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OPTION PRICING UNDER UNCERTAINTY: A COMPARATIVE ANALYSIS OF THE BLACK–SCHOLES MODEL AND THE BINOMIAL HEDGING MODEL USING SELECT NSE-LISTED INDIAN EQUITIES

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ABSTRACT

This study undertakes a comparative empirical evaluation of the Black–Scholes Model (BSM) and the Binomial Hedging Model in valuing options and hedge positions of five companies listed on the National Stock Exchange (NSE) of India — HDFC Asset Management Company Ltd., Bharti Airtel Ltd., Larsen & Toubro Ltd., Adani Power Ltd., and MRF Ltd. — across sixteen monthly observations spanning April 2024 to July 2025. Using monthly opening and closing prices as proxies for spot and near-term reference prices, the study computes the BSM parameters (S/X, d1, d2, N(d1), N(d2)), the resultant call and put premiums, and a Binomial Hedge Model that scales the spot price across nine hedge-ratio scenarios (0.05 to 0.80), from which variance and standard deviation of the hedged position are derived. Descriptive and comparative statistical analysis reveals those instances where the BSM produced negative and hence economically implausible put premiums for two of the five companies, and a degenerate, boundary-value outcome for Adani Power arising from an extreme standardised moneyness input. In contrast, the Binomial Hedge Model produced internally consistent, monotonically scaling risk measures across all companies, with variance shown to scale with the square of the hedge ratio. The study concludes that the two models are complementary rather than substitutable: the BSM offers an efficient closed-form estimate when volatility and moneyness inputs are correctly calibrated, whereas the Binomial framework offers a more transparent, tractable and numerically robust device for scenario-based hedge-ratio risk management, particularly when the underlying's price behaviour departs from the log-normal, constant-volatility assumptions of the BSM.

KEYWORDS: Black–Scholes Model; Binomial Option Pricing; Hedge Ratio; Option Premium; National Stock Exchange (NSE); Derivatives Pricing; Volatility; Risk Management.

1. INTRODUCTION

Derivative instruments, and options in particular, occupy a central place in modern risk management because they allow market participants to isolate, price and transfer specific sources of uncertainty. Since options confer a right rather than an obligation, arriving at a fair premium requires a model of how the underlying asset's price might evolve. Two frameworks have dominated both the academic literature and market practice: the continuous-time Black–Scholes Model (BSM), which yields a closed-form solution under the assumption of geometric Brownian motion, and the discrete-time Binomial Model, which represents price evolution as a sequence of up-and-down movements and is also widely adapted, as in this study, into a Binomial Hedge Model that scales exposure by a chosen hedge ratio. While both models rest on the same no-arbitrage foundation, they differ substantially in their computational structure, their assumptions about the path of the underlying, and their practical suitability for pricing versus hedging decisions.

The Indian derivatives market has grown considerably since the introduction of exchange-traded equity derivatives on the NSE, and a sizeable body of research has examined whether the Black–Scholes model is a reliable descriptor of option premiums in this market. However, comparatively fewer studies place the BSM side by side with a hedge-ratio-based Binomial framework using the same underlying dataset across companies drawn from different sectors of the economy. This study addresses that gap by applying both models to five NSE-listed companies — HDFC Asset Management Company Ltd. (financial services), Bharti Airtel Ltd. (telecommunications), Larsen & Toubro Ltd. (infrastructure and capital goods), Adani Power Ltd. (power and utilities) and MRF Ltd. (tyre manufacturing) — thereby capturing a cross-section of volatility regimes and business characteristics.

2. Review of Literature

2.1 Foundational Theories of Option Pricing

The modern theory of option pricing began with Black and Scholes (1973), who derived a closed-form solution for European option premiums by constructing a continuously rebalanced, riskless hedge between the option and its underlying stock. Merton (1973) extended this framework, relaxing several restrictive assumptions and formally establishing

option pricing theory on a rigorous arbitrage-free footing, while also introducing pricing formulae for options on dividend-paying stocks. Black (1976) further extended the model to commodity futures contracts, demonstrating the broader applicability of the risk-neutral valuation principle beyond simple equity options. Together, these works established the theoretical vocabulary — the notions of delta, risk-neutral probability, and volatility-driven value — that continues to underpin both the Black–Scholes and Binomial traditions.

2.2 The Binomial Framework and Its Evolution

Cox, Ross and Rubinstein (1979) formalised the discrete-time Binomial Option Pricing Model, showing that as the number of time steps increases, the binomial price converges to the Black–Scholes value, while retaining the flexibility to price American-style and early-exercise features that the continuous-time model cannot easily accommodate. Rendleman and Bartter (1979) independently proposed a similar two-state approach around the same period, and the underlying discrete-state logic has been traced by some commentators to the informal treatment in Sharpe's (1978) investments text. Subsequent refinements sought to improve the rate of convergence and numerical stability of lattice models: Boyle (1977) introduced Monte Carlo simulation as a complementary numerical technique, Boyle (1988) generalised the lattice approach to two state variables, and Kamrad and Ritchken (1991) proposed multinomial lattices that converge faster than the standard binomial tree. Jiang and Dai (2004) provided a rigorous mathematical treatment of the convergence properties of binomial and related tree methods for both European and path-dependent American options, while Talponen and Turunen's exposition of the Cox–Ross–Rubinstein model offers a more tractable, non-technical route to the same results using static hedging arguments. Jarrow and Rudd (1983) proposed an alternative binomial parameterisation that is frequently cited for its improved convergence characteristics relative to the original Cox–Ross–Rubinstein tree.

2.3 Empirical Validation of the Black–Scholes Model in Developed Markets

Empirical assessment of the Black–Scholes model began soon after its publication. MacBeth and Merville (1979) tested the model against observed call option prices and documented systematic biases related to the moneyness and time to expiration of the contract, findings that anticipated the later literature on volatility smiles. Schwartz (1977) examined the valuation of warrants using a small sample of option prices, again finding measurable divergence between theoretical and market values. Whaley (1981) and Geske (1979) extended the analytical machinery of option pricing to American call options on dividend-paying stocks and to compound options respectively, both demonstrating that seemingly small departures from the original Black–Scholes assumptions can materially change

theoretical premiums. More recently, McKenzie and Subedar's investigation of the Black–Scholes model using Australian Stock Exchange data, and related empirical work on the United States market, have continued to find that pricing errors are systematically related to moneyness, contract maturity and prevailing volatility regimes, underscoring that the model's accuracy is contingent on how faithfully its inputs are estimated rather than on any single universal deficiency in its structure.

2.4 Empirical Applications of Option Pricing Models in Indian Markets

A substantial stream of Indian literature has tested the Black–Scholes model's applicability to NSE-traded contracts. Rastogi's empirical study of theoretical option pricing models compared Black–Scholes and Binomial Tree valuations for a large cross-section of NSE-listed companies against observed market premiums and examined put–call parity as a no-arbitrage check. Arora and Sharma (2019) similarly tested the pricing efficiency of the Black–Scholes model with reference to Indian equity options and reported mixed evidence of efficiency across strike and maturity categories. Khan, Gupta and Siraj (2013) proposed a modified Black–Scholes formulation incorporating an adjusted risk-free rate and tested it against the standard formula on the NSE derivatives market, while Chauhan and Gor (2020) undertook a comparable exercise for selected Indian call options. Srivastava and Shastri (2020) tested the applicability of the Black–Scholes model across ten actively traded NSE stocks and found that the model's performance varied by sector and by the volatility characteristics of the underlying stock. Mohanti and Priyan examined the market efficiency of the Nifty index options using the Black–Scholes model in conjunction with a dynamic hedging strategy, an approach methodologically close to the hedge-ratio orientation of the present study. Mishra (2012) priced Nifty index options using the Black–Scholes framework and compared theoretical and traded premiums, and Kumar and Agrawal (2017) investigated the model's efficiency for call options written on eight NSE-listed stocks, concluding that the model considerably mispriced options on several occasions when implied volatilities were unusually high. Mundhra and Agarwal examined mispricing in the Indian derivatives market more broadly, while Sehgal and Vijayakumar tested the pricing efficiency of the Indian index options market using alternative historical and implied-volatility estimators, concluding that the choice of volatility estimator materially affects the perceived accuracy of the Black–Scholes model.

2.5 Hedging Strategies and Hedge-Ratio-Based Studies

Because option premiums are only one dimension of practical risk management, several studies have focused specifically on hedge-ratio and delta-hedging performance. Sharma,

Vaish, Pandey and Gupta (2010) constructed a delta-neutral portfolio using Nifty options traded on the NSE and rebalanced it over the option's life, finding that hedging profitability depended heavily on the expiry cycle examined. Avellaneda and Parás (1994) modelled dynamic hedging portfolios in the presence of transaction costs, showing that the classical continuously-rebalanced hedge is an idealisation that breaks down once realistic frictions are introduced — a caution equally relevant to any discrete-interval Binomial Hedge Model. Taleb's practitioner-oriented treatment of dynamic hedging similarly emphasises the gap between the theoretical hedge ratios generated by pricing models and the practical difficulties of maintaining them in volatile or illiquid markets.

2.6 Volatility Modelling and Its Implications for Option Pricing

Because both the Black–Scholes and Binomial models require a volatility input, the accuracy of the volatility estimate is often more consequential than the choice of model itself. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) framework to model time-varying volatility, and Bollerslev (1986) generalised it to the GARCH model, both demonstrating that financial return volatility clusters over time rather than remaining constant, in direct tension with the constant-volatility assumption of the classical Black–Scholes formula. Heston (1993) proposed a closed-form option pricing model that allows volatility itself to follow a stochastic process, offering an alternative that can better accommodate the volatility smile observed in traded option prices. These volatility-modelling contributions collectively suggest that any BSM- or Binomial-based valuation exercise using a single historical standard deviation, as in the present study, should be interpreted as a simplification whose accuracy depends on the stability of the underlying's volatility regime over the estimation window.

2.7 Binomial and Option-Pricing Logic Beyond Traded Derivatives: Real Options

The discrete, tractable structure of the Binomial model has also made it the tool of choice for valuing managerial flexibility in capital budgeting, an application area generally termed real options. Myers's early work on corporate investment and borrowing decisions is widely credited with articulating the idea that investment opportunities themselves contain option-like flexibility. Dixit and Pindyck (1994) and Trigeorgis (1996) subsequently developed comprehensive frameworks for valuing the option to delay, expand, contract or abandon an investment project, while Copeland and Antikarov (2001) provided a practitioner's guide translating these ideas into a binomial lattice methodology usable by corporate finance practitioners. Huhn (2005) demonstrated the use of binomial decision trees to solve real-option valuation problems by embedding risk-neutral probabilities directly into a decision-

tree structure, and Damodaran's teaching material on real option valuation illustrates, with worked examples, that Black–Scholes and Binomial approaches can yield materially different valuations for the same real investment opportunity, with the Binomial estimate typically capturing a wider range of managerial flexibility.

2.8 Research Gap

The literature reviewed above establishes, first, that the Black–Scholes model's empirical accuracy is highly sensitive to the quality of its volatility and moneyness inputs, and second, that the Binomial framework is prized less for superior theoretical accuracy than for its numerical robustness, flexibility, and suitability for hedge-ratio-based risk management. However, few Indian studies place the two models side by side using an identical dataset spanning companies from different sectors and directly compare the internal consistency of the resulting premium and hedge-variance estimates. The present study is designed to fill this gap using a five-company, sixteen-month dataset covering financial services, telecommunications, infrastructure, power, and manufacturing.

3. RESEARCH METHODOLOGY

3.1 Objectives of the Study

- To compute and analyse the Black–Scholes Model parameters (S/X, ln(S/X), d1, d2, N(d1), N(d2)) and the resulting call and put option premiums for five NSE-listed companies.
- To compute the Binomial Hedge Model value of each company's spot price across nine hedge-ratio scenarios (0.05 to 0.80) and to derive the variance and standard deviation of the hedged position at each ratio.
- To compare the internal consistency, plausibility, and risk-management usefulness of the BSM-based option premiums against the Binomial Hedge Model outputs.
- To identify company-specific and sector-specific patterns in option pricing behaviour and hedging risk across the sample.
- To draw practical conclusions and recommendations for the calibration and joint use of the two models in an Indian equity derivatives context.

3.2 Research Design

The study adopts a descriptive-cum-analytical, quantitative research design based entirely on secondary, ex-post facto market data. No primary data collection or survey instrument is used; instead, historical monthly price data is transformed through the two option-pricing frameworks under study and the resulting numerical series are analysed using descriptive statistics.

3.3 Sample and Period of the Study

Five companies listed on the National Stock Exchange of India were purposively selected to represent a cross-section of sectors and volatility profiles: HDFC Asset Management Company Ltd. (financial services/asset management), Bharti Airtel Ltd. (telecommunications), Larsen & Toubro Ltd. (infrastructure and capital goods), Adani Power Ltd. (power and utilities), and MRF Ltd. (tyre and rubber manufacturing). The dataset comprises sixteen monthly observations of opening and closing share prices, spanning the period April 2024 to July 2025.

3.4 Data Source and Tools

The data used are secondary in nature, comprising month-end opening and closing prices for each company, as compiled in the accompanying workbook (CP_BSM_BINOMIAL.xlsx). All computations — the Black–Scholes parameters, call and put premiums, the Binomial Hedge Model values, and the variance/standard deviation of the hedged position — were performed in Microsoft Excel and cross-verified using Python-based statistical routines (pandas/NumPy) for this paper.

3.5 Model Specification

The Black–Scholes call and put premiums are given by:

$C = S \cdot N(d1) - X \cdot e^{(-rt)} \cdot N(d2)$ $\quad P = X \cdot e^{(-rt)} \cdot N(-d2) - S \cdot N(-d1)$

where $d1 = [\ln(S/X) + (r + \sigma^2/2)t] / (\sigma\sqrt{t})$ and $d2 = d1 - \sigma\sqrt{t}$; S is the closing (spot) price, X is the opening price used as the reference/strike proxy for the period, r is the risk-free rate, σ is volatility, and t is the time to expiry. N(·) denotes the cumulative standard normal distribution function, so that N(d1) and N(d2) represent the risk-adjusted probabilities used in the valuation. The dataset expresses moneyness through the ratio S/X and its natural logarithm, from which d1 and d2 are derived exactly as specified above.

The Binomial Hedge Model used in the workbook computes a hedged position value as the product of the spot price and an assumed hedge ratio, h: Hedged Value = Spot × h, evaluated at nine discrete hedge ratios (0.05, 0.10, 0.20, 0.25, 0.35, 0.50, 0.70 and 0.80). The variance and standard deviation of the resulting hedged value series are then computed for each hedge ratio and each company, providing a discrete, scenario-based measure of hedging risk that parallels the role played by delta in continuous-time hedging.

3.6 Limitations of the Study

- The study relies on monthly rather than daily price observations, and on the opening price of each period as a proxy reference (strike-equivalent) value rather than an actual traded strike price, which may not reflect real contract terms.

- Volatility, the risk-free rate and time-to-expiry parameters embedded in the workbook are not separately disclosed in the raw data and are treated as given; any error or unconventional scaling in these inputs propagates directly into the d1, d2, N(d1) and N(d2) values, as discussed in Section 5.
- The sample of five companies, while sectorally diverse, is not statistically representative of the full universe of NSE-traded, option-eligible securities, and results should be read as indicative rather than generalisable.
- The Binomial Hedge Model, as implemented in the source workbook, computes a single-period scaled exposure rather than a full multi-step recombining lattice; it should therefore be understood here as a hedge-ratio risk model rather than a full option-pricing lattice.

4. Data Analysis and Data Interpretation

4.1 Descriptive Statistics of Spot (Closing) Prices

Company	Mean Close (₹)	Std. Dev. (₹)	Minimum (₹)	Maximum (₹)
HDFC AMC Ltd.	4,300.61	521.03	3,629.55	5,647.65
Bharti Airtel Ltd.	1,645.59	193.94	1,322.85	2,009.40
L&T Ltd.	3,593.99	156.20	3,164.75	3,812.55
Adani Power Ltd.	596.09	84.20	478.75	756.65
MRF Ltd.	150.96	22.52	112.40	193.70

Table 1 shows that HDFC AMC Ltd. carried both the highest average price level and, in absolute rupee terms, the highest price volatility (standard deviation of ₹521.03) over the study period, consistent with the sharp run-up from roughly ₹3,630 to ₹5,648 seen in the underlying data. MRF Ltd., despite being a high-priced stock in absolute terms in earlier years, traded in a comparatively narrow band (₹112.40 to ₹193.70) during this window, giving it the lowest absolute price dispersion of the five companies. Bharti Airtel and L&T occupy an intermediate position, while Adani Power's dispersion, though modest in rupee terms, is large relative to its average price level.

4.2 Black–Scholes Parameter Summary (Moneyness and Probability Terms)

Company	Mean S/X	Mean d1	Min d1	Max d1	Mean N(d1)	Mean N(d2)
HDFC AMC Ltd.	0.9795	0.0619	-0.396	0.657	0.5227	0.4551
Bharti Airtel Ltd.	0.9773	0.0111	-0.497	0.665	0.5033	0.4561
L&T Ltd.	1.0079	1.3266	0.580	2.178	0.8889	0.8617
Adani Power Ltd.	1.0118	13.1359	13.128	13.143	1.0000	0.0000
MRF Ltd.	1.0232	0.9298	0.375	2.157	0.7992	0.7329

For HDFC AMC and Bharti Airtel, the mean S/X ratio is close to unity (0.98) and the mean d1 is close to zero (0.06 and 0.01 respectively), indicating that, given the parameterisation used in the workbook, the reference contract for these two companies was close to at-the-money over the study period, with N(d1) hovering near 0.50–0.52 — the textbook signature of an at-the-money option. L&T and MRF, by contrast, show consistently large positive d1 values (mean 1.33 and 0.93), pushing N(d1) to 0.89 and 0.80 respectively; under the model's assumptions this indicates a persistently in-the-money position, which is also reflected in the higher call relative to put premiums observed for these two companies in Table 3. Adani Power is a clear outlier: its d1 values cluster tightly around 13.13, an order of magnitude beyond the range seen for any other company, driving N(d1) to its ceiling of 1.0 and N(d2) to its floor of approximately 0.0 in every single month of the sample. Because the cumulative normal distribution saturates once its argument exceeds roughly 4–5 standard deviations, this pattern is a strong indication that the volatility or time-to-expiry input feeding into Adani Power's d1/d2 formula was materially smaller (or the S/X spread proportionally larger) than for the other four companies, producing a mathematically degenerate rather than a substantively meaningful result. This observation is developed further in Section 5.

4.3 Call and Put Option Premiums

Company	Mean Call (₹)	Mean Put (₹)	Min Put (₹)	Max Put (₹)	Months with Negative Put
HDFC AMC Ltd.	453.29	63.41	-594.05	364.30	3 of 16
Bharti Airtel Ltd.	228.79	-82.53	-318.17	104.05	13 of 16
L&T Ltd.	190.41	96.66	20.00	276.01	0 of 16
Adani Power Ltd.	602.11	600.42	600.42	600.42	0 of 16
MRF Ltd.	11.04	11.51	1.85	27.42	0 of 16

A basic no-arbitrage requirement of any option pricing model is that both call and put premiums must be non-negative. Table 3 shows that this condition is violated for HDFC AMC in three of sixteen months and, more strikingly, for Bharti Airtel in thirteen of sixteen months, with put premiums as low as -₹594.05 and -₹318.17 respectively. Such outcomes cannot represent a traded market price and instead point to an inconsistency between the assumed volatility/rate inputs and the put–call parity relationship implicit in the workbook's formulae; they should be read as a diagnostic finding about model calibration rather than as evidence that the Black–Scholes framework itself is unusable for these stocks. L&T, Adani

Power and MRF, in contrast, produced uniformly non-negative put premiums across the full sample, with Adani Power's put premium remaining constant at ₹600.42 every month — a direct consequence of the N(d1) = 1 / N(d2) ≈ 0 degeneracy identified in Section 4.2, since a put premium computed as X·e^(−rt)·N(−d2) − S·N(−d1) with N(−d1) ≈ 0 and N(−d2) ≈ 1 collapses to a value driven almost entirely by the discounted reference price rather than by the stock's own price movement.

4.4 Binomial Hedge Model: Variance and Standard Deviation by Hedge Ratio

Company	Var @ 0.05	SD @ 0.05	Var @ 0.50	SD @ 0.50	Var @ 0.80	SD @ 0.80
HDFC AMC Ltd.	678.68	26.05	67,867.63	260.51	173,741.13	416.82
Bharti Airtel Ltd.	95.79	9.79	9,579.14	97.87	24,522.61	156.60
L&T Ltd.	57.42	7.58	5,741.98	75.78	14,699.47	121.24
Adani Power Ltd.	17.72	4.21	1,772.41	42.10	4,537.36	67.36
MRF Ltd.	1.27	1.13	126.80	11.26	324.60	18.02

Table 4 confirms, across all five companies, that the variance of the hedged position scales exactly with the square of the hedge ratio — for example, HDFC AMC's variance at a 0.50 hedge ratio (67,867.63) is precisely 100 times its variance at a 0.05 hedge ratio (678.68), matching the mathematical identity Var(h·S) = h²·Var(S) that underlies the Binomial Hedge Model as implemented in the workbook. This internal consistency, replicated for every company and every hedge-ratio pair, is a useful validation check that is absent from the BSM outputs discussed above, where negative premiums and boundary-saturated probabilities reveal inconsistencies that are not self-correcting within the model. In risk-ranking terms, HDFC AMC carries the largest absolute hedging risk at every hedge ratio, consistent with its high absolute price level and standard deviation, while MRF carries the smallest, and Bharti Airtel, L&T and Adani Power occupy the middle of the ranking in that order. This ranking is unaffected by the hedge ratio chosen, since scaling by h² preserves the relative ordering of the underlying price variances.

5. Comparative Analysis of the Black–Scholes Model and the Binomial Hedging Model

The two frameworks examined in this study address related but distinct questions. The Black–Scholes Model, as applied here, attempts to answer 'what should this option be worth today, given a single volatility and moneyness estimate?' — a question best suited to instruments with reasonably stable, well-estimated inputs and limited early-exercise features. The Binomial Hedge Model, in the form implemented in the accompanying workbook, instead answers 'how much does my exposure and its risk change as I vary my hedge ratio?'

— a scenario-planning question of direct relevance to a risk manager who must decide how aggressively to hedge a position, rather than what a single fair-value premium should be.

On the evidence of this dataset, the Binomial Hedge Model proved numerically more robust: because it is built from a simple linear scaling of the spot price, every company's output remained internally consistent, monotonic, and free of the boundary or sign violations that affected the BSM outputs for two of the five companies. The Black–Scholes results, by contrast, were considerably more sensitive to the specific volatility and moneyness parameterisation used, to the point of producing a fully saturated, non-informative result for Adani Power and economically impossible negative premiums for HDFC AMC and Bharti Airtel. This is consistent with the literature reviewed in Section 2: MacBeth and Merville (1979), Kumar and Agrawal (2017) and others have documented that Black–Scholes mispricing tends to be concentrated in extreme-moneyness or high-volatility conditions, precisely the conditions that appear to have produced the anomalous Adani Power result here. At the same time, the Black–Scholes outputs, where they behaved sensibly (L&T and MRF, and the majority of HDFC AMC and Bharti Airtel observations), provided richer information than the Binomial Hedge Model alone, since N(d1) and N(d2) carry an interpretable probability-weighted meaning and directly generate both call and put premiums from a single parameter set. The Binomial Hedge Model, as implemented here, does not itself generate an option premium; it generates a hedged position value and its associated variance, which is informative for sizing a hedge but does not substitute for a fair-value estimate. In this sense, the two models are complementary components of a single risk-management workflow: the Black–Scholes model (or, where its assumptions are strained, a full multi-step binomial lattice as originally specified by Cox, Ross and Rubinstein, 1979) for fair-value estimation, and a hedge-ratio-based variance analysis, of the kind implemented here, for calibrating how large a hedge to take once a position and its option exposure have been established.

6. FINDINGS

1. The Black–Scholes Model produced negative, and therefore economically implausible, put premiums in 3 of 16 months for HDFC AMC and 13 of 16 months for Bharti Airtel, indicating a calibration inconsistency between the assumed volatility/rate parameters and put–call parity rather than a fundamental flaw in the model's structure.

2. Adani Power Ltd. exhibited an extreme and constant d1 (mean 13.14, range 13.13–13.14) across all sixteen months, saturating N(d1) at 1.0 and N(d2) at effectively 0.0, and yielding a

constant put premium of ₹600.42 every month — a clear case of a degenerate, boundary-value outcome driven by an extreme input rather than by genuine market dynamics.

3. L&T Ltd. and MRF Ltd. showed persistently positive and comparatively large d1 values (means of 1.33 and 0.93), consistent with a persistently in-the-money parameterisation and correspondingly higher, more stable call premiums relative to put premiums.

4. The Binomial Hedge Model's variance scaled exactly with the square of the assumed hedge ratio for every company (e.g., HDFC AMC's variance at the 0.50 ratio was precisely 100 times its variance at the 0.05 ratio), confirming the model's internal mathematical consistency and providing a useful cross-check absent from the BSM outputs.

5. HDFC AMC carried the highest absolute price volatility (standard deviation ₹521.03) and, consequently, the highest hedging variance at every hedge ratio examined; MRF Ltd. carried the lowest on both counts (standard deviation ₹22.52), with Bharti Airtel, L&T and Adani Power occupying an intermediate, sector-dependent position.

6. Companies whose price behaviour was closer to at-the-money on average (HDFC AMC, Bharti Airtel; mean S/X near 0.98) were the same companies for which the Black–Scholes put premium turned negative, suggesting that at-the-money contracts in this dataset were the most sensitive to the specific volatility input used, consistent with the sensitivity documented in the reviewed Indian and international literature.

7. Taken together, the results support the view, consistent with the reviewed literature (McKenzie & Subedar; Kumar & Agrawal, 2017; Sehgal & Vijayakumar), that the Black–Scholes model's practical reliability depends primarily on the quality of its volatility and moneyness inputs, while the Binomial Hedge Model's principal strength lies in its numerical robustness and its direct usefulness for scenario-based hedge-ratio decision-making rather than in generating an independent fair-value premium.

7. CONCLUSION

This study set out to compare the Black–Scholes Model and a Binomial Hedge Model using monthly price data for five NSE-listed companies drawn from different sectors of the Indian economy. The analysis shows that neither model can be judged unconditionally superior: the Black–Scholes Model, where correctly parameterised, offers an efficient, information-rich closed-form estimate of both call and put premiums, but is demonstrably fragile in the presence of extreme or poorly calibrated volatility and moneyness inputs, as the Adani Power and Bharti Airtel results illustrate. The Binomial Hedge Model, while simpler in the form implemented here, proved more numerically robust and internally consistent across every

company in the sample, and offers direct, interpretable guidance for scenario-based hedge-ratio decisions, even though it does not by itself generate an option premium.

From a practitioner's standpoint, the findings suggest that Indian equity derivatives desks and researchers should not treat the Black–Scholes Model as a mechanical formula to be applied uniformly across all underlyings; rather, its volatility and moneyness inputs should be re-estimated and stress-tested company by company, with particular attention to boundary cases where d1 or d2 might approach the saturation region of the normal distribution. Where such instability is detected, a full multi-step Binomial lattice, rather than the single-period hedge-ratio scaling used here, is likely to provide a more reliable cross-check on the Black–Scholes premium, consistent with the convergence properties documented by Cox, Ross and Rubinstein (1979) and Jiang and Dai (2004). More broadly, the study reinforces the conclusion recurring throughout the reviewed literature: the choice between the Black–Scholes and Binomial families of models is less consequential, in most practical settings, than the discipline with which their common inputs — volatility, moneyness, and time to expiry — are estimated and validated. Future research could extend this analysis using daily rather than monthly data, actual traded strike prices and expiry dates, implied rather than historical volatility, and a full multi-step binomial lattice, in order to test whether the anomalies identified here persist under a more granular and market-consistent parameterisation.

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