023\)](#) reveal a positive correlation between disclosed earnings forecasts and oversubscription, suggesting that detailed earnings forecasts increase investor confidence and interest, leading to higher demand for IPO shares.

Conversely, [Liu et al. \(2022\)](#) highlighted geographic disparities in Chinese IPO subscriptions, confirming that firms in remote areas saw lower retail investor subscriptions, emphasising location as a prominent factor in China's IPO market. [Karki et al. \(2024\)](#) examined the role of firm-specific factors and perceptions of oversubscription influence IPO investment decisions in Nepal, finding that corporate profile, financial position, and short-term returns significantly affect investment choices, with market rumours and sector performance also playing roles. [Kim and Shin \(2024\)](#) found evidence towards sector-specific factors, such as issue size and disparities in the KOSDAQ index, to be the key factors influencing institutional investors' participation in book-building IPOs in South Korea, whereas company-specific fundamentals such as financial data and prospectus details were found to be less influential in shaping investor behaviour.

In India, large syndicates reduce underpricing, increase subscription rates, improve liquidity, and reduce volatility, thereby creating value for issuers in the Indian market ([Sahoo & Sahoo, 2022](#)). [Priyesh and Jijo \(2024\)](#) found no impact of pre-IPO earnings management on institutional investor demand. [Shetty et al. \(2023\)](#) provide evidence that speculative indicators like Grey Market Premium, IPO ratings, and broker recommendations are related to subscription rates, often outweighing fundamental IPO attributes. [Wadhwa and Sahoo \(2024\)](#) discovered a positive influence of structural capital efficiency on investor demand and found that human capital productivity negatively affects it, owing to the possibility in difficulties assessing young firms' human resources. The Islamic stock market segment in Indonesia reveals that investor enthusiasm is influenced by company size, offer price, market conditions, firm-specific characteristics and adherence to Islamic compliance principles ([Rasyad et al., 2022](#)). Similar results are obtained by [Tajuddin et al. \(2018\)](#), finding a positive association between Shariah-compliant status on subscription of IPOs on Bursa Malaysia.

According to [Albada et al. \(2019\)](#), IPOs with reputed underwriters have lower OSR than those with non-reputable underwriters. [Geertsema and Lu \(2016\)](#) found the correlational behaviour of underpricing and OSR in Chinese IPOs to be due to strategic investor behaviour and regulatory constraints. [Li et al. \(2016\)](#) reveal through logistic regression that demographics factors such as age and education, market conditions, and cognitive biases all shape investment decisions, challenging the assumption that subscriptions are

purely irrational. Larger firm size, smaller offer sizes, investor sentiment, perceived firm quality and bullish market sentiment contribute to higher oversubscription rates (Low & Yong, 2011). McGuinness (2009) reveal significant differences between dual-tranche and single-tranche IPOs, where retail subscription rates, market conditions, and issuer characteristics all influence returns and subscription demand. Kaustia and Knüpfer (2008) found a strong positive correlation between investors' personally experienced past IPO returns and their future IPO subscription decisions in Finland during 1995 to 2000. Fung et al. (2004) investigated the opportunity cost of subscriptions that affect IPO returns in Asia, showcasing that subscription costs significantly reduce real IPO returns in oversubscribed offerings and during high-interest-rate periods.

2.1.1. Underwriter Reputation

Lead managers collaborate with companies throughout the issue process. They offer advice on how to organise the offering, plan its marketing to potential investors, and help establish the issue's offer price (Bubna & Prabhala, 2011). Albada et al. (2019) examined how prestige signalling like underwriter reputation predicts the subscription levels of Malaysian IPOs, finding that underwriter reputation was negatively associated with subscription levels, signifying that reputed firms suffer if the costs of the public issue are high. Smaller companies often face challenges in attracting general investors for capital market fundraising, which makes the success of their IPOs uncertain. Consequently, these companies seek out reputable underwriters to manage the offering. As stated by Rock (1986), underwriters depend on information inaccessible to the general public to set the issue price as less than its real value to warrant greater subscription to the IPO. Investors consider this as an indicator of risk and are willing to invest in IPOs supported by prominent lead managers (Shaw & Michaely, 1994). Ritter (1984) states that stocks issued to uninformed investors have a higher likelihood of being traded at a lower price. The prestige of underwriters' signals issuer confidence in the IPO. It reduces information asymmetry and regulates earnings management practices (Azevedo et al., 2018). Hence, the first hypothesis is stated as follows:

H1. *IPOs backed by reputed underwriters attract greater oversubscription.*

2.1.2. Hot Market Conditions

Prevailing market conditions at the time of going public is crucial in the success of an IPO. A hot market is a period when a large number of IPOs are available for listing, compared to other times. This type of market is perceived as volatile, and investors perceive it as favourable, due to numerous investment choices (Loughran & Ritter, 2004). Early movers opt for such time periods to capitalise on high investor optimism (Ahmad-Zaluki & Kect, 2012; Ljungqvist et al., 2006; Treßel, 2025). Low and Yong (2011) state that an increase in IPO volume correlates with a greater likelihood of lower-quality firms, which may decrease investors' interest in the IPO. Therefore, it is proposed that

H2. *IPOs listed during hot market periods exhibit significantly higher oversubscription.*

2.1.3. Underpricing

Underpricing is related to "Winner's Curse" (Loughran & Ritter, 2004), which refers to the returns from an IPO on its first trading day. Individual investors lack access to market information available to institutional investors. As a result, well-informed investors can purchase shares at lower prices, whereas less informed investors are at a disadvantage (Rock, 1986). Welch (1989) argued that high-value firms intentionally underprice their shares and aim to recover initial losses through higher prices in later market offerings.

Only firms with a good reputation are able to recover their losses in the future and signal to investors as a proxy of the firm's reputation (Arora & Singh, 2020). Recent research has found that information asymmetry is a major contributor to oversubscription (Liu et al., 2022; Wadhwa & Sahoo, 2024). Udasi et al. (2021) found that smaller companies are more likely to underprice because there is less publicly available information. When small businesses go public, they often lack a strong corporate image to attract investors. Subscribers lack access to Key Performance Indicators (KPIs) necessary for due diligence. Lead managers typically set the offer price of an IPO low in order to attract investors and avoid a failed offering. Cornelli and Goldreich (2003) show that oversubscribed IPOs tend to deliver higher listing returns, which can be attributed to underwriters not fully adjusting the issue price to meet investor demand. IPOs that attract high demand are often more underpriced, while those with lower demand are generally considered overpriced (Bansal & Khanna, 2013). Suresha et al. (2023) found contrasting evidence, stating that underpricing is more prevalent in moderate to large issue sizes, with returns increasing in a linear pattern, suggesting that investors tend to be over-optimistic about larger IPOs. Drawing on signalling theory (Spence, 1973), this study treats the positive association between the two variables as a unidirectional causal relationship.

H3. *Highly underpriced IPOs are linked with larger oversubscription.*

2.1.4. Issue Type

Setting a fair IPO offer price can become especially difficult because it requires striking a balance between appropriately representing the issuers' worth and meeting the expectations of investors, as found by Colak et al. (2025). Fixed-price mechanisms produce a high volume of information asymmetry owing to their autocratic nature (Albada, 2024). Cornelli and Goldreich (2003) maintain that after collecting bids from investors, lead managers construct a demand curve and set the issue price below the aggregate market price. In book-building mechanisms, investors have the opportunity to assess a reasonable value for the IPO (Dhamija & Arora, 2017a).

However, book-building IPOs can be expensive as a result of associated expenses. Hence, smaller companies frequently choose fixed-price offerings (Albada et al., 2023; Kao et al., 2022). Mehmood et al. (2020) explored effect of pricing mechanisms on subscription levels of IPOs in Pakistan and disclosed a negative relationship, indicating that type of pricing can lessen investor interest in the IPO. As such, the fourth hypothesis is stated as follows:

H4. *Book-building IPOs attract higher oversubscription as compared to fixed-price IPOs.*

2.1.5. Offer Price

The offer price is based on the estimated intrinsic value of the firm. Rasyad et al. (2022) investigated IPOs in Indonesia's Sharia Stock Index, specifically finding that offer price has a negative impact on oversubscription levels. Low and Yong (2011) investigated the relationship between subscription rates and pre-listing information for IPOs in Malaysia, finding a negative correlation between offer price and oversubscription. A higher price may deter investors from bidding.

H5. *Lower offer price is positively associated with oversubscription.*

2.1.6. Issue Size

A smaller issue size prompts investors to subscribe at the earliest, driven by the fear of missing out on a promising investment opportunity. A significant float of shares can

lead to a negative investor sentiment (Dhamija & Arora, 2017b). In contrast, the limited availability of stocks in an issue drives the investor demand toward a high subscription response (Low & Yong, 2011). This expectation is formulated into a hypothesis as follows:

H6. *Small issue size is correlated to an increase in oversubscription.*

2.1.7. Listing Delay

Investors view a significant gap between the issue close and the listing day as a signal of distress. Prolonged delays prompt investors to reassess their investment choices. Due diligence may further reveal information not available at the time of issue (Low & Yong, 2011). The uncertainty associated with listing delays considers the duration from the day an IPO is filed to the day it is listed as an indicator of potential information leaks following the establishment of the offer price (Chowdhry & Sherman, 1996). Thus, investors participating in the IPO face additional risks and anticipate higher initial returns as compensation.

H7. *Listing delay has a negative relationship with oversubscription.*

2.2. Machine Learning in IPO Research

Machine learning (ML) techniques such as Random Forest (RF) models can identify complex non-linear relationships and interaction effects that traditional Ordinary Least Squares (OLS) often miss (Supsermpol et al., 2025). Previous studies have investigated underpricing of IPOs using machine learning algorithms; little is known about IPO oversubscription. The ability to explain machine learning models is based on SHapley Additive exPlanations (SHAP) analysis, which has been widely used in previous research (Cha et al., 2026; García-Céspedes et al., 2025; Gu et al., 2020; J. Zhang et al., 2026). The machine learning component acts as a robustness check to verify if the SHAP importance rankings correspond with the OLS significance hierarchy.

3. Data and Research Methodology

3.1. Sample and Data

This study uses cross-sectional data collected from 1014 SME IPOs listed on NSE Emerge and BSE SME exchange collected from the period July 2012 to December 2024. The study period is chosen to reflect a full market cycle in India's IPO landscape, capturing the post-pandemic surge in retail investor participation and record issuance in the period of 2023 and 2024. IPO-related information is obtained from the prospectus of issuing firms. Oversubscription rates are sourced from the Capitaline database, and the closing prices of each stock are manually extracted from the official website of NSE and BSE.

3.2. Measurement of Variables

The main variable studied is the oversubscription ratio, which is the number of shares applied for divided by the number of shares offered. Offer price is measured in Indian rupees (INR) at the time of listing. Issue Type captures the pricing mechanism that takes the value of 1 for fixed price and 0 for book building. Listing delay is the difference between issue close and listing date. Following Ritter (1984), a year is classified as a hot market when annual IPO volume exceeds the full-sample mean of 78 listings. The hot markets variable is treated as dichotomous, taking the value 1 in years where the number of IPOs issued exceeds the average number of issues in the entire period. To confirm robustness, two alternative definitions are tested using the annual median (47 IPOs) and top tercile threshold (103 IPOs), respectively, and reported in Appendix A. Underpricing is treated as a proxy for the pricing discount at the time of subscription, consistent with Arora and Singh (2020), and is calculated as the percentage change between the offer price

and closing price on the first day of trading. Underwriter reputation takes value 1 where issue is managed by a prestigious underwriter and 0 otherwise. Issue size is measured as the natural logarithm of the total value of shares offered in INR. Table 1 provides formal definitions of the variables.

Table 1. Variable definitions.

Variable	Meaning	Definition	References
OSR	Oversubscription	Natural logarithm of times an IPO is subscribed	(Das et al., 2023)
OP	Offer Price	Price at which stocks are offered to the public during the IPO	(Arora & Singh, 2023)
IS	Issue Size	Natural logarithm of the total volume of funds raised	(Suresha et al., 2023)
LD	Listing Delay	Number of days between closing of issue and listing on exchange	(Arora & Singh, 2023)
IT	Issue Type	Dummy: 1 if fixed price 0: book building otherwise	(Mehmood et al., 2020)
UR	Underwriter Reputation	1: IPO underwritten by a prestigious underwriter 0: IPO underwritten by a non-prestigious underwriter	(Megginson & Weiss, 1991)
UP	Underpricing	(Closing price at first day of listing—offer price)/offer price $\times$ 100	(Sandhu & Guhathakurta, 2020; Bubna & Prabhala, 2011)
HM	Hot Market	1: years where the number of IPOs is greater than the average number of IPOs issued in the entire period 0: otherwise	(Ahmad-Zaluki & Kect, 2012)

Source(s): Author's own work.

3.3. Tools and Techniques

We utilise OLS regression and quantile regression models (Albada et al., 2023; Low & Yong, 2011; Mehmood et al., 2020; Rasyad et al., 2022; Tajuddin et al., 2018). The *lm()* function from base R version 4.2. is used for OLS estimation. Quantile regression is performed using *quantreg* package developed by Koenker and Bassett (1978) in R with bootstrap standard errors computed over 200 replications (Wang et al., 2025). The Random Forest model is trained using the *randomForest* package with *ntree* = 500, *mtry* = 3, and a fixed seed of 42 to ensure reproducibility. The train–test partition is generated using *createDataPartition()* from the *caret* package (Kuhn, 2008), allocating 80 per cent of observations to training (*n* = 814) and 20 per cent to the held-out test set (*n* = 200). SHAP values are computed via the *kernelshap* package with visualisations produced using *shapviz*.

3.4. Estimated Models

3.4.1. OLS Cross-Sectional Regression

The following cross-sectional OLS regression model is estimated to identify the determinants of IPO oversubscription:

$$OSR_i = \beta_0 + \beta_1 OP_i + \beta_2 IT_i + \beta_3 HM_i + \beta_4 LD_i + \beta_5 UR_i + \beta_6 UP_i + \beta_7 IS_i + \varepsilon_i \quad (1)$$

where OSR_i is oversubscription for IPO *i*. OP_i is offer price in INR. UR_i is the underwriter reputation dummy calculated based on the work of Megginson and Weiss (1991). UP_i denotes underpricing (Arora & Singh, 2021). LD_i is listing delay. HM_i is hot market. IT_i is the Issue Type treated as dichotomous where 1 represents a fixed-price issue and 0 for a

book-building mechanism. IS_i is the log of issue size in the INR value of IPO proceeds. β_0 is intercept; ε_i is an error term.

3.4.2. Quantile Regression

Quantile regression is suitable when distribution is skewed (Wang et al., 2025). Four quantiles are selected for this study, representing different levels of subscription. The 25th quantile estimates lightly subscribed IPOs, the 50th shows the median, the 75th quantile represents highly subscribed issues, whereas the 90th quantile presents the most subscribed offerings in the sample. The goodness of fit at each quantile is determined by the pseudo r square which draws parallel comparisons with r squared in OLS. To examine whether the determinants of oversubscription vary across the distribution, the following quantile regression model is estimated at $\tau \in \{0.25, 0.50, 0.75, 0.90\}$:

$$Q_\tau(OSR_i|X_i) = \beta_0(\tau) + \beta_1(\tau)OP_i + \beta_2(\tau)IT_i + \beta_3(\tau)HM_i + \beta_4(\tau)LD_i + \beta_5(\tau)UR_i + \beta_6(\tau)UP_i + \beta_7(\tau)IS_i \quad (2)$$

Here, $Q_\tau(OSR|X)$ represents the τ th quantile of the oversubscription rate conditional on the explanatory variables. $\beta_j(\tau)$ captures the marginal effect of variable j at quantile τ , allowing effects to vary across the distribution. Standard errors are derived through a bootstrap process with 200 replications, showing no distributional assumptions about the error term.

3.4.3. Random Forest

This study employs a Random Forest model, a machine learning technique introduced by Breiman (2001). Predictive performance is compared between the Random Forest and OLS using three metrics computed on the test set: (1) Root Mean Squared Error, (2) Mean Absolute Error, and (3) the coefficient of determination.

The Random Forest model generates predictions by averaging the outputs of $B = 500$ decision trees, each trained on a bootstrap sample of the data, where $\hat{OSR}_i$ is the predicted oversubscription rate for IPO i , B shows the number of trees in the forest, b is the index denoting an individual tree, $T_b(X_i)$ is equal to the prediction from tree b for IPO i , given its covariate vector X_i , and lastly, $(1/B)$ sum provides the average across all B trees.

$$\hat{OSR}_i = \frac{1}{B} \sum_{b=1}^B T_b(X_i) \quad (3)$$

3.4.4. SHAP Analysis

To understand the important variables that drive prediction in the Random Forest model, this study estimates SHAP values developed by Lundberg and Lee (2017) that are grounded in game theory (García-Céspedes et al., 2025; Yang et al., 2025). For each of the 200 test-set IPOs, a SHAP value is computed for every variable. A positive SHAP value reflects that the variable pushed the predicted oversubscription above the average for that observation and vice versa.

Variable importance in Random Forest model is quantified using mean absolute SHAP values, calculated as follows:

$$\phi_j^- = \frac{1}{n} \sum_{i=1}^n |\phi_{ij}| \quad (4)$$

In Equation (4), ϕ_j^- is the SHAP value of variable j for IPO i and n is the number of test-set observations. $|\phi_{ij}|$ is the absolute value of the SHAP value. The results are presented both as a ranked table and as a beeswarm chart in which each dot represents one IPO, the horizontal position shows the size and direction of that IPO's SHAP value, and the

colour of the dot ranges from blue for lower values of the variable to red for higher values (Cha et al., 2026; Yang et al., 2025).

4. Empirical Results

4.1. Descriptive Statistics

Table 2 reports the Descriptive Statistics. The oversubscription ratio transformed into log to control for heterogeneity shows an average of 2.39, with a range between 0.00 and 8.84 times, confirming that the distribution is positively skewed. Offer price has a mean value of 72.90, with the highest priced IPO at ₹1229. The mean of Issue Type is 0.4592, meaning 45.2 per cent of the IPOs comprises fixed-price offerings and the remaining 54.8 per cent are book-built. The listing delays an average of 08 days, ranging between 03 days and 29 days. The average underpricing was 30.1 times. A minimum value of −47.50 represents overpriced IPOs, signifying investors incurred losses on their initial returns. The average issue size was ₹1.2 crores. Among the dummy variables, 75.6 per cent of IPOs were listed during hot market periods. The negative skewness of −1.20 reflects that most observations are placed in hot market years, whereas 77.7 per cent involved reputed underwriters, reflecting that IPO-bound firms concentrate around a small number of large, established lead managers.

Table 2. Descriptive Statistics.

Variable	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
OSR	1014	2.4035	1.8033	2.1085	0.0000	8.8360	0.455	−1.205
OP	1014	72.898	57.000	73.765	10.000	1229.0	7.028	85.696
IT	1014	0.4517	0.0000	0.4979	0.000	1.000	0.195	−1.966
HM	1014	0.7564	1.0000	0.4295	0.000	1.000	−1.197	−0.570
LD	1014	8.1174	8.0000	2.9213	3.000	19.000	0.313	0.139
UR	1014	0.7771	1.0000	0.4164	0.000	1.000	−1.334	−0.222
UP	1014	30.130	9.7401	52.235	−47.50	411.00	2.709	10.197
IS	1014	2.6481	2.6837	0.9806	0.174	5.2878	−0.050	−0.605

Source(s): Author's own work. Notes: SD = standard deviation.

4.2. Correlation Analysis

Table 3 shows the results of the Pearson correlation matrix and Variance Inflation Factor (VIF). Listing delay exhibits a strong negative correlation with oversubscription ($r = -0.613$, $p < 0.001$). Hot market conditions ($r = 0.566$, $p < 0.001$) and underpricing ($r = 0.566$, $p < 0.001$) are positively related to oversubscription. Underwriter reputation shows no significant correlation with oversubscription ($r = 0.025$, $p = 0.422$) To rule out multicollinearity, a VIF test was conducted. All VIF values are under 2.0, indicating no multicollinearity concern.

Table 3. Pearson correlation matrix and Variance Inflation Factors (VIFs).

	OSR	OP	IT	HM	LD	UR	UP	IS	VIF
OSR	1.000								—
OP	0.146 ***	1.000							1.285
IT	−0.308 ***	−0.137 ***	1.000						1.206
HM	0.480 ***	0.194 ***	−0.298 ***	1.000					1.432
LD	−0.613 ***	−0.212 ***	0.281 ***	−0.486 ***	1.000				1.550
UR	0.025	0.001	0.029	0.038	−0.023	1.000			1.009
UP	0.566 ***	0.065 **	−0.177 ***	0.165 ***	−0.317 ***	0.043	1.000		1.127
IS	0.357 ***	0.469 ***	−0.362 ***	0.422 ***	−0.453 ***	−0.035	0.198 ***	1.000	1.735

Source(s): Author's own work. Notes: *** $p < 0.01$; ** $p < 0.05$.

4.3. Results of OLS Regression

Table 4 presents the output of the OLS regression model in Equation (1). Given the detection of heteroscedasticity via the Breusch–Pagan test ($BP = 75.37$, $p < 0.001$), all OLS standard errors are corrected using the HC3 heteroscedasticity-consistent estimator (Davidson & MacKinnon, 1993). Issue Type negatively affects the *OSR* at the 1% significance level, which shows that book-building IPOs are more oversubscribed than fixed-price IPOs by 0.304 units (Arora & Singh, 2020). Conversely, listing delay has a significant negative effect with a coefficient value of -0.260 , implying that a lower delay in listing attracts more subscriptions. The hot market conditions add 1.070 units to *OSR*, indicating that investors are active during the periods of high IPO volume. Underpricing has the strongest effect on *OSR*. A 1% increase in underpricing raises the *OSR* by 0.016 units. Offer price (OP), underwriter reputation (UR), and issue size (IS) are found to be insignificant. The model explains 57.5% of variation in oversubscription ($R^2 = 0.5754$).

Table 4. OLS regression results.

Variable	Coefficient	SE	<i>t</i> -Statistic	<i>p</i> -Value
Intercept	3.405 ***	0.272	12.493	<0.001
OP	−0.000	0.000	−0.294	0.768
IT	−0.304 ***	0.099	−3.049	0.002
HM	1.070 ***	0.114	9.340	<0.001
LD	−0.260 ***	0.018	−14.189	<0.001
UR	−0.034	0.994	−0.346	0.728
UP	0.016 ***	0.001	11.868	<0.001
IS	−0.001	0.060	−0.022	0.982
R^2	0.5754			
Adjusted R^2	0.5724			
F-statistic	194.740			
F <i>p</i> -value	<0.001			
Observations	1014			

Source(s): Author’s own work. Notes: *** $p < 0.01$.

4.4. Quantile Regression Results

This study employs quantile regression approach to illustrate how the predictors quantify *OSR* at various points in the distribution. The results of the quantile regression are displayed in Table 5.

Issue Type loses significance at the 90th quantile, revealing it to be a crucial determinant for lower and medium-subscribed IPOs ranging from the 25th to 75th quantile. Hot market grows dramatically across all quantiles, meaning that hot market influence is not uniform, and it increases from the 75th to 90th quantiles, influencing highly subscribed IPOs. Underpricing shows a strong positive influence on *OSR* across all quantiles; however, its effect slightly tapers off at the 90th quantile, implying that extreme IPO demand is driven by market momentum for popular issues. Listing delay rises throughout the quantiles, indicating that an extended delay in listing significantly diminishes investors’ enthusiasm at higher levels of subscription (Suresha et al., 2023). Finally, this study demonstrates that issue size, offer price and underwriter reputation are insignificant in explaining *OSR* across all stages of subscription. (Mehmood et al., 2020; Ong et al., 2020). Pseudo R squared is the quantile regression equivalent of R squared in OLS, which shows the best fit for highly subscribed IPOs (0.4305).

Table 5. Results of quantile regression.

Variable	Q25	Q50	Q75	Q90
Intercept	2.101 *** (0.370)	3.281 *** (0.451)	3.164 *** (0.323)	3.903 *** (0.455)
OP	−0.000 (0.001)	0.000 (0.001)	−0.000 (0.000)	−0.000 (0.000)
IT	−0.309 *** (0.109)	−0.389 *** (0.142)	−0.269 *** (0.102)	−0.105 (0.156)
HM	0.410 *** (0.121)	0.821 *** (0.168)	1.956 *** (0.173)	2.575 *** (0.259)
LD	−0.192 *** (0.035)	−0.233 *** (0.030)	−0.188 *** (0.019)	−0.207 *** (0.021)
UR	−0.056 (0.125)	−0.060 (0.154)	−0.049 (0.080)	0.008 (0.135)
UP	0.018 *** (0.001)	0.022 *** (0.002)	0.017 *** (0.001)	0.014 *** (0.001)
IS	0.049 (0.062)	−0.014 (0.074)	−0.012 (0.071)	−0.150 (0.091)
Pseudo R ²	0.240	0.395	0.430	0.393
Observations	1014	1014	1014	1014

Source(s): Author's own work. Notes: Bootstrap standard errors in parentheses. *** $p < 0.01$.

4.5. Random Forest Benchmarking

Table 6 shows that Random Forest outperforms OLS on three metrics, namely the RMSE, MAE and the R squared. The Random Forest explains 67.1 per cent of the variance in oversubscription on the held-out test set, compared with 57.9 per cent for OLS; the R squared showed an increase of 9.2 percentage points. RMSE fell from 1.367 to 1.210 in RF and MAE fell from 1.1157 to 0.8361, showing improved predictor power. The gap in performance confirms that non-linear relationships exist that are not exposed by OLS. These results are supported using SHAP analysis to uncover the hidden patterns among variables.

Table 6. Model comparison OLS regression vs. Random Forest (held out test set, $n = 200$).

	RMSE	MAE	R ²
OLS regression	1.3671	1.1157	0.5787
Random Forest	1.2103	0.8361	0.6709

Source(s): Author's own work. Notes: Both models trained on 814 IPOs (80%) and evaluated on 200 held-out IPOs (20%). Random Forest: ntree = 500, mtry = 3, seed = 42.

4.6. SHAP Variable Importance Analysis

The SHAP method, derived from game theory (Yang et al., 2025), tests the dataset ($n = 200$) to predict the contribution of each variable towards OSR. Table 7 displays the results of SHAP analysis. The absolute mean SHAP values give a final importance ranking. The results show that underpricing ($UP = 0.7841$) and listing delay ($LD = 0.7240$) are the two most important variables. The mean SHAP value for underpricing was highest in cases of greater underpriced IPOs, which showed positive OSR. Lower underpricing led to low OSR. Listing delay is associated with negative SHAP values, emerging as the second most important variable. The hot market is a strong third with a value of 0.4268. Hot markets exhibit positive clusters. This signifies that favourable markets increase investor interest, emphasising the role of investor sentiments in market activities. Issue Type display mixed SHAP values, suggesting that issue mechanisms are dependent on firm-specific contexts. Critically, variables such as issue size, offer price and underwriter reputation show minimal impact, with SHAP values concentrating around zero (0.0874, 0.0806, 0.0265)

and underwriter reputation being the weakest predictor despite being insignificant in OLS, revealing that issue-specific factors play a lesser important role in driving the subscription for SME IPOs.

Table 7. SHAP variable importance.

Variable	Description	Mean SHAP	OLS Significance
UP	Underpricing	0.7841	*** (rank 1 in OLS)
LD	Listing Delay	0.7240	*** (rank 2 in OLS)
HM	Hot Market	0.4268	*** (rank 3 in OLS)
IT	Issue Type	0.1159	*** (rank 4 in OLS)
IS	Issue Size	0.0874	n.s. in OLS
OP	Offer Price	0.0806	n.s. in OLS
UR	Underwriter Reputation	0.0265	n.s. in OLS

Source(s): Author's own work. Notes: *** $p < 0.01$; n.s. = not significant in full-sample OLS.

SHAP beeswarm plots shown in Figure 2 present the patterns derived from SHAP results.

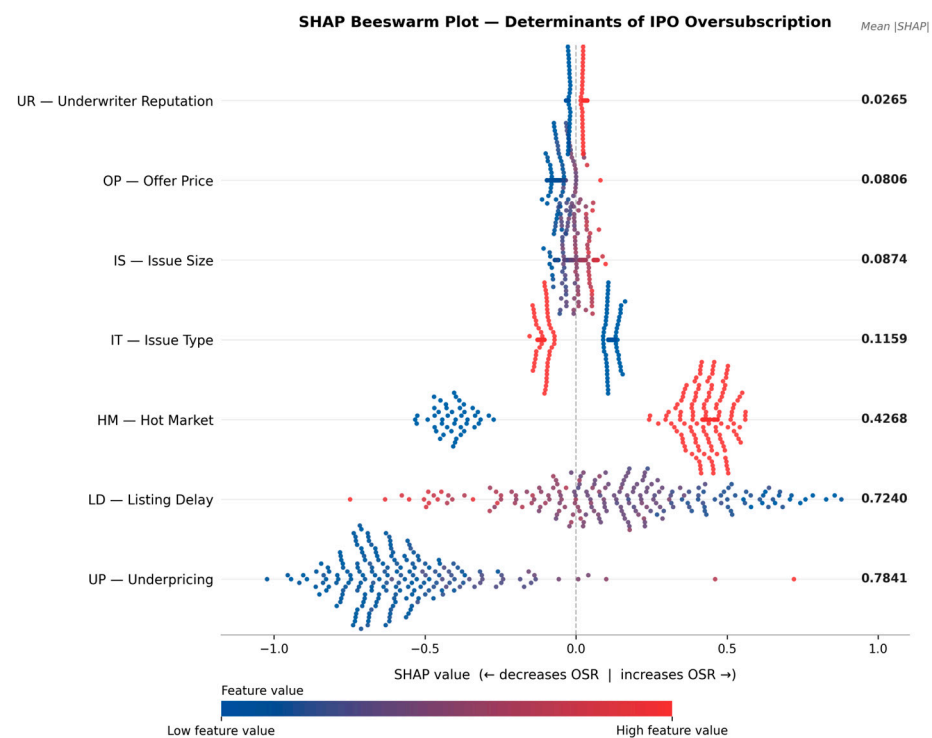


Figure 2. SHAP beeswarm plot. Source(s): Author's own work.

5. Discussion

The results demonstrate the vital role of underpricing in IPO markets, as evidenced by both traditional regression and machine learning analyses. Underpricing is essential for investors when evaluating expected gains from IPO participation (M. Zhang & Du, 2025). Consequently, investors could focus on the potential gains they expect to achieve when the company first lists on the respective exchange. This explains the observed results for underpricing (Arora & Singh, 2025; Wadhwa & Sahoo, 2024). Delays in listing are perceived as negative signals, suggesting inadequate issuer preparation to meet regulatory requirements. Prolonged listing delays tend to diminish investor interest, increasing the likelihood of withdrawal from the IPO process (Arora & Singh, 2020; Das et al., 2023; Krishnamurti & Kumar, 2002). Positive market sentiments are pivotal. Active markets are linked to higher

investor participation, as evidenced by their positive effect on oversubscription (Jain & Kanjilal, 2017). Periods characterised by a high volume of IPOs typically experience increased oversubscription, reflecting investor confidence in the SME segment and encouraging investment in SME securities as alternative investment avenues. Additionally, the type of issue mechanism significantly determines oversubscription. Book-building mechanisms tend to elicit a stronger response from investors as they aid in price discovery, thereby reducing information asymmetry in the markets (Mehmood et al., 2025; Sherman, 2005).

Notably, investors do not prioritise reputation of underwriters when subscribing to SME IPOs. Since SME IPOs are fully underwritten, the risk of failure is mitigated, ensuring investor participation regardless of the underwriter's brand. The present findings contrast with Arora and Singh (2020). A plausible explanation is that market regulators in India mandate SME IPOs to be fully underwritten by lead managers (Tripathi et al., 2017), a measure intended to prevent IPO failure. This provides security to issuing companies and may be interpreted by investors as assurance of bid success. Additionally, factors such as issue size and issue price do not substantially influence investor opinions.

6. Implications

6.1. Practical Implications

The findings have important implications for issuers, market regulators, and investors. Issuers should carefully time and position their IPOs to attract the right investors. Market volatility is important when deciding the best time for an IPO. Launching in a quiet market can help a company stand out and attract more interest, leveraging the early mover advantage. IPOs that use the book-building method are especially appealing because the price discovery becomes more transparent. Companies should focus on this process so investors can better judge the value of their shares. Stock exchanges may facilitate systems that support book building, thereby reducing the information gaps. Effective time management is crucial for a successful public offer. Issuers and lead managers must thoroughly prepare and avoid errors to enable prompt listing of shares following the offer's closure. For regulators, these results offer useful insights into regulatory processes that influence subscription rates. Finally, investors should pay attention to market trends to find better opportunities. Uninformed investment decisions can lead to investing in poor-quality IPOs and early losses.

6.2. Societal Implications

Policymakers are encouraged to foster a sustainable atmosphere for small businesses and promote financial inclusion in India. Increased participation of SMEs in India's capital market shows promoter confidence in attracting public funding for small enterprises which have otherwise been debt-heavy. This reinforces India's commitment to the fair execution of the sustainable development goals established by the United Nations. Raising equity capital can thereby reduce SMEs' reliance on the banking sector. Promotional campaigns for SME exchanges can be undertaken to attract issuers from diverse regions of India, particularly the rural SMEs, which are often neglected. Viable environments for small businesses through innovation will drive employment prospects and improve the health of India's economy.

6.3. Limitations and Future Research

This study has a few limitations. It does not consider institutional factors that affect IPO subscriptions. Since institutional investors usually have more information than retail investors, they make decisions differently. Further, alternative measures of investor demand can be explored. Lastly, new research can explore investor sentiments during an IPO event.

7. Conclusions

By utilising a detailed dataset of 1014 issues spanning across 12 years from 2012 to 2024, the current study provides rich empirical evidence on SME IPOs in the Indian context. It further adds to the extensive body of literature concerning IPOs. The current research is an attempt to bring attention to alternate avenues of investment in India's capital markets by focusing on the SME segment. The findings are beneficial for various stakeholders. This study concludes that investors in India are primarily guided by prevailing market sentiments.

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Appendix A. Robustness Check: Alternative Hot Market Definitions

Table A1. OLS Regression under three alternative hot market definitions (n = 1014).

	Definition 1	Definition 2	Definition 3
	Original	Above Annual Median	Top Tercile Years Only
Hot market years	2017, 2018, 2022, 2023, 2024	2016, 2017, 2018, 2022, 2023, 2024	2017, 2018, 2023, 2024
Hot market IPOs (n)	767	825	665
Annual IPO threshold	>78 IPOs	>47 IPOs	>103 IPOs
HM coefficient	1.0707 ***	0.8096 ***	0.6929 ***
HC3 standard error	(0.1146)	(0.1229)	(0.1167)
t-statistic	9.344	6.590	5.936
R ²	0.5754	0.5586	0.5592
Observations	1014	1014	1014

Source(s): Author's own work. Notes: Each column reports the hot market (HM) coefficient from a separate OLS regression using the full set of control variables (OP, IT, LD, UR, UP, IS) with HC3 heteroscedasticity-consistent standard errors in parentheses. Definition 1 is the original specification used throughout the paper: a year is classified as hot when annual IPO volume exceeds the full-sample annual mean (78 IPOs). Definition 2 uses the annual median (47 IPOs) as the threshold. Definition 3 restricts hot market classification to the top tercile of years by IPO volume (above 103 IPOs). All three definitions yield a positive and statistically significant hot market coefficient, confirming the robustness of the main finding. *** $p < 0.001$.

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