



Beyond Black-Scholes: Evidence of Systematic Mispricing in the Indian Options Market and the Case for a Behavioral Pricing Model

Isha Tewari^{1*}, L. K. Singh²

^{1*}Research Scholar, Department of Management Studies, Bhimtal, Kumaun University, Nainital, Uttarakhand, India, Email: ishatewari15995@gmail.com, ORCID ID: 0000-0002-8204-3180

²Professor, Department of Management Studies, Bhimtal, Kumaun University, Nainital, Uttarakhand, India, Email: l_k_singh@yahoo.co.in

Abstract

This study examines whether Black-Scholes option prices deviate systematically from observed market prices in the Indian equity derivatives market, and whether the pattern of deviation supports a behavioral interpretation. Black-Scholes theoretical prices were computed for 69,372 call-option observations across 47 Nifty-50 constituent stocks between January 2023 and December 2024. Pricing errors were tested company-wise and in aggregate using paired-sample and one-sample t-tests, and compared across moneyness categories using the Friedman test with Kendall's coefficient of concordance. Because pricing errors are strongly serially correlated, all inference is reported both naively and with Newey-West HAC standard errors, cluster-level aggregation and false discovery rate control, with effect sizes accompanying every test. Black-Scholes prices differ significantly from market prices, with a median absolute error of 18.9 percent of premium, although the effect size is small. The direction of deviation is not stable: market prices were below the model prices in 2023 and above them in 2024, and the sign tracks the annual volatility input rather than investor behavior, so no behavioral reading of the direction is defensible. The robust finding concerns magnitude. Using moneyness reconstructed from contemporaneous strike-to-spot ratios, median absolute percentage error is 4.6 percent for in-the-money contracts, 21.5 percent for at-the-money contracts and 70.1 percent for out-of-the-money contracts. Every one of the 47 companies displays this ordering, and it holds within each year of the sample separately. Relative mispricing therefore concentrates in the segment whose value depends entirely on small-probability outcomes, which points toward probability weighting rather than loss aversion as the mechanism most likely to carry explanatory power in this market. The study further documents that where volatility is estimated annually rather than implied from contract prices, the direction of measured mispricing follows that input, a result bearing on how existing Indian evidence on the sign of Black-Scholes error should be interpreted.

Keywords: Black-Scholes model; Option mispricing; Moneyness; Probability weighting; Indian derivatives market

1. Introduction

The Black-Scholes (1973) option pricing model assumes a rational, informed investor who can form a riskless hedge. The profile of India's actual options market participants gives reason to question that assumption. SEBI's own research found that 89 percent of individual equity F&O traders lost money in FY22 (SEBI, 2023). An updated study covering FY22–FY24 found the picture had worsened: 93 percent of individual traders, over one crore unique participants, incurred losses, with aggregate losses exceeding ₹1.8 lakh crore. Traders under 30 grew from 31 percent to 43 percent of the base, and over three-quarters reported annual income below ₹5 lakh (SEBI, 2024a). SEBI's regulatory reset that followed, set out in a circular of 1 October 2024 and phased in from 20 November 2024, raised minimum index-derivative contract sizes, restricted each exchange to weekly expiries on a single benchmark index and required upfront collection of option

premiums (SEBI, 2024b). It reflects the regulator's own conclusion that trading behavior in this market departs from rational, risk-calibrated decision-making.

Subsequent evidence indicates that this intervention altered participation without correcting outcomes. SEBI's follow-up studies report that over 91 percent of individual traders continued to lose money in FY25, and that 87.7 percent did so in FY26, when aggregate net losses stood at ₹91,685 crore (SEBI, 2025, 2026a). Participation contracted sharply over this period, yet the average net loss per trader rose to approximately ₹1.17 lakh in FY26. The loss rate has declined only marginally across four successive studies, from 89 percent in FY22 to 87.7 percent in FY26, despite substantial structural reform in the interim.

SEBI's companion study of trading behaviour over the same period reports patterns that bear directly

on the premise of this paper (SEBI, 2026b). Around 90 percent of traders who lost money in two consecutive years lost again after continuing to trade, and loss rates did not improve with accumulated trading experience. Losses during loss-making quarters exceeded gains during profitable quarters for most traders, and lower-income and younger participants recorded substantially higher turnover relative to their cash-market holdings, which the regulator reads as indicating greater speculative activity. Persistent participation in the face of repeated and asymmetric losses is difficult to reconcile with the rational, risk-calibrated agent that the Black-Scholes framework assumes, and it is precisely the kind of pattern a behavioral pricing framework is designed to formalise.

This paper tests that proposition directly, using two years of options data spanning 47 Nifty-50 constituent stocks, and asks two empirical questions. First, do Black-Scholes prices deviate significantly from market prices, and does the pattern of deviation match what behavioral finance would predict? Second, does this mispricing vary systematically with moneyness and market volatility? Once that evidence is established, the paper turns to a third, non-empirical question: given this evidence, and given what researchers have found when they have actually built and tested behavioral option pricing models elsewhere, what kind of behavioral model would suit the Indian market, and why?

The paper is deliberately scoped as the diagnostic stage of a larger research programme on behavioral option pricing in the Indian derivatives market. Before a behavioral pricing model can be constructed and evaluated against traditional alternatives, three things must first be established on Indian data: that a systematic pricing gap exists and is not an artefact of sample or specification, that the gap is patterned in a way consistent with behavioral mechanisms rather than randomly distributed, and that the gap varies across market conditions in a way a state-dependent model could exploit. This study answers the first two and shows why the third cannot be answered where volatility is estimated annually, which is itself a result of consequence for the next stage. Constructing the behavioral model itself, calibrating its parameters to Indian data, and benchmarking it against Black-Scholes and other traditional models are the subsequent stages, and Section 7 specifies what that model should look like and why. The contribution here is to ground the case for behavioral option pricing in current, India-specific evidence rather than treat it as self-evident, and in doing so to establish the empirical baseline against which any such model must later be judged.

2. Literature Review

2.1 The Changing Structure of the Indian Options Market

SEBI's investor-loss studies (SEBI, 2023, 2024a) and its regulatory response (SEBI, 2024b) document a market marked by rapid retail growth, mass and persistent losses, and heavy concentration in short-dated speculative contracts. This structural profile

postdates most of the existing academic evidence on Black-Scholes performance in India.

2.2 Black-Scholes and Its Known Empirical Limitations

The Black-Scholes (1973) formula remains the standard option-valuation benchmark, despite well-documented anomalies such as volatility smiles and skews (Mayhew, 1995). Proposed explanations include non-normal skewness and kurtosis in returns (Corrado & Su, 1996), moneyness- and maturity-dependent implied volatility (Dumas, Fleming, & Whaley, 1998), and the possibility that the model's hedge portfolio is not, in practice, riskless (Omberg, 1991). The standard model also does not account for dividends, which is itself a documented source of systematic deviation from market prices (Merton, 1973).

2.3 Prior Evidence on Black-Scholes Mispricing in India

Varma (2002) found severe volatility mispricing in early-stage Nifty options. Mitra (2008) documented systematic underpricing of in-the-money options and overpricing of out-of-the-money options. Singh (2013) showed that stochastic volatility models reduced Black-Scholes pricing errors by 20–30 percent for Nifty index options. Coelho and Reddy (2017) applied paired-sample t-tests to banking stock options from the Nifty Bank index and found a significant difference between Black-Scholes model prices and market prices, with both the Black-Scholes and Black models tending to underestimate call premiums; the present study's aggregate test extends that design to a substantially larger cross-section. Srivastava and Shastri (2018) similarly reported that Black-Scholes values bore limited relevance to observed market values for Indian stock options. Swapna and Reddy (2020) found that substituting GARCH volatility for historical volatility improved pricing efficiency, and that models using historical volatility tended to underestimate stock option premiums, which is directly relevant to the volatility-input limitation acknowledged in this study. Chauhan and Gor (2021) compared modified Black-Scholes specifications across five sectors of the Indian market and found that a generalized model with a modified distribution produced the lowest RMSE. Singh and Kumar (2024), covering Nifty and Bank Nifty options from 2009 to 2020, found that no single deterministic model consistently outperformed the others across moneyness-maturity categories: Black-Scholes and Practitioner Black-Scholes remained competitive despite their relative simplicity. Taken together, this literature establishes that Black-Scholes mispricing

in India is well documented, that volatility specification materially affects measured error, and that added model complexity does not by itself resolve the problem. What it does not establish is whether the residual error carries a behavioral signature, which is the question this study takes up.

2.4 Behavioral Finance and Evidence That Calibrated Models Can Work

Kahneman and Tversky's (1979) Prospect Theory, later extended into its cumulative form by Tversky and Kahneman (1992), describes decision-makers as loss-averse and risk-seeking over losses, with probability perceptions that depart systematically from objective probabilities. Two functions carry the behavioral content: a value function governing risk attitude and loss aversion, and a weighting function governing probability perception. This is the theoretical basis for reading systematic underpricing as loss aversion and OTM overpricing as a lottery effect. The framework has a substantial supporting literature in finance. Thaler (1980) established that decision-makers group outcomes into mental accounts in ways that depart predictably from economic theory. Shefrin and Statman (1993) applied prospect theory directly to the design of derivative products, showing that covered calls appeal to investors who are risk-averse over gains and risk-seeking over losses. Barberis, Huang and Santos (2001) demonstrated that the reference point of the value function shifts with prior gains and losses, making investors less loss-averse after gains and more so after losses. Abbink and Rockenbach (2006) found in an option pricing experiment that valuations were probability-dependent in ways the arbitrage-free price cannot accommodate. A body of empirical work shows that option pricing models built on these foundations can significantly outperform Black-Scholes, provided their parameters are calibrated to the market being studied rather than imported unmodified. Wolff, Lehnert and Versluis (2009) found that prospect-theory-based pricing models significantly improved fitting performance over Black-Scholes for S&P 500 index options, with performance comparable to the Heston (1993) stochastic volatility model. Baele, Driessen, Ebert, Londono and Spalt (2019), publishing in the Review of Financial Studies, showed that a Cumulative Prospect Theory model with a single probability-weighting parameter, estimated using the Generalized Method of Moments on the market's own option-return data, could explain both the puzzlingly low returns on out-of-the-money puts and calls and the variance premium in U.S. equity index options. Sun and Peng (2024) embedded a prospect-theory value function within a Heston (1993) stochastic-volatility framework and found the resulting model significantly improved pricing accuracy for short-maturity, out-of-the-money SSE 50ETF options in the Chinese market, with little improvement for in-the-money options. Siddiqi (2015, 2019) took a different

starting point: the anchoring-and-adjustment heuristic, under which investors anchor on the underlying stock's own volatility and adjust insufficiently to price call-option volatility. He showed that anchoring-adjusted Black-Scholes, Heston (1993) and Bates (1996) models captured the implied-volatility skew and several option-return puzzles using just one additional parameter, with novel predictions that held up well empirically.

2.5 Research Gap

Most of the evidence available on option mispricing in the Indian market comes from past market periods and may not be representative of the current market structure, which is increasingly retail-oriented, and no study could be found that directly links SEBI's investor-loss and regulatory-reform evidence to a test of option pricing accuracy. In isolation, the literature on behavioral option pricing internationally indicates that while calibrated models can be effective, there is no Indian specific advice on which behavioral mechanism, or which calibration, is most appropriate for the Indian market participant profile. This paper will address the first gap empirically, and the second with a literature-based argument based on that evidence.

3. Objectives

- To check whether the theoretical Black-Scholes prices differ significantly from the actual market prices in the Indian derivatives market and whether the nature of the deviation is consistent with the behavioural mechanisms identified in the literature.
- To investigate whether the moneyness categories and market volatility conditions have a systematic impact on the accuracy of the Black-Scholes prices.
- To evaluate, based on these results and available literature, which type of behavioral option pricing model would be appropriate for the Indian market.

4. Hypotheses

H1. There is no significant difference between Black-Scholes theoretical option prices and actual market option prices.

H2. There is no significant difference in relative (percentage) mispricing across in-the-money, at-the-money and out-of-the-money contracts.

H3. There is no significant difference in Black-Scholes pricing accuracy across low-, medium- and high-volatility market conditions.

These three hypotheses do not carry equal evidential weight, and the results treat them accordingly. H2 is the study's primary test: moneyness is observed at the contract level and is independent of the volatility input, so the comparison is unaffected by the estimation choices described in Section 5.2. H1 concerns the existence and magnitude of deviation, which the data establish clearly, although the direction of that deviation proves unstable across the

sample period for reasons set out in Section 6.2. H3 is reported for completeness but cannot be interpreted causally, because volatility-tercile membership is determined by the same annual estimate that mechanically influences pricing error. Objective 3 is addressed through literature synthesis rather than statistical test, since it asks which model design the existing evidence base supports, not a property measurable in these data.

5. Data and Methodology

5.1 Sample

The sample comprises 69,372 call-option observations on 47 Nifty-50 constituent stocks traded on the NSE, covering 2 January 2023 to 26 December 2024. The panel is simply balanced in terms of construction, with 47 stocks each contributing 1476 observations (738 per year) and the extract having a moneyness label, with the number of observations split equally between ITM, ATM and OTM. This equal split is a sampling design choice, not a feature of the underlying market, where OTM contracts dominate traded volume, so sample proportions should not be read as market proportions.

Two adjustments are applied before the moneyness analysis in Section 6.3. First, the supplied moneyness labels are static: they are assigned once per contract and not updated as the spot price moves, so they do not describe the contract's position relative to its strike on the observation date. In 7,499 records the labelled category places the contract on the opposite side of the strike from where the contemporaneous strike-to-spot ratio places it. Moneyness is therefore reconstructed from that ratio at each observation date, using thresholds of K/S below 0.975 for ITM, 0.975 to 1.025 for ATM, and above 1.025 for OTM. Because reconstruction is contract- and date-specific, the reconstructed categories are not equal in size.

Second, four screens are applied: 55 records duplicating another record on every economic field; 12 records in two stock-date groups reporting conflicting spot prices or maturities; the 738 records of the BAJAJFINSV 2023 stock-year, whose assigned annual volatility of 230.45 percent is implausible; and 57 records from December 2023 in which ASIANPAINT carries a volatility estimate that could not have been computed from information available at that date. These screens retain 68,510 records. The moneyness results in Section 6.3 use this screened sample with reconstructed categories; the aggregate tests in Sections 6.1, 6.2 and 6.4 use the full extract of 69,372 records, so that they remain directly comparable with the outlier-sensitivity analysis in Section 6.5. Each table states which sample it reports.

5.2 Model Computation

Black-Scholes theoretical prices were computed in MATLAB R2023a (MathWorks, 2023) using the built-in `blsprice` function, which implements the standard

closed-form formula, without adjustment for dividends. The pricing error for each observation is defined as the market premium minus the Black-Scholes theoretical price, so a negative error denotes market underpricing relative to the model.

The four remaining inputs are as follows. Time to maturity is measured in years and ranges from 1 to 35 calendar days (0.0027 to 0.0959 years), so the sample consists entirely of short-dated contracts. The risk-free rate varies over the sample period between 6.36 and 7.04 percent, taking 20 distinct values across the two years, and is matched to each observation by date. Volatility is an annualized estimate assigned at the stock-year level: one value per stock for 2023 and one for 2024, giving 94 stock-year cells and 90 distinct volatility values across the sample. This last point is a material design feature rather than a detail. Because volatility does not vary by contract or by day, it does not capture the contract-specific implied volatility surface, and observations sharing a stock-year are not statistically independent in this input. Section 5.3 and Section 6.4 address the consequences directly.

5.3 Statistical Tests

H1 was tested two ways: an aggregate paired-sample t-test comparing market premiums to Black-Scholes prices across the full sample, and company-wise one-sample t-tests classifying each company by the sign and significance of its mean pricing error at the 5 percent level. H2, the moneyness hypothesis, is the study's primary test. Because each company contributes one median percentage error per moneyness category, the comparison is matched within companies, and it is therefore evaluated using the Friedman (1937) test with Kendall's coefficient of concordance as the associated effect size (Kendall & Babington Smith, 1939), followed by paired Wilcoxon comparisons with Holm (1979) adjustment. H3 was tested by splitting the sample into volatility terciles and comparing pricing error across regimes using one-way ANOVA and the Kruskal-Wallis test, with Bonferroni-corrected pairwise comparisons. Rupee-denominated errors scale with price level and premium size, so all tests are supplemented with percentage-error measures (error as a share of the option premium) and an outlier-sensitivity check that excludes observations with implausible volatility inputs.

Three further procedures address the statistical dependence in the data, which is substantial and which naive tests would otherwise misrepresent. First, effect sizes are reported alongside every significance test, because at $N = 69,372$ even a negligible difference registers as highly significant, and the practical size of the mispricing is the question of substantive interest. Cohen's d (Cohen, 1988) is used for the t-tests and η^2 and ϵ^2 for the omnibus tests. Second, pricing errors for the same underlying are strongly serially correlated: the mean

lag-one autocorrelation within a stock is 0.66 (median 0.69). Company-level tests are therefore re-estimated with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors (Newey & West, 1987), and the aggregate test is re-

run on cluster means at both the stock-year ($N = 94$) and stock ($N = 47$) levels. Third, because 47

company-level tests are conducted simultaneously, results are reported under Benjamini-Hochberg false

discovery rate control (Benjamini & Hochberg, 1995) and under the more conservative Bonferroni correction. Throughout, both the naive and the corrected figures are presented, so the extent to which each conclusion depends on the independence assumption is visible rather than hidden. Finally, every principal test is re-estimated on each calendar year separately, since a result that reverses between sub-periods describes the sample rather than the market.

6. Results and Discussion

6.1 Descriptive Statistics

Table 1. Descriptive statistics: market premium vs. Black-Scholes theoretical price (full extract, $N = 69,372$).

Measure	N	Mean (₹)	Std. Dev. (₹)	Median (₹)
Market Premium	69,372	75.12	134.22	28.80
Black-Scholes Price	69,372	80.07	138.52	31.19

6.2 Significance of Black-Scholes Mispricing (H1)

The overall paired-sample t-test comparing market premiums to Black-Scholes theoretical prices was highly significant ($t(69,371) = -39.19$, $p < .001$), rejecting H1. The mean pricing error is -₹4.95, or -6.6 percent of the mean premium. The associated effect size, however, is small: Cohen's $d = -0.15$. This combination of an extreme test statistic and a modest effect size is a direct consequence of the sample size, and it means the result should be read as strong evidence that the deviation is not zero rather than as evidence that it is large.

Because pricing errors are strongly serially correlated, the aggregate test was re-run on cluster means. At the stock-year level the deviation is marginal ($t(93) = -1.84$, $p = .069$), and at the stock level it is significant ($t(46) = -2.12$, $p = .040$), with a Wilcoxon signed-rank test on stock means strongly significant ($p < .001$). The naive statistic of -39.19 therefore overstates the strength of the evidence once the dependence structure is respected.

The direction of the deviation is less stable than the pooled figure suggests, and this requires explicit statement. Disaggregated by year, the mean pricing error is -₹7.76 in 2023 and +₹2.26 in 2024: market prices sit below Black-Scholes values in the first year of the sample and above them in the second. The reversal is systematic rather than marginal, and it tracks the volatility input. Volatility enters the computation as one annual estimate per stock-year, those estimates are higher in 2023 than in 2024, and the Black-Scholes price is increasing in volatility.

Across the 94 stock-year units the rank correlation between assigned volatility and mean pricing error is -0.665 ($p < .001$). The sign of the aggregate error is therefore governed by the volatility specification, and this study does not interpret it as evidence of loss aversion or of any other directional bias. The analysis that follows rests on the magnitude of relative mispricing across moneyness categories, which is not subject to this confound because volatility is held fixed within each stock-year by construction.

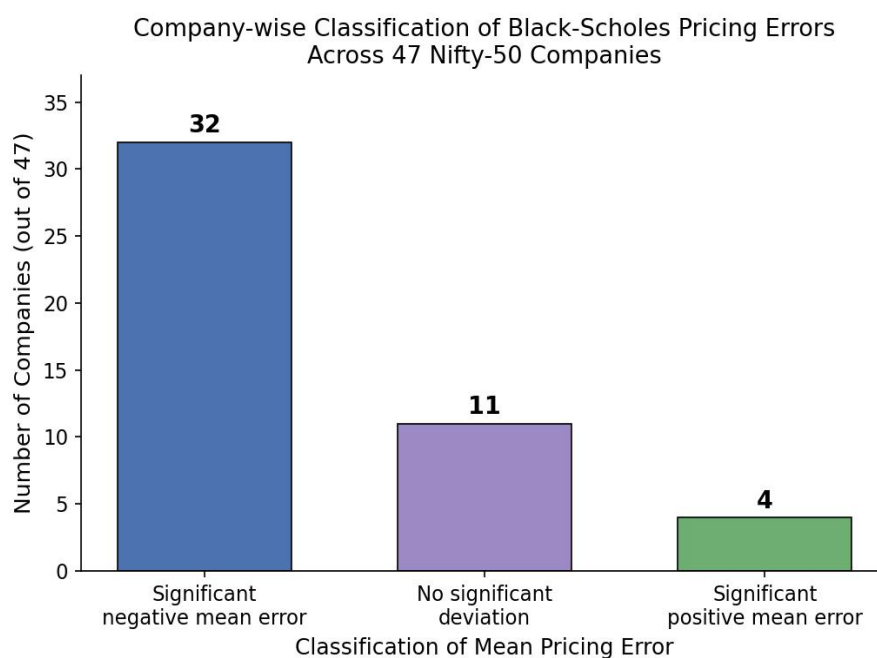
Company-wise one-sample t-tests on the pooled sample classified 32 of 47 companies (68.1 percent) as showing a significant negative mean error, 4 companies (8.5 percent) as showing a significant positive mean error, and 11 companies (23.4 percent) as showing no significant deviation (Table 2, Figure 1). These labels describe the pooled sample and, for the reason given above, are not read here as behavioral classifications. These counts are also sensitive to the independence assumption, and Table 2a reports how they change under successively stricter corrections. Applying Newey-West HAC standard errors reduces the underpricing count to 26 companies (55.3 percent); adding false discovery rate control reduces it to 23 (48.9 percent); and Bonferroni correction, the most conservative option, leaves 19 (40.4 percent). The headline proportion is therefore not robust as a point estimate, and because the underlying sign is governed by the volatility input, the asymmetry it describes reflects the specification rather than an independent finding.

Table 2. Company-wise classification of mean Black-Scholes pricing error (full extract; N = 47 Nifty-50 companies).

Classification of Mean Pricing Error	Number of Companies	% of Sample
Significant negative mean error	32	68.1%
No Significant Deviation	11	23.4%
Significant positive mean error	4	8.5%

Table 2a. Sensitivity of the company-wise classification to serial-correlation and multiple-comparison corrections (N = 47 companies).

Correction Applied	Negative mean error	No Significant Deviation	Positive mean error
None (naive t-test)	32 (68.1%)	11 (23.4%)	4 (8.5%)
Newey-West HAC	26 (55.3%)	18 (38.3%)	3 (6.4%)
HAC + Benjamini-Hochberg FDR	23 (48.9%)	21 (44.7%)	3 (6.4%)
HAC + Bonferroni	19 (40.4%)	26 (55.3%)	2 (4.3%)

**Figure 1. Distribution of companies by sign and significance of mean pricing error.**

Signed median errors by moneyiness are reported in Figure 2 for completeness. They are small relative to the dispersion of the error distribution and, for the reasons set out above, are not interpreted directionally.

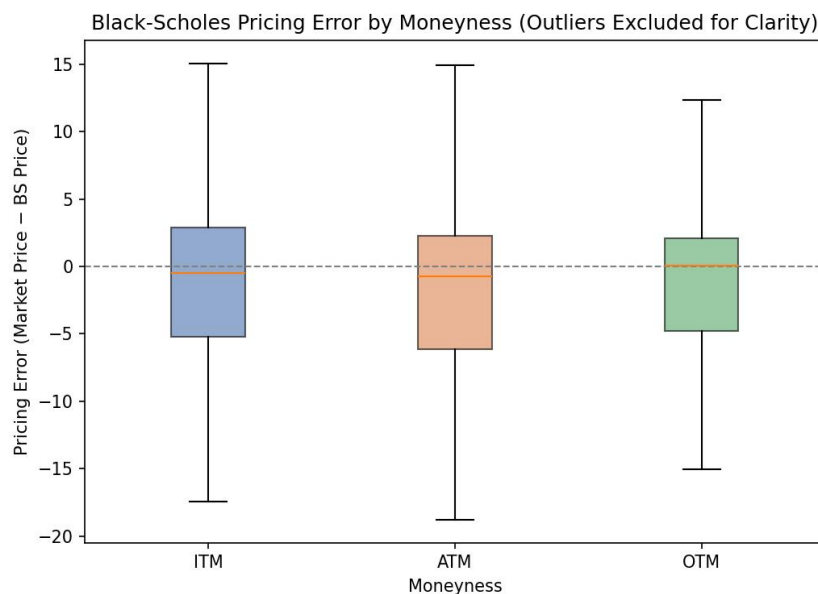


Figure 2. Black-Scholes pricing error by moneyness (outliers beyond $\pm ₹100$ excluded for visual clarity).

6.3 Relative (Percentage) Mispricing by Moneyness (H2)

Moneyness in the original extract was assigned once per contract and not updated as spot prices moved. Recomputing it from the contemporaneous strike-to-spot ratio at each observation date, with ITM defined as K/S below 0.975, ATM as K/S between 0.975 and 1.025, and OTM as K/S above 1.025, is therefore a precondition for any economic comparison across categories. The reclassification is material: 7,499 records in the original extract sit on the opposite side of the strike from their assigned label. All results in this section use the reconstructed categories on the screened sample of 68,510 records.

Rupee-denominated error alone is scale-dependent: OTM premiums are small in rupee terms, so a modest rupee error corresponds to a large percentage error, while the reverse holds for higher-premium ITM contracts. Measured as a percentage of the option premium, median absolute error is 4.6 percent for ITM contracts, 21.5 percent for ATM and 70.1 percent for OTM (Table 3, Figure 3). The ordering is

monotonic and the spread is wide: relative mispricing in the OTM segment is roughly fifteen times that of the ITM segment. This is the segment whose value depends entirely on small-probability outcomes, and therefore the segment in which probability weighting is theorised to matter most.

This ordering is the central finding of the study, and it is unusually consistent. Because each company contributes one median value per moneyness category, the comparison is matched within companies and is tested using the Friedman (1937) test, which respects that structure. The statistic is 94.00 ($p < .001$) with Kendall's coefficient of concordance $W = 1.00$ (Kendall & Babington Smith, 1939), the maximum attainable value. Every one of the 47 companies in the sample displays the $ITM < ATM < OTM$ ordering in its category medians, without exception. All three paired comparisons remain significant after Holm (1979) adjustment. The ordering also holds in each year taken separately, with medians of 5.0, 29.2 and 71.7 percent in 2023 and 4.2, 15.4 and 69.0 percent in 2024, which indicates that it is a property of the cross-section rather than of a particular market episode.

Table 3. Rupee and percentage pricing error by contemporaneous moneyness (screened sample, $N = 68,510$; ITM 22,547, ATM 25,168, OTM 20,795).

Moneyness	Rupee MAE (₹)	Median % Error vs. Premium
ITM	9.66	4.6%
ATM	14.10	21.5%
OTM	6.64	70.1%

Because percentage error is measured against premium, and OTM premiums are small, part of the

raw gradient reflects the denominator. Two checks indicate it is not only that. Restricting the sample to

contracts with premiums of at least ₹5 leaves the ordering intact, as does restricting it to maturities beyond seven days. Excluding the 7,266 records whose premium falls below the zero-dividend lower bound, which are concentrated in the ITM category, moves the ITM median only from 4.56 to 4.45

percent and leaves the Friedman statistic and the 47-of-47 ordering unchanged. A definitive separation of the scale component from the behavioral one would require bid-ask and volume data that this extract does not retain, and is identified in Section 10 as a requirement for the next stage.

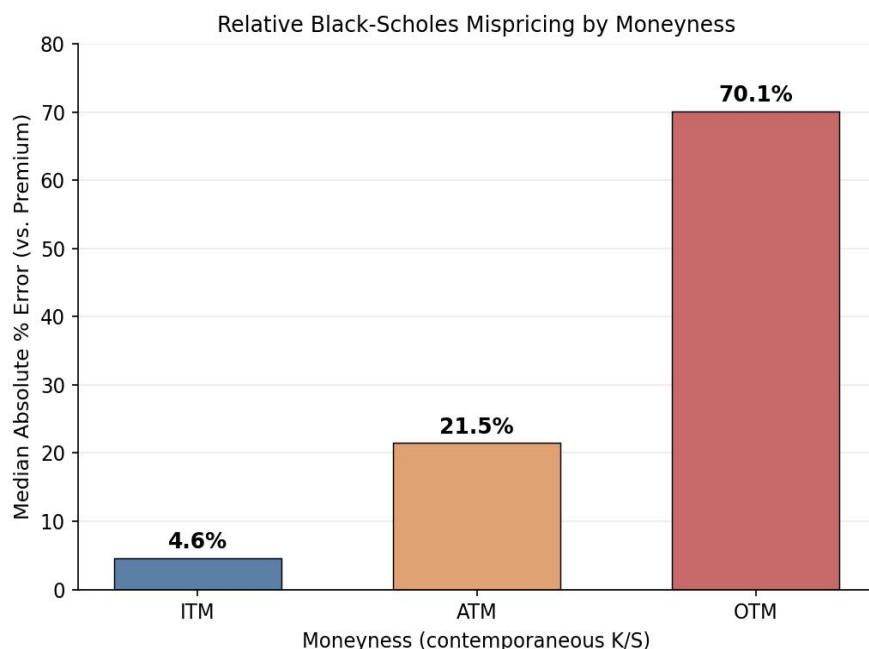


Figure 3. Relative Black-Scholes mispricing by moneyness (median absolute percentage error vs. premium).

6.4 Performance Across Volatility Regimes (H3)

Observations were partitioned into low-, medium-, and high-volatility terciles based on the volatility input used in pricing (mean volatility 18.6 percent, 24.3 percent, and 40.4 percent respectively). It is important to be precise about what this variable is. As described in Section 5.2, volatility is estimated once per stock per year, not per contract per day. The terciles therefore partition 94 stock-year cells (32

low, 31 medium, 31 high), and every observation within a stock-year carries an identical volatility value. Rupee MAE was ₹10.70 in the low-volatility tercile, ₹6.86 in the medium-volatility tercile, and ₹20.19 in the high-volatility tercile (Table 4, Figure 4). Measured as a percentage of premium, median absolute error was 16.5 percent (low), 15.7 percent (medium),

Table 4. Mean absolute error and percentage error by volatility regime (terciles of the annual stock-year volatility input; full extract, N = 69,372).

Volatility Regime	N	Mean IV	BS MAE (₹)	Median % Error vs. Premium
Low	23,673	18.6%	10.70	16.5%
Medium	22,878	24.3%	6.86	15.7%
High	22,821	40.4%	20.19	26.5%

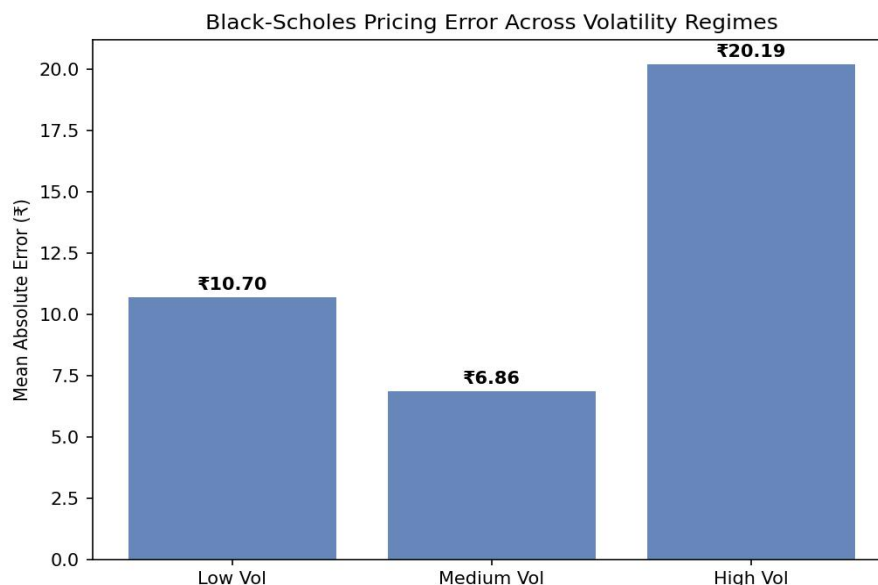


Figure 4. Black-Scholes pricing error across volatility regimes.

Formal tests were run at two levels. Treating all 69,372 observations as independent, a one-way ANOVA on absolute pricing error across terciles is highly significant ($F(2, 69369) = 1143.38, p < .001$), as is a Kruskal-Wallis test ($H(2) = 749.29, p < .001$). These figures are reported for completeness, but they overstate the evidence: because volatility is constant within a stock-year, observations within a tercile are heavily clustered, and the effect sizes are small in any case ($\eta^2 = 0.032; \epsilon^2 = 0.011$).

The cluster-appropriate tests aggregate to the 94 stock-year units, and they separate the rupee and percentage findings sharply. On rupee MAE, the difference across terciles is not statistically significant (ANOVA $F(2, 91) = 2.34, p = .102$; Kruskal-Wallis $H(2) = 1.18, p = .554$). The apparent near-threefold rise in rupee MAE is driven by a small number of extreme stock-years and by the mechanical scaling of premiums with volatility, and does not survive a test that respects the data's clustering. On percentage error, by contrast, the difference is significant (Kruskal-Wallis $H(2) = 18.76, p < .001$), and it remains so after excluding the anomalous BAJAJFINSV 2023 stock-year discussed in Section 6.5 (ANOVA $F(2, 90) = 8.18, p < .001$; Kruskal-Wallis $H(2) = 17.40, p < .001$). Pairwise comparisons with Bonferroni correction locate the effect precisely: the high-volatility tercile differs from both the low tercile ($p = .002$, rank-biserial $r = 0.50$) and the medium tercile ($p < .001, r = 0.58$), while low and medium do not differ from each other ($p = .805$). This also resolves the apparent non-monotonicity in the rupee figures: the low-versus-medium ordering is not statistically distinguishable, so the pattern is a single sharp deterioration in the high-volatility regime, not a U-shape.

H3 cannot be resolved within this design. Volatility terciles are defined by the same annual estimate that governs pricing error, so sorting observations by

volatility and then testing whether error varies across the resulting groups is not an independent test. The terciles are also confounded with calendar time: because the volatility estimates fall for 44 of 47 stocks between the two years, the high-volatility group is drawn overwhelmingly from 2023 and the low-volatility group from 2024. The descriptive pattern, a sharp deterioration in relative accuracy in the highest-volatility group, is consistent with the hypothesis but cannot be separated from a year effect. H3 is therefore reported as inconclusive rather than rejected, and the design required to resolve it is set out in Section 10.

6.5 Robustness: Outlier Sensitivity

The 738 observations (1.1% of sample) have a volatility input above 100 percent. These do not appear in the sample, but are precisely the one stock-year, BAJAJFINSV in 2023, for which the estimated annual volatility is 230.45 percent. Volatility is assigned per stock-year, so this one implausible value is carried over to all 738 observations of that stock-year, from 2 January to 29 December 2023. The direction and significance of H1 is not affected when these observations are excluded ($t(68,633) = -30.13, p < .001$, Cohen's $d = -0.12$), and the overall Black-Scholes MAE drops from ₹12.55 to ₹10.38. The core conclusion does not depend on this subset. The headline MAE figure is sensitive to it, though, so the cleaned figure is the more defensible one to cite. This episode also is a nice example of the structural aspect of the design to mention: with volatility estimated annually, a single bad estimate contaminates an entire stock-year rather than a handful of contracts.

6.6 Summary of Findings

Table 5 summarises the three hypotheses, together with the tests bearing on each, the associated effect sizes, and the verdict each can support. They are deliberately not presented as uniformly resolved,

because they are not.

Table 5. Summary of hypothesis tests, effect sizes and verdicts.

Hypothesis	Test and Result	Effect Size	Verdict
H1	Paired t-test, market premium vs. Black-Scholes price: $t(69,371) = -39.19$, $p < .001$. Cluster-robust: stock level $t(46) = -2.12$, $p = .040$; Wilcoxon $p < .001$.	Cohen's $d = -0.15$ (small)	Rejected as to existence. Direction reverses by year and is not interpreted.
H1 (firm level)	Company-wise t-tests: 32 of 47 firms show a significant negative mean error (68.1%). Under HAC 26 (55.3%); with FDR 23 (48.9%); with Bonferroni 19 (40.4%).	Median $ d = 0.16$ across firms	Counts attenuate under correction; sign governed by volatility input, so not read behaviorally.
Moneyness	Friedman test on company-level category medians: $\chi^2(2) = 94.00$, $p < .001$. Medians 4.6% (ITM), 21.5% (ATM), 70.1% (OTM). Holds within each year separately.	Kendall's $W = 1.00$ (maximum); ordering holds for 47 of 47 companies	Rejected. The study's primary and most robust finding.
H2	Cluster level (94 stock-years). Rupee MAE: $F(2, 91) = 2.34$, $p = .102$. Percentage error: $H(2) = 18.76$, $p < .001$.	Not reported; test not independent	Inconclusive. Terciles are circular with the pricing input and confounded with year.

One finding is robust, one is established only as to existence, and one is not established. The robust finding is the moneyness gradient: relative mispricing rises monotonically from ITM to ATM to OTM, every company in the sample displays the ordering, and it holds in both years. Black-Scholes prices do differ significantly from market prices, but the effect size is small and the direction of the difference is governed by the volatility input rather than by market behavior. The relationship between volatility regime and pricing accuracy cannot be identified in this design. The paper accordingly rests its interpretation on the moneyness result alone.

6.7 Discussion

This study's empirical contribution rests on a single finding. Relative mispricing rises monotonically with moneyness, and does so with unusual consistency: every company in the sample displays the ITM to ATM to OTM ordering, Kendall's concordance is at its maximum value, and the pattern reproduces in each year separately. It updates the moneyness pattern reported by Mitra (2008) on a larger and more recent sample, using contemporaneous rather than static moneyness classification. These are precisely the segments where behavioral finance predicts probability-weighting and sentiment effects should be strongest, and where Sun and Peng (2024) independently found behavioral pricing adjustments deliver their largest gains in a different market.

These findings should be read alongside competing, non-behavioral explanations that this study cannot rule out. Black-Scholes prices here are not dividend-adjusted. If the underlying stocks pay dividends, the dividend-unadjusted formula would systematically overprice calls relative to the market (Merton, 1973), which would independently produce negative pricing

errors. Bid-ask spreads, liquidity discounts, and transaction costs, none of which are observed in this dataset, could produce the same directional pattern without any behavioral mechanism. This concern is not hypothetical: Singh and Kumar (2024) find that contract liquidity materially affects measured pricing efficiency in Indian index options, with heavily traded contracts priced more accurately. The premium and maturity restrictions reported in Section 6.3 show that the ordering is not confined to the smallest premiums or nearest maturities, but they cannot separate a scale effect from a liquidity effect, since low-premium OTM contracts are both the least liquid and the ones behavioral theory predicts should be most mispriced. Distinguishing the two requires bid-ask and volume data and is left to subsequent work. What remains is a magnitude result rather than a direction result. The concentration of relative mispricing in OTM contracts is consistent with probability weighting, since it is in the tails that subjective and objective probabilities diverge most sharply. That consistency is suggestive rather than demonstrative: this design identifies where Black-Scholes fails most severely, not why.

7. The Case for a Behavioral Option Pricing Model

With those caveats in place, the pattern documented here is hard to explain as pure noise. Relative mispricing is large and concentrates in the out-of-the-money segment in the specific way probability-weighting accounts predict, holding across every company in the sample and in both years. That is a narrower claim than a behavioral reading of the direction of mispricing would be, but it is the claim the evidence supports, and it gives behavioral option pricing research in India a firmer empirical basis than it has previously had. But that case only holds if calibrated behavioral models actually improve on

Black-Scholes in practice, not just in theory. Evidence from elsewhere speaks to that.

That evidence exists, and it is substantial. Wolff, Lehnert and Versluis (2009) showed that prospect-theory-based pricing significantly improved on Black-Scholes for S&P 500 options, with the aggregated version's performance comparable to the Heston stochastic-volatility model. Baele, Driessen, Ebert, Londono and Spalt (2019), in the Review of Financial Studies, showed that a Cumulative Prospect Theory model with a single probability-weighting parameter, estimated using GMM on the market's own option-return data rather than imported from laboratory experiments, successfully explained both the long-standing OTM option-return puzzle and the variance premium in U.S. index options. Sun and Peng (2024) showed that embedding prospect theory within a stochastic-volatility base model produced significant accuracy gains for short-maturity OTM options on Chinese SSE 50ETF options, with little gain for in-the-money contracts. That segment pattern closely mirrors this study's own finding that relative mispricing in India is concentrated in OTM contracts. Siddiqi (2015, 2019) took a different approach: a single-parameter anchoring-adjusted model, built on investors anchoring on the underlying stock's own volatility rather than the full CPT value-and-weighting-function apparatus. It captured the implied-volatility skew and several option-return puzzles with strong empirical support, including novel predictions that held up out of sample. Two further strands bear on the choice of specification. Breuer and Perst (2005) compared behavioral pricing with Black-Scholes in a multi-period continuous-time setting and found that the preferred instrument varied systematically with market drift, an early indication that behavioral pricing performance is state-dependent rather than uniform. Nardon and Pianca (2019) evaluated European options under continuous cumulative prospect theory and argued specifically that probability weighting may be among the principal causes of the gap between observed and Black-Scholes prices; adopting a constant relative sensitivity weighting function whose parameters

map directly onto curvature and elevation, they showed how these features propagate into option prices and implied volatilities. Their emphasis on the weighting function, rather than the value function, is directly relevant to the findings reported below.

The findings from this study, combined with the investor-profile evidence provided by SEBI for the model, justify a parsimonious, locally calibrated behavioral model, rather than a fully specified model with parameters that are directly imported from other markets. The results show that relative mispricing is not uniformly distributed on the pricing surface, but skewed towards the OTM segment. A targeted behavioral adjustment might thus be a

better option than applying a uniform adjustment to all moneyness levels. Also, the calibration strategy is more important than the choice of the behavioral mechanism, but this study's results do restrict the options. The most statistically sound of the results reported here is that relative mispricing increases monotonically from ITM to ATM to OTM and that the ordering of each company in the sample is the same and the pattern is repeated on an annual basis. The observed gradient is more consistent with the probability distortion rather than the curvature of the value function. Probability weighting is particularly applicable to the tails of the distribution where the objective or actual probability of the tails is small and could be significantly different from the subjective probability weighting of the tails. OTM options are particularly sensitive to probability-weighting effects as they rely strongly on such infrequent events. The finding thus suggests that the weighting function is most likely to explain this market. That's the approach taken by Nardon and Pianca (2019) and the one that Baele et al. (2019) are able to extract from market data with a single free parameter instead of the complete set of experiments. All of this suggests that a Cumulative Prospect Theory specification with its weighting function estimated from Indian option data is a natural first choice. Skewed evidence of a trading base by SEBI, which is young, first-time and low-income (SEBI, 2024a), is at least consistent with the single-parameter anchoring mechanism that underpins Siddiqi's (2015) and (2019) models. The design of this study does not provide any empirical basis to compare the performance of the two in the Indian market and such a comparison should be made on Indian data and not assumed. The evidence presented here suggests that the requirement common to both roads is that parameters have to be estimated locally (either through GMM or nonlinear least squares) and that the model should be evaluated in the OTM and high-volatility ranges found in this study to be the most mispriced, rather than the simple Black-Scholes model employed here. This paper does not construct and validate such a model. The purpose of this study is to provide empirical justification for the development of such a model and to determine the characteristics that the model specification should have. The next step of this research is to construct and test the model.

8. Conclusion

This study finds that there are systematic differences between the Black-Scholes theoretical prices and market prices in the Indian equity options market and the magnitude of the relative pricing error varies widely across the different moneyness categories. Using contemporaneous classification, relative mispricing rises from 4.6 percent of premium for in-

the-money contracts to 70.1 percent for out-of-the-money contracts, and every one of the 47 companies in the sample displays this ordering. The concentration of mispricing in the segment whose value depends entirely on small-probability outcomes points toward probability weighting as the behavioral mechanism most likely to carry explanatory power in this market. The study is equally clear about what it does not establish. The direction of mispricing reverses between the two years of the sample and follows the annual volatility input, so neither loss aversion nor a lottery effect can be inferred from the sign of the pricing error, and the relationship between volatility regime and pricing accuracy cannot be identified in a design where the conditioning variable and the outcome share a mechanical link. Combined with SEBI's evidence of a persistently loss-making retail participant base, and with international evidence that locally calibrated behavioral models improve on Black-Scholes, the case for developing such a model for the Indian market rests on the moneyiness evidence presented here.

9. Limitations

Several limitations qualify these findings. Black-Scholes prices are not dividend-adjusted. Dividend omission is a competing explanation for negative pricing errors (Merton, 1973). The most consequential limitation, however, is the volatility input, which is a single annualized estimate per stock-year rather than a contract-specific implied volatility. Three consequences follow: the model is not fitted to the observed volatility surface; part of the measured pricing error reflects this input approximation rather than market behavior; and the volatility-regime analysis in Section 6.4 compares groups of stock-years rather than genuinely observation-level conditions. Pricing errors are also strongly serially correlated, with a mean lag-one autocorrelation of 0.66 within stocks. Section 5.3 describes the HAC and cluster-level corrections applied in response, and Table 2a reports how much the company-level results attenuate under them; naive significance levels are reported alongside for transparency but should not be relied upon. All results are in-sample fit statistics; no out-of-sample or train/test evaluation was performed. The sample is also restricted to call options on Nifty-50 constituents, large-cap, relatively liquid names that are not necessarily where SEBI's evidence of retail speculative activity is most concentrated, over a two-year window; put options and non-index constituents are not covered, and the equal moneyiness strata are a design choice rather than a reflection of traded volume. Finally, volatility terciles serve as a proxy for market condition, in the absence of direct sentiment measures such as India VIX or Put-Call Ratio in the underlying dataset.

10. Future Research Directions

This study establishes the diagnostic baseline; three stages follow from it. The first is to construct the locally calibrated behavioral pricing model specified in Section 7, estimating its parameters directly from Indian options data via GMM or nonlinear least squares rather than importing values from experimental literature. The second is to benchmark that model against Black-Scholes and against the other traditional specifications that prior Indian work has found competitive, including Black's model, GARCH-based variants, and stochastic-volatility alternatives (Singh, 2013; Swapna & Reddy, 2020; Singh & Kumar, 2024), with evaluation concentrated in the OTM and high-volatility segments identified here as most severely mispriced. The third is to test whether the behavioral model's advantage is state-dependent, using the volatility-regime framework developed in Section 6.4 but with contract-level implied volatility in place of the annual stock-year estimates used here. That last substitution is a precondition for the whole programme rather than a refinement: it would sharpen every result in this paper and is necessary before regime-conditional performance can be assessed credibly. Extending the analysis to put options, which would also allow the loss-aversion component of prospect theory to be identified rather than remaining structurally inert as it is for calls, and adding direct sentiment proxies such as India VIX and the Put-Call Ratio, would complete the evidence base. Including bid-ask spreads and volume of trading is a key feature: it would enable the behavioral interpretation of the moneyiness gradient to be separated from the liquidity explanation identified by Singh and Kumar (2024) for the Indian index options data set, and which the present data set is not able to support.

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