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A Study on Predicting IPO Underpricing in India: An Integrated Analysis of Financial Factors and Investor Sentiment

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ABSTRACT:

The aim of the study is to investigate the relationship of financial factors with IPO under-pricing in India, the presence of mediator between the investor demand and the financial factors-IPO under-pricing, the presence of moderator between financial factors-IPO under-pricing and the market conditions and to examine whether the four elements can be integrated into a predictive model or not. The 6 constructs examined (financial factors, investor sentiment, investor demand, perceived under-pricing, market conditions, usefulness of the market and framework) were measured with the structured 22 item questionnaire on a 5 point Likert scale. The remaining data from 19 unique respondents were analysed using chi square and fisher exact tests, one way ANOVA, multiple linear regression, bootstrap mediation and bootstrap moderation. Results: All the reliabilities for the scales ranged from .80 to .92(Cronbach's α)

The variance of perceived under-pricing was split between financial factors (β = .81) and investor sentiment (β = .83) which when combined explained 73% of the variance in investor demand, mainly through the lens of sentiment. The sentiment-under-pricing link was mediated by investor demand (indirect effect = 0.59, 95% CI [0.12, 1.08]), but not strongly the link between financial factors and the sentiment. A strong direct correlate of perceived under-pricing and no significant mediation of any path was market conditions. The integrated model was successful with an R^2 of .89 and the respondents stated that it was useful (M = 3.53, p = .009). Restrictions/originality: A small sample size and a perceived rather than an observed outcome for listing day and results are therefore exploratory. The study aims to bring the perception of financial, sentiment, demand and market-condition effects together to form the first integrated test in the Indian IPO market. The article introduces and analyses the impact of IPO under-pricing on Investor Sentiment, Investor Demand, Financial Factors, Market Conditions, Mediation, and India.

1. Introduction:

One of the most important equity capital sources is Initial Public Offering (IPO) – this is the first public sale of shares by a private company. Through an IPO, companies can raise funds for growth, much as they can do through bond or stock sales, and boost their market recognition and financial health. While there is no identical information between the issuers, the underwriters and investors, determining the correct price of the offer is not easy. The uncertainty has one clear implication, namely that IPO underpricing exists: the market price of the stock on the day of the listing is greater than the offer price. If there is too much underpricing, it can cost the companies that issue the shares wealth, if there is not too much underpricing it can give the investors short term profit. It has been observed in numerous markets and the field of financial research continues to be very active. The reasons for why IPOs are underpriced are explained by several theories, such as: Information asymmetry, Signalling and market timing. If uninformed investors have less information than the informed investors, they are more uncertain and will need to be compensated in the form of underpricing, and the more uncertain the firm the more underpricing, and the shorter the history, the more underpricing. In the signalling theory, it is argued that good quality firms charge less than the average quality firms because they are trying to signal their quality and prospects (Welch, 1989). The market timing theory suggests that firms may decide to go public during a favorable investor mood and high investor demand for these firms (Loughran & Ritter, 2002). The current study builds upon some empirical research, which has identified factors influencing underpricing that are related to financial and

firm-specific factors. The size, age, profitability, earning, book value, leverage position, liquidity, offer price, and offer size can affect investor's risk and value perception, and market conditions and macro-economic factors can also affect the demand and pricing of an IPO. Recent research indicates that ratios like ROA, ROE, EPS, leverage ratios, liquidity ratios, size ratios and valuation ratios are important for IPO prediction models. The mood of the investors, their confidence and expectations are also playing a very important role in IPO pricing. Positive sentiment boosts demand and initial returns and recent studies have been able to isolate sentiment from written disclosures, like prospectuses, and make inferences about how the market views risk, growth, management, and prospects that can be derived from them that financial data don't. One of the benefits of machine learning (ML) is that it allows to model non-linear and complex relationships between a large number of variables. Singh and Kalra (2024) conducted a systematic review of 21 IPO studies and found that the machine learning models Artificial Neural Networks, Random Forest, Support Vector Machines, XGBoost and text analytics show promising prospects to do IPO evaluation and prediction. ML techniques are able to handle complex financial data while traditional econometric models may be less suited to capture the non-linear interactions. Although these developments, few of the studies consider financial aspects along with sentiment of investors while analyzing Indian IPOs. This study thus develops an integrated framework that includes financial and market conditions, investor sentiment and investor demand, thereby understanding and predicting IPO underpricing, which would benefit investors, issuing companies and underwriters.

2. Research Gap and Problem Statement:

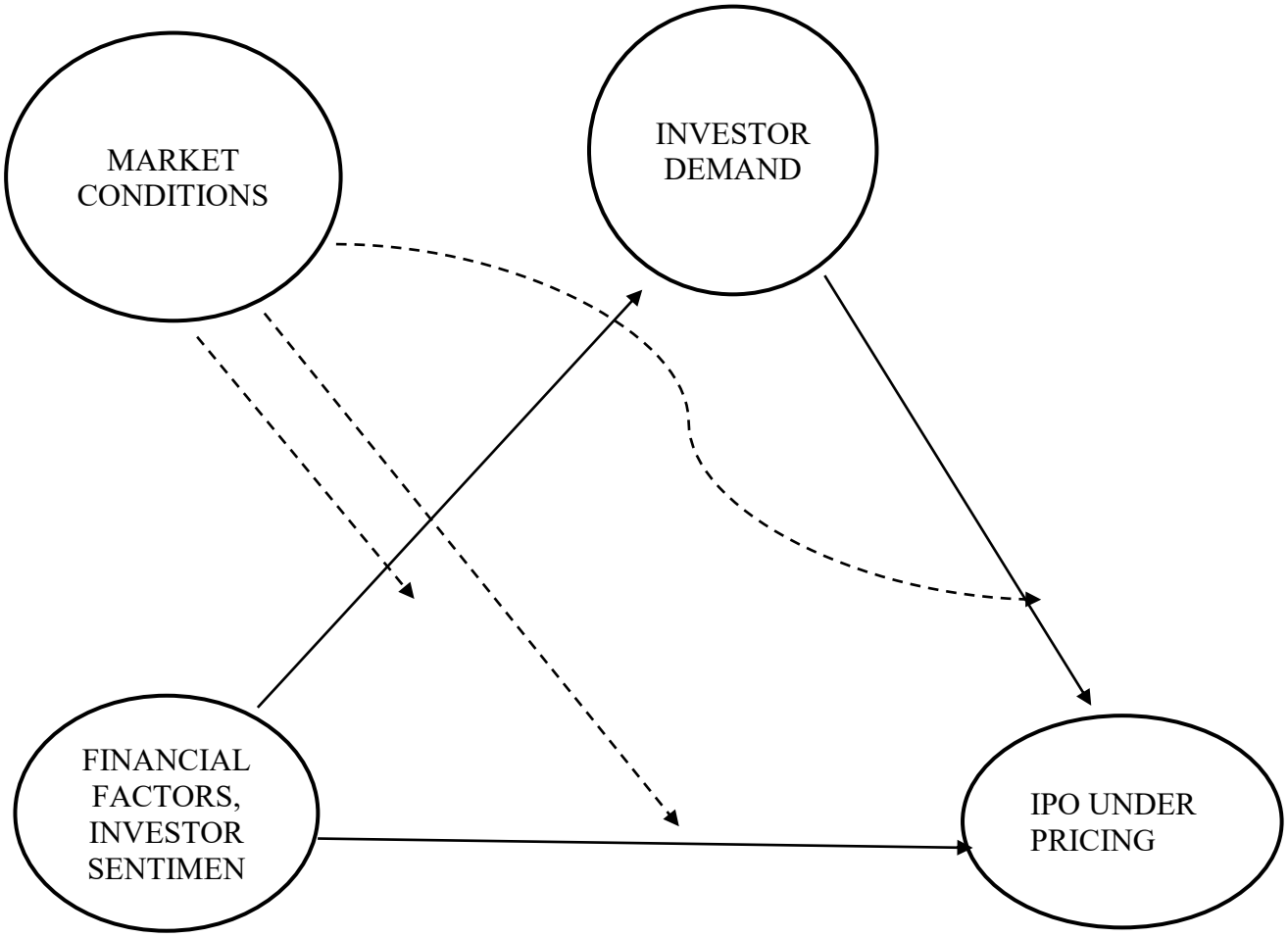
The literature on underpricing of IPOs has largely focused on financial-, firm-specific- and market-based determinants, and there has been little attention to investor sentiment and text-based information in the Indian IPO market. Furthermore, most of the studies conducted so far are limited in scope, in time, or in their data, in that they provide results only on a particular market and for a limited time. Hence there is a need to have an integrated model with both the traditional financial and the sentiment-based variables in textual form to understand the phenomenon of underpricing of IPOs in India. This study aims to fill this void by investigating the role of investor sentiment in addition to the usual financial and issue-specific factors to gain a better understanding and prediction of IPO underpricing. The factors affecting the IPO underpricing are financial, firm-specific, market and investor-related factors, but these factors have been studied separately in existing studies. Very few studies have incorporated financial factors and investor sentiment into the explanation and prediction of underpricing of initial public offerings, especially in India. Investor demand plays a mediating role between financial factors, investor sentiment and IPO underpricing, but this has not been sufficiently explored. Hence, it is important to have an integrated predictive framework that combines the financial variable, investor sentiment, investor demand and market conditions to explain the IPO underpricing phenomenon in India better.

3.**Research Questions**:

What is the impact of financial factors and investor sentiments on IPO underpricing in Indian market? Do investors' demand come between the relationship between financial factors, investor sentiment/investor IPO underpricing, and what do the market conditions do?

4. Conceptual Framework

Financial factors and investor sentiment are treated as independent variables. Investor demand is the mediator through which they may affect IPO underpricing, the dependent variable. Market conditions act as a moderator of the demand–underpricing path and of the paths from financial factors and sentiment to underpricing and to demand.



5. Objectives

- To examine the impact of financial factors on IPO underpricing.
- To assess the impact of investor sentiment on IPO underpricing.
- To examine the effect of financial factors and investor sentiment on investor demand.
- To understand the mediating role of investor demand in the relationship between financial factors, investor sentiment and IPO underpricing.
- To examine the moderating role of market conditions on the relationships between investor demand and underpricing, financial factors (and investor sentiment) and underpricing, and financial factors (and investor sentiment) and investor demand.
- To develop and evaluate a predictive framework for IPO underpricing that integrates financial factors, investor sentiment, investor demand and market conditions.

6. Research Hypotheses

(H0_1): financial factors do not influence IPO underpricing

(H1_1): financial factors influence IPO underpricing

(H0_2): investor sentiment do not impact IPO underpricing

(H1_2): investor sentiment impact IPO underpricing

(H0_3): Investor demand is not influenced by financial factors and investor sentiment

(H1_3): Investor demand is not influenced by financial factors and investor sentiment

(H0_4): investor demand do not show mediating effect on financial factors, investor sentiment and ipo underpricing

(H1_4): investor demand do not show mediating effect on financial factors, investor sentiment and ipo underpricing

(H0_5): Market conditions do not show moderating effect on financial factors, ipo underpricing and investor demand.

(H1_5): Market conditions show moderating effect on financial factors, ipo underpricing and investor demand.

(H0_6): Predictive framework cannot be made by integrating all elements

(H1_6): Predictive framework can be made by integrating all elements.

7. Review of Literature

Neghab, Cevik and Basar(2023) examined the determinants of IPO underpricing in the U.S. using explainable machine learning techniques and found that offer price, firm assets, equity retained, industry and market conditions significantly influenced underpricing. The study's limitation is that it did not incorporate investor sentiment and investor demand , particularly their mediating relationship with IPO underpricing , providing scope for further research.
Katsafados et al. (2020) examined U.S. IPO underpricing using textual information from S-1 prospectuses and financial variables, finding that their combination improved the prediction of IPO underpricing. However , the study did not specifically examine investor sentiment and investor demand, creating scope to investigate their influence and mediating role in IPO underpricing.

Sonsare et al (2023) studied the different machine learning models for predicting IPO underperformance in India and concluded that ANN model had the highest predictive accuracy with issue price, industry size and firm size being important factors.

Pathak (2024) compared the machine learning methods for predicting the stock prices and concluded that XG Boost outperforms Linear Regression and SVR in predicting the stock price. Yet, the study only investigated one stock and failed to take into consideration IPO underpricing, investor sentiment, and investor demand, suggesting a need for further study.

Gonenc (1999) examined the long term performance of U.S.IPOs and found that venture capital backing and institutional ownership influenced IPO performance, while investment banker reputation had limited impact. The study focused on long term performance rather than IPO underpricing, investor sentiment, and investor demand indicating a gap for further research.

Martins(2025) examined U.S.IPO underpricing using machine learning models and financial, IPOI specific and market sentiment variables, finding that classification models effectively predicted underpriced IPOs.

Dash and Mishra(2023) reviewed machine learning approaches to sentiment analysis in the Indian stock market and found that investor sentiment significantly influences stock prices and market volatility.

Nigudkar et al. (2025) examined IPO pricing and post listing performance in India and found that P/E ratio, PAT, and retail investor participation did not significantly influence IPO performance.

Singh and Kumar(2008) found that higher IPO oversubscription , particularly by retail and non institutional investors, was positively associated with short run IPO underpricing in India.

Supsermpol et al. (2025) found that integrating financial, market, macro-economic, and textual sentiment factors significantly improved the prediction of IPO underpricing in the Thai capital market.

Agrawal and Ananthakumar studied Indian IPO underperformance using machine learning techniques and found that Gradient Boosting performed best, with market returns and firm specific financial factors being important predictors.

Singh and Kalra(2024) reviewed machine learning applications in IPO forecasting and found that ANN and other advanced ML techniques generally outperformed conventional methods.

AL-DAWERI et al. (2026) examined IPO underpricing in Malaysia using machine learning techniques and found that investor demand, measured through oversubscription, and divergence of opinion were the strongest predictors.

Singh et al. (2026) examined green and non green IPOs in India and found that green IPOs demonstrated relatively better long term performance, although green status was not a significant independent predictor.

Colak, Fu and Hasan(2025) examined IPO first day returns using machine learning models and found that XGBoost provided superior predictive performance , with price revision, underwriter agency, and free float fraction as key determinants.

Katti and Phani(2016) reviewed the literature on IPO underpricing and identified information asymmetry, signaling, firm specific, issue specific, and market factors as key determinants.

Sai Kiran et al.(2025) found that integrating financial indicators with social media sentiment using ML and LSTM models improved the prediction of IPO success and short term returns in India.

8. Research Methodology

8.1 Research design

The study is designed as a quantitative, cross sectional survey study with a secondary literature approach. Primary data was collected from a structured, self-administered questionnaire that was used to capture information from students and those who are salaried but have different exposure to the IPO market.

8.2 Sampling and data screening

Non-probability (convenience) sampling was used. The questionnaire was exported to the web and had 92 records of responses. These records had been screened and were found to be 21 separate submissions, each of which was submitted four or five times using the same name, e-mail address, and answers and with the same times. There were two other submissions with the same e-mail address and answers as an earlier one (re-submissions). An analysis sample of 19 unique respondents was obtained after all duplicates were removed. Two answer options for the "number of IPOs applied" item were also auto-converted to dates in Excel, which were restored. 7 of the 19 respondents answered the same to all 22 items (straight-lining) and are included in the main analysis, and the influence of these is checked in a sensitivity analysis (Section 9.10).

8.3 Instrument

There are two sections of the questionnaire: (a) demographic and investment-profile questions (age, gender, occupation, annual income, stock-market experience, number of IPOs applied for in the last three years) and (b) 22 statements rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The six constructs listed in Table 1 are measured by the statements. The scores on composites are item means. The complete list of items is attached in Appendix A.

Table 1. Constructs and items

Construct	Code	Items
Financial factors	FF	Q1–Q4 (4)
Investor sentiment	IS	Q5–Q8 (4)
Investor demand	ID	Q9–Q12 (4)
Perceived IPO underpricing	UP	Q13–Q15 (3)
Market conditions	MC	Q16–Q19 (4)
Predictive-framework usefulness	PF	Q20–Q22 (3)

8.4 4 Analytical procedures

Analyses conducted on Microsoft Excel (formulas, LINEST, CORREL, COUNTIFS, CHIDIST, FDIST), and validated in Python (NumPy/SciPy); SPSS syntax that will replicate all tests is included in this paper. Cronbach's alpha was used as a measure of reliability. The association between categorical variables was determined by Pearson chi-square (expected cell counts less than five, then Fisher exact tests). One-way ANOVA (Levene's test, Tukey HSD post-hoc,

eta-squared, Kruskal–Wallis as a non-parametric check) was used to test for differences in construct scores among age, income and IPO-participation groups. Ordinary least squares regression was used to test all hypotheses except hypothesis H6, for which the leave-one-out cross-validated R^2 (Q^2) was used, reporting standardised coefficients, VIF, Durbin–Watson, Shapiro–Wilk tests of residuals, Cook's distance and leave-one-out cross-validated R^2 (Q^2). Mediation (H4) was carried out using the product-of-coefficients approach with 5,000 bootstrap resamples and percentile 95% confidence intervals (Preacher & Hayes, 2008); the Sobel test is reported for comparison. Moderation (H5): Mean centred interaction terms. All statistical results were based on a .05 level of significance

9. Data Analysis and Results

9.1 Sample profile

Table 2. Respondent profile ($N = 19$)

Variable	Category	n	%
Age	Below 25	13	68.4%
	25–35	3	15.8%
	36–45	1	5.3%
	46–55	1	5.3%
	Above 55	1	5.3%
Gender	Female	11	57.9%
	Male	8	42.1%
Occupation	Student	11	57.9%
	Salaried	8	42.1%
Annual income	Below ₹5 lakh	12	63.2%
	₹5–10 lakh	3	15.8%
	₹10–20 lakh	1	5.3%
	Above ₹20 lakh	3	15.8%
Market experience	Less than 1 year	14	73.7%
	1–3 years	1	5.3%
	3–5 years	3	15.8%
	More than 5 years	1	5.3%

Variable	Category	n	%
IPOs applied (3 yrs)	None	11	57.9%
	1–3	4	21.1%
	4–6	1	5.3%
	More than 6	3	15.8%

The sample is young and inexperienced as 68.4 % are below 25 years, 63.2 % reported a monthly income less than ₹5 lakh and 73.7 % have less than 1 year of market experience. Gender completely overlaps with occupation (all 11 women are students; all 8 men are salaried), restricting what can be said about gender and occupation distinctively.

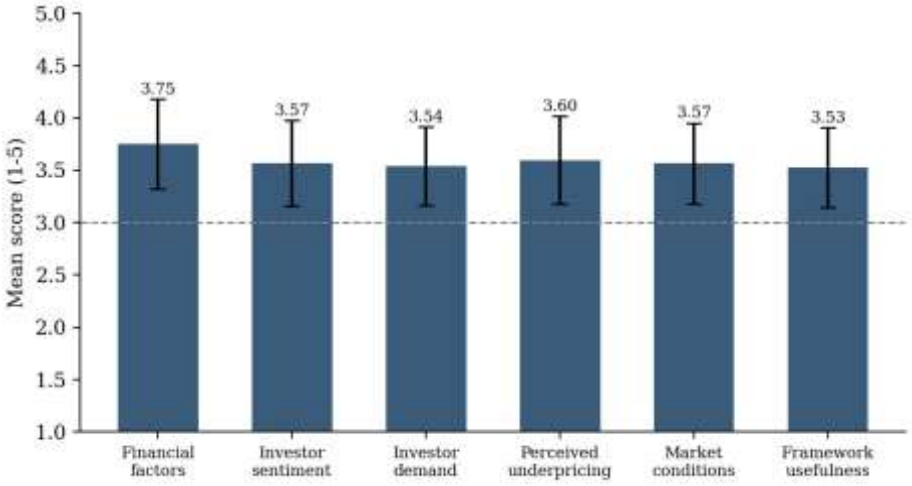
9.2 Reliability and descriptive statistics

Table 3. Reliability and descriptive statistics of the constructs

Construct	Items	α	Mean	SD	Skew	Shapiro–Wilk p
Financial factors	4	.88	3.75	0.89	-1.74	.003
Investor sentiment	4	.88	3.57	0.85	-1.36	.027
Investor demand	4	.85	3.54	0.78	-2.03	.001
Perceived underpricing	3	.92	3.60	0.87	-1.18	.007
Market conditions	4	.89	3.57	0.80	-1.65	.004
Framework usefulness	3	.80	3.53	0.79	-1.91	< .001

Note. Scale 1–5. All α exceed the .70 benchmark (Nunnally, 1978). All composites depart from normality (negative skew).

The internal consistency of all constructs is good ranging from α = .80 to .92. The mean scores vary from 3.53 to 3.75, which means that the respondents tend to agree on all constructs (Figure 2). The factors with the highest agreement are the financial factors (M = 3.75). Non-parametric tests are used together with the parametric tests due to the small sample size and the composites are negatively skewed.



9.3 Correlation analysis

Table 4. Pearson correlations among constructs ($N = 19$)

	FF	IS	ID	UP	MC	PF
FF	—	.79	.76	.81	.86	.81
IS	.79	—	.84	.83	.87	.84
ID	.76	.84	—	.90	.86	.95
UP	.81	.83	.90	—	.92	.88
MC	.86	.87	.86	.92	—	.91
PF	.81	.84	.95	.88	.91	—

Note. All correlations significant at $p < .001$.

All pairs of constructs are highly and significantly correlated (r .76 to .95) and each p < .001. Market conditions (r = .92) and investor demand (r = .90) are the two variables that have the strongest correlation with perceived underpricing. Such high correlations suggest that in this sample the constructs are very similar and can be expected to pose problems for regression (Section 9.9) and discriminant validity (Section 10).

9.4 Tests of Independence using the Chi-square statistic

Chi-square tests were used to determine if there was association between the level of constructs (high: mean ≥ 4.0, moderate/low: < 4.0) and respondent characteristics. All tables are 2 × 2 with df = 1. The Fisher exact p value is the

main p value reported; the Fisher exact p value and the asymptotic chi-square value are displayed because at least one table has at least one expected count less than 5 (the minimum expected counts range from 2.1 to 3.8).

Table 5. Chi-square and Fisher exact tests ($N = 19$)

Variables tested	$\chi^2(1)$	p	Fisher p	Cramér's V	Min. expected
Gender × Occupation	19.00	< .001	< .001	1.00	3.37
Occupation × Investment experience	0.89	.345	.603	.22	2.11
Occupation × IPO participation	0.35	.552	.658	.14	3.37
Gender × Investor sentiment level	6.74	.009	.020	.60	3.79
Occupation × Investor demand level	2.77	.096	.170	.38	3.79
IPO participation × Perceived underpricing level	0.54	.463	.650	.17	3.79
Investment experience × Predictive-framework acceptance	0.43	.510	.628	.15	2.37

Note. High/low levels split at a composite mean of 4.0. Significant results (Fisher $p < .05$) are: Gender × Occupation and Gender × Investor sentiment level.

There were two associations that were important. The first result was that gender and occupation were perfectly associated ($\chi^2(1) = 19.00$, Fisher $p < .001$, $V = 1.00$) and this was not a substantive result, but rather a result of the way the sample was collected. Second, women were more likely than men to report high investor-sentiment scores: 8 of 11 women versus 1 of 8 men scored ≥ 4.0 ($\chi^2(1) = 6.74$, $p = .009$; Fisher $p = .020$; $V = .60$). This difference is due to gender and not student status as it occurs with both genders. There was no significant relationship between occupation and investment experience, IPO participation, and investor-demand level (all Fisher $p > .16$), and no significant relationship between IPO participation and experienced underpricing or acceptance of the predictive framework (Fisher $p > .16$), nor was there any significant relationship between investment experience and experienced underpricing or experienced acceptance of the predictive framework (Fisher $p > .16$).

9.5 One-way ANOVA

One-way ANOVA was used to compare the six scores of constructs by age group (below 25, 25–35, above 35), income group (below ₹5 lakh, ₹5–10 lakh, above ₹10 lakh) and IPO-participation group (none, 1–3, 4 or more). Group sizes were 13/3/3, 12/3/4 and 11/4/4 respectively, so all tests have low power (df = 2, 16). There were no significant

differences between age and IPO participation on any of the constructs (all $p \geq .215$, and $p \geq .571$ respectively). Only income had significant effects (Table 6).

Table 6. One-way ANOVA by annual income group

Construct	Below ₹5L	₹5–10L	Above ₹10L	F	P	η^2	K–W *p*	Levene p
Financial factors	4.00	2.92	3.63	$F(2,16) = 2.04$	.162	.20	.496	.048
Investor sentiment	3.90	2.42	3.44	$F(2,16) = 5.58$	.014	.41	.042	.592
Investor demand	3.77	2.50	3.63	$F(2,16) = 4.48$	.029	.36	.114	.369
Perceived underpricing	3.86	2.44	3.67	$F(2,16) = 4.38$	.030	.35	.105	.592
Market conditions	3.88	2.58	3.38	$F(2,16) = 4.52$	.028	.36	.059	.190
Framework usefulness	3.78	2.67	3.42	$F(2,16) = 2.97$	.080	.27	.190	.154

Note. n = 12, 3 and 4. K–W = Kruskal–Wallis. Levene's test is significant only for financial factors (p = .048).

Income groups differed on investor sentiment ($F(2,16) = 5.58$, $p = .014$, $\eta^2 = .41$), investor demand ($p = .029$), perceived underpricing ($p = .030$) and market conditions ($p = .028$), with large effect sizes ($\eta^2 = .35$–$.41$). The differences between the ₹5–10 lakh (lowest) group (n = 3) and the below-₹5 lakh group ($p = .012$ for sentiment, .023 for demand, .024 for underpricing and .025 for market conditions) were found using Tukey tests. The Kruskal–Wallis test was used to verify that there were no differences for the other items, with the only difference found for sentiment ($p = .042$). All three, two of whom answered all 1s, 2s, 3s to all items, are in the ₹5–10 lakh group, and 18 ANOVAs were conducted ($\alpha = .05/18 = .003$) so the results should be interpreted with caution.

9.6 Multiple linear regression

H1 and H2 (direct effects). Table 7 indicates that financial factors and investor sentiment have significant effects on the perceived underpricing in simple regressions, for both models (M1 and M2). When entered together (M3), the model is significant, $F(2,16) = 24.07$, $p < .001$, $R^2 = .75$, but only investor sentiment retains a significant coefficient ($\beta = .52$, $p =$

.021); financial factors are marginal (β = .39, p = .071). The two predictors are highly collinear (VIF = 2.67), making it difficult to determine the unique contribution of each predictor.

Table 7. Regression results (*N* = 19)

Model (DV)	Predictor	b	SE	β	t	P	VIF
M1: UP	FF	0.789	0.141	.81	5.61	< .001	—
	R^2 = .649, adj. R^2 = .628, F(1,17) = 31.44, p < .001						
M2: UP	IS	0.854	0.138	.83	6.18	< .001	—
	R^2 = .692, adj. R^2 = .674, F(1,17) = 38.22, p < .001						
M3: UP	FF	0.387	0.200	.39	1.94	.071	2.67
	IS	0.534	0.209	.52	2.55	.021	2.67
	R^2 = .751, adj. R^2 = .719, F(2,16) = 24.07, p < .001						
M4: ID	FF	0.214	0.185	.24	1.16	.265	2.67
	IS	0.594	0.194	.65	3.06	.007	2.67
	R^2 = .731, adj. R^2 = .697, F(2,16) = 21.70, p < .001						
M5: UP	FF	0.243	0.168	.25	1.45	.169	2.89
	IS	0.135	0.213	.13	0.63	.535	4.22
	ID	0.672	0.218	.60	3.09	.008	3.71
	R^2 = .847, adj. R^2 = .817, F(3,15) = 27.76, p < .001						
M8: UP	FF	0.041	0.169	.04	0.24	.813	3.84
	IS	-0.059	0.202	-.06	-0.29	.775	5.02
	ID	0.482	0.205	.43	2.35	.034	4.36
	MC	0.615	0.255	.57	2.41	.030	7.17
	R^2 = .892, adj. R^2 = .861, F(4,14) = 28.93, p < .001						

Note. UP = perceived underpricing; ID = investor demand; FF = financial factors; IS = investor sentiment; MC = market conditions. b = unstandardised coefficient, β = standardised coefficient. Constants are not shown.

H3 (drivers of investor demand). The variance in investor demand was explained by 73.1% of the financial factors and sentiment ($F(2,16) = 21.70$, $p < .001$). Significant predictor ($\beta = .65$, $p = .007$): investor sentiment; not significant ($\beta = .24$, $p = .265$): financial factors but financial factors alone predict demand strongly ($\beta = .76$, $p < .001$). There is one influential case (Cook's D = 1.55; respondent rating of 1 to all items) and this is sensitive to that respondent.

Adding investor demand. The addition of investor demand, to sentiment and financial-factor model (M5), increases R^2 from .75 to .85 and makes investor demand the only significant predictor ($\beta = .60$, $p = .008$), while sentiment and financial factors are no longer significant predictors. This is the style to expect during mediation, and is formally tested next.

Regression diagnostics. No serious autocorrelation as evidenced by Durbin-Watson values (1.55-2.59). The residuals for M1, M3, M4 and M8 were approximately normal (Shapiro–Wilk $p \geq .086$) but not for M2 and M5. The VIFs were all less than 5 for M3–M5, and greater than 5 for model M8, with VIF = 7.17, which is above the conservative 5.0 threshold, in the four-predictor model indicating multicollinearity. Cook's D exceeded 1 only in M1 (1.08) and M4 (1.55)

9.7 Mediation analysis (H4)

Table 8. Bootstrap mediation of the effect on perceived underpricing through investor demand

Path	a	b	Total c	Direct c'	Indirect a×b	95% bootstrap CI	Sobel p
FF → ID → UP	0.662	0.755	0.789	0.289	0.500	[-0.050, 0.714]	.001
IS → ID → UP	0.771	0.759	0.854	0.269	0.585	[0.124, 1.083]	.002
FF → ID → UP (controlling IS)	0.214	0.672	0.387	0.243	0.144	[-0.182, 0.447]	.279
IS → ID → UP (controlling FF)	0.594	0.672	0.534	0.135	0.399	[-0.007, 0.889]	.030

Note. 5,000 bootstrap resamples (seed 2026), percentile CI. An indirect effect is supported when the CI excludes zero. Path a: X → ID; path b: ID → UP controlling for X; c' is the direct effect of X on UP controlling for ID.

Investor sentiment, however, was indirectly significant (a×b = 0.59, 95% CI [0.12, 1.08]) and directly not significant (c′ = 0.27, p = .194), meaning that there was full mediation when analysing investor sentiment only. For financial factors, the Sobel test was statistically significant (p = .001); however, the bootstrapped interval around the difference contained 0.000 [-0.050, 0.714]. The Sobel test was performed because it is based on the assumption of a normal sampling distribution of a×b, which is not realistic at n = 19, therefore the result of the bootstrap is preferred: mediation for financial factors is not robustly supported. Both indirect effects are reduced when the other predictor is held constant

(indirect effect on sentiment: [-0.007, 0.889] borderline; indirect effect on financial factors: [-0.182, 0.447]). H4 is thus found to be somewhat supported, particularly in investor sentiment.

9.8 Moderation analysis (H5)

Table 9. Moderation by market conditions (mean-centred interaction models)

Path	b (interaction)	SE	T	p	ΔR²
ID → UP × MC	0.075	0.074	1.01	.331	.007
FF → UP × MC	-0.008	0.080	-0.10	.926	.000
IS → UP × MC	-0.008	0.074	-0.10	.920	.000
FF → ID × MC	-0.166	0.083	-2.00	.063	.056
IS → ID × MC	-0.125	0.075	-1.67	.115	.036

Note. df = 15 for each interaction term. No interaction is significant at the .05 level.

None of the five interaction terms was significant (all $p \geq .063$). The nearest was financial factors → investor demand ($b = -0.166$, $p = .063$) suggesting a less strong impact of financial factors on demand on more favourable market conditions, but this fall short of significance. Market conditions did have a strong main effect on perceived underpricing (M7: $\beta = .92$, $R^2 = .85$). There is not enough power in the study to detect moderate interaction effects and the null hypothesis for H5 is not rejected.

9.9 Integrated predictive framework (H6)

The integrated model (M8) involving financial factors, sentiment, demand and market conditions is important; it accounts for 89.2% of the variance in perceived underpricing (adj.). $R^2 = .861$, $F(4,14) = 28.93$, $p < .001$). Only investor demand ($\beta = .43$, $p = .034$) and market conditions ($\beta = .57$, $p = .030$) are individually significant. Statistically, the integrated model fits better than any of its single-predictor models: incremental F tests show that it outperforms the financial-factor-only model ($F = 10.51$, $p = .001$), sentiment-only model ($F = 8.64$, $p = .002$) and demand-only model ($F = 3.72$, $p = .037$). However, it doesn't significantly outperform the market-conditions-only model ($F = 2.01$, $p = .159$).

The story that predictive accuracy tells is more conservative. When predicting the reaction of the market and investor demand to the integrated model, the R^2 (Q^2) was found to be .73 compared to .82 for market conditions alone and .76 for investor demand alone. The addition of predictors consequently increased the in-sample fit, but not the out-of-sample accuracy, as was consistent with the multicollinearity and overfitting in a sample of 19. On the perception side, the mean usefulness score ($M = 3.53$, $SD = 0.79$) was significantly above the neutral value of 3 ($t(18) = 2.91$, $p = .009$, $d = 0.67$) with 63.2% of the respondents' scores at 3.5 or higher. There was the lowest level of agreement for trust in a data-driven model (42.1% answered 4 or 5), followed by the combined model predicting better than any single factor (57.9%) and the framework being useful for retail investors (63.2%). The elements are thus supported (not superior prediction), that it can be combined into a statistically significant model that the respondents find useful.

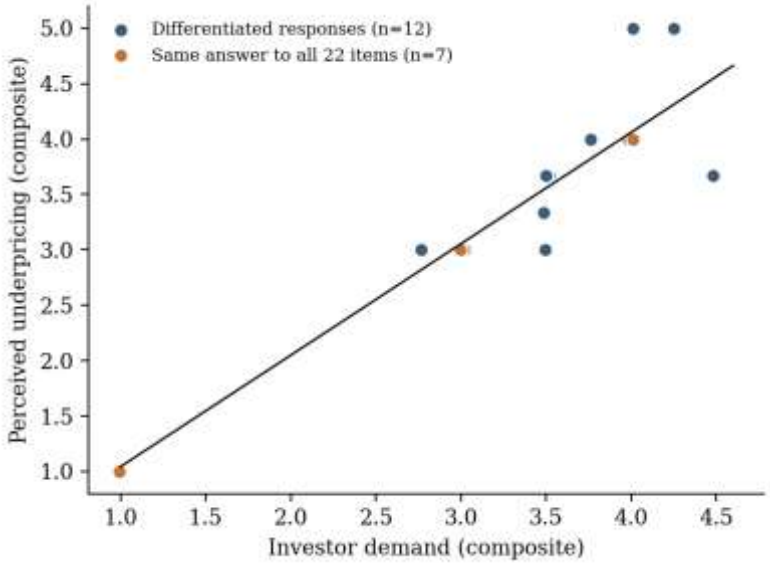


Figure 3. Investor demand and perceived underpricing. Orange points are respondents who gave the same answer to all 22 items.

9.10 Sensitivity analysis

Seven of the 19 respondents responded to all 22 items the same way (4 of the 19 respondents selected all 4s, 2 selected all 3s, 1 selected all 1s). Removing them (n = 12) significantly alters the results: the model of underpricing on financial factors and sentiment is no longer significant (R^2 = .37, p = .128), the demand model is not significant (R^2 = .25, p = .275) and the correlation of financial factors to underpricing drops from r = .81 to r = .46 (p = .129). The integrated model stays significant (R2 = .75, p = .028) and the demand of the investors is no longer significant (p = .081). The strength of the reported relationships, therefore, relies on many respondents providing the same response and can be either a result of genuine consistency of views or low-effort responding (Krosnick, 1991). Comparing with analysing the 92 raw records as independent observations would yield R^2 = .81 and $p \approx 10^{-33}$, which is merely a spurious consequence of repeating rows, and is not valid.

9.11 Summary of hypothesis testing

Table 10. Summary of hypothesis tests

Hypothesis	Key evidence	Decision
H1: FF → UP	M1: β = .81, R^2 = .65, p < .001; controlling IS: p = .071	H0 rejected (bivariate); attenuated when IS controlled
H2: IS → UP	M2: β = .83, p < .001; controlling FF: β = .52, p = .021	H0 rejected
H3: FF, IS → ID	M4: R^2 = .73, F(2,16) = 21.70, p < .001; IS significant, FF not	H0 rejected (driven by IS)
H4: mediation by ID	IS: indirect = 0.59, CI [0.12, 1.08]; FF: CI [-0.05, 0.71]	Partially supported (IS only)

Hypothesis	Key evidence	Decision
H5: moderation by MC	All five interactions $p \geq .063$	H0 not rejected
H6: integrated framework	M8: $R^2 = .89$, $p < .001$; $Q^2 = .73$ (below single-factor models); PF mean 3.53, $p = .009$	Supported for fit and perceived usefulness; predictive superiority not shown

10. Discussion

The results suggest that respondents who believe that fundamentals and sentiment are important also believe that IPO underpricing will be more likely, and that investor demand seems to be the conduit between sentiment and underpricing. This is in line with the market-timing arguments, which state that market sentiment leads to higher demand, and higher demand leads to higher listing-day prices; and in line with the evidence that shows listing-day prices are positively associated with oversubscription in India (Singh & Kumar, 2008), and that oversubscription is among the strongest predictors in Malaysia (Al-Daweri et al., 2026). Furthermore, the dominance of sentiment over financial factors when both are taken into account, is consistent with the concerns raised by ei et al (2025) and Nigudkar et al (2025) that conventional fundamentals, such as P/E and PAT, explain little of the IPO performance, and by Supsermpol et al (2025) and Sai Kiran et al (2025) that sentiment can be added to the IPO prediction models.

Underpricing was most associated with market conditions, but also had no impact on the relative strength of the other associations. This is not the moderating role that was assumed in the framework. Two possible explanations exist: One is that the interaction tests have very low power, and the other is that the market-conditions items are conceptually similar to the underpricing items (both ask about how conditions affect listing outcomes), making the market conditions a co-varying belief and not a separate moderator.

These conclusions are tempered by a number of features of the data. First, all constructs are assessed through the use of the same measurement tool at a single time, and items that state a relationship and solicit agreement (e.g., that fundamentals influence underpricing). High correlations ($r = .76 – .95$) are thus not necessarily due to distinct causal effects, but to a general tendency to agree (a common “method” effect or due to poor discriminant validity: a correlation of .95 corresponds to 90% shared variance between two constructs). Second, the effect is an under priced result. The study is not conducted on actual listing day returns. Third, the link between demand and underpricing and the mediation effect are partly embedded in the underpricing construct, as this construct is composed of Q13–Q15, which refer to investor demand. Fourth, it is a sample of only 19 respondents, comprising mostly young inexperienced students and salaried respondents, and both gender and occupation are confounded. Fifth, the sensitivity analysis shows that the main relationships depend on the respondents who gave identical answers to all items.

11. Implications

The results indicate that for retail investors perceived demand signals (oversubscription and grey-market premium) and sentiment are key factors in their definition and thinking about underpricing, and that they are willing to receive data-based decision aids. For issuers and underwriters, the role played by demand means that they need to pay attention to the book-building and communication that affects demand. The study provides an instrument for survey and a template for analysis that can be used on larger samples and in conjunction with actual IPO information.

12. Limitations and Directions for Future Research

The number of subjects studied, and the kinds of subjects studied. The estimates are not precise because 19 people were sampled by convenience sampling and the tests are under-powered and results cannot be generalised. For stable

regression, mediation, and moderation estimates, there must be at least 100-150 independent respondents with real variation of occupation and gender.

• Perception-based outcome. The dependent variable is a concept of underpricing. Finally, further research is required to correlate investor sentiment (such as the text of the prospectus, tone of the media or grey-market premium) and financial ratios with the actual returns of the listed IPO shares during the listing day, and then use the ML techniques outlined in the literature review to model these actual returns.

• Data quality. No duplicate submissions, no uniform-answer responses, at collection (one response per e-mail, attention-check items, reverse-worded items).

• Measurement. Include a separate block for items that are underpriced (or, use listing day returns), and reword items so that constructs are more distinct; once sample size allows, consider using confirmatory factor analysis or PLS-SEM.

13. **Conclusion**

This paper investigated financial factors, investor sentiment, investor demand and market conditions as correlates of perceived underpricing of IPOs for 19 unique respondents in India. The reliability of all scales was good. Underpricing was positively related to each of financial factors and sentiment, while the investor demand was the most significant factor in perceived underpricing, and the effect of sentiment on underpricing was mediated statistically by demand. All paths were related to market conditions, but this relationship was not moderated by market conditions. An integrated model was useful for respondents and provided a good fit (R2 = .89), but failed to out-predict the single factor models in a cross-validation process. Due to the small sample, outcome being perceived, and uniform-answer respondents, the results should be treated as exploratory and as a foundation for a larger study which would incorporate survey results with actual IPO returns.

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Appendix A: Questionnaire items

Q	Construct	Statement (5-point Likert)	Mean
Q1	FF	The issue price fixed by the company influences the extent of underpricing observed on listing day.	3.68
Q2	FF	A company's firm size (assets/net worth) has a significant bearing on the degree of IPO underpricing.	3.68
Q3	FF	The Price-to-Earnings (P/E) ratio and profitability (PAT) of a company affect its listing-day performance.	3.84

Q	Construct	Statement (5-point Likert)	Mean
Q4	FF	Overall, financial fundamentals of a company are a reliable predictor of IPO underpricing.	3.79
Q5	IS	Positive news/media coverage and social media buzz about a company increase my willingness to invest in its IPO.	3.84
Q6	IS	Overall market sentiment/mood (bullish or bearish) affects how I evaluate an IPO's pricing.	3.79
Q7	IS	Herd behaviour (following what other investors are doing) influences my IPO investment decisions.	3.32
Q8	IS	I believe that IPOs with high investor sentiment/hype tend to be more underpriced on listing day.	3.32
Q9	ID	A company's strong financial performance and attractive issue pricing increase my demand (application/subscription) for its IPO.	3.53
Q10	ID	Positive investor sentiment surrounding an IPO increases the number of shares/lots I apply for.	3.32
Q11	ID	The level of oversubscription and grey market premium (GMP) reported before listing influences my decision to apply.	3.58
Q12	ID	Both financial fundamentals and market sentiment jointly determine how much I am willing to invest in an IPO.	3.74
Q13	UP	High investor demand (oversubscription) is the main reason strong-fundamental or high-sentiment IPOs get underpriced on listing.	3.47
Q14	UP	The relationship between a company's financial factors/sentiment and its listing-day gains works mainly through the level of investor demand generated.	3.68
Q15	UP	Without strong investor demand, favourable financial factors alone would not result in significant underpricing.	3.63
Q16	MC	The relationship between investor demand and IPO underpricing is stronger during a bullish (rising) market than during a bearish (falling) market.	3.37
Q17	MC	The impact of financial factors and investor sentiment on IPO underpricing changes depending on overall market conditions at the time of listing.	3.63

Q	Construct	Statement (5-point Likert)	Mean
Q18	MC	During periods of high market volatility, investor demand becomes a less reliable indicator of eventual IPO returns.	3.53
Q19	MC	I adjust my IPO investment strategy based on prevailing market conditions (bull/bear/volatile).	3.74
Q20	PF	A model that combines financial factors, investor sentiment, investor demand, and market conditions together would predict IPO underpricing more accurately than using any single factor alone.	3.63
Q21	PF	I would trust a data-driven/predictive model (e.g., machine learning based) that uses these combined factors to guide my IPO investment decisions.	3.21
Q22	PF	Such an integrated predictive framework would be useful for retail investors like me in making informed IPO investment decisions.	3.74

Note. Mean of the 19 unique respondents.