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Research paper

"Market Efficiency and Option Pricing in India: Empirical Evidence From The National Stock Exchange"

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Abstract

This study evaluates the pricing efficiency of Nifty 50 index options on the National Stock Exchange of India from April 2022 to March 2024 using the Black-Scholes model. This study applies the model by assessing pricing accuracy using historical volatility and weighted implied volatility (WSIV). The findings reveal significant price discrepancies, with call options trading below their fair value and put options trading above their fair value, indicating market inefficiencies. These inefficiencies persist despite regulatory reforms due to short-selling constraints that hinder effective dynamic risk hedging. The use of futures prices in the valuation model fails to eliminate inefficiencies, suggesting that Indian investors rarely employ futures for delta-hedging purposes. Notably, the WSIV method yields a systematic underestimation of theoretical option prices, contrasting with the patterns observed in more developed markets. The persistent pricing inefficiencies are attributed to Indian investors' reliance on historical volatility for option valuation. This study has important implications for academic researchers, market practitioners, and regulators, providing insights into the applicability and limitations of the Black-Scholes model in emerging markets, identifying arbitrage opportunities, and highlighting the need to address structural issues and trading asymmetries to enhance market efficiency.

Keywords: *Volatility hedging; Arbitrage Pricing; Market Behavior; National Stock Exchange; Retail Investors; Algorithmic trading; SEBI (Securities and Exchange Board of India)*

1. Introduction

Worldwide financial markets have expanded substantially over the past three decades. Modern financial instruments have benefited from a triple expansion of advanced products along with higher liquidity and improved profitability, according to Sehgal S. and Vijayakumar (2009). A major expansion has occurred in the derivatives segment, with its range of products, including options, futures, forwards, and swaps. Market players utilise these instruments as essential tools to protect against multiple financial risks as they speculate on the market (Staritz et al. 2018).

Derivatives now represent the largest increase in the global market. Between 2024 and 2025, banking institutions are expected to reach their highest yearly trading revenue since 2010, which is projected to be $225 billion. The major factors for this growth emanate from equity derivatives and credit agreements. Several factors, such as geopolitical events, market volatility, and rising interest rates, have driven market expansion. The CME Group achieved the highest average daily volume (ADV) total of 26.5 million contracts in 2024, an increase of 9% compared to 2023. Major records emerged within all six asset classes, including interest rates, agriculture, foreign exchange, and metal product investments, as growth expanded in these sectors.

The Indian derivatives market has undergone a significant transformation in recent years. Indian traders completed 85 billion options transactions in 2023, making India the world's leader in options trading activities. The share of retail traders equaled thirty-five percent of the trading volume, while institutions managed the remaining forty-five percent. The 2020 regulatory reforms appear to have supported the growth of retail participation in options trading. The regulatory changes introduced barriers for corporations and foreign investors, leading to an increase in retail traders entering the market.

Accelerated market development has triggered multiple safety concerns among parties. The Securities and Exchange Board of India (SEBI) reported through its survey that 90 percent of retail traders operating in the market experienced financial losses in options and derivative contracts throughout March 2022, amounting to five and a half billion dollars. An increase in the minimum contract size for derivatives and restrictions on weekly options contracts are two steps that the Securities and Exchange Board of India (SEBI) has taken in response to the issue of speculative trading. These efforts resulted in a decrease of seventy percent in the daily volumes of index options, which severely impacted the income of brokerage firms.

There has been much curiosity in the academic community regarding the effectiveness of options markets, particularly in developing market economies such as India. Traditional pricing models, such as the Black-Scholes model, have also been studied in India. Research suggests that the Black-Scholes model provides a basis, but its assumptions may not completely represent the intricacies of the Indian market, requiring revisions to account for market-specific characteristics of the Indian market. The global derivatives market is continuously evolving, driven by growing involvement and innovation. The increase in derivatives trading in India has democratised market access but also exposed retail investors to problems. Maintaining market efficiency and protecting investors is of utmost importance, which calls for continuous research and regulatory frameworks that can adapt to changing conditions.

2. Literature Review

Kou, G., & Lu, Y. (2025). Emerging technologies, such as AI, machine learning, blockchain, AR/VR, and quantum mechanics, are set to transform the future of finance by offering more precise, secure, and agile solutions. This study explores their development and potential applications in financial systems, highlighting the opportunities and challenges of leveraging these innovations for improved financial performance. Technology-driven finance is becoming a crucial path for industry evolution.

Brunetti (2023). This study employs a statistical arbitrage strategy to assess the efficiency of the index options market by utilising a statistical hedge strategy, specifically pairs trading. This strategy aims to identify potential mispricing of options based on deviations from the long-run relationship between their implied volatilities. The results show that pairs trading in the index options market does not generate significant profits, suggesting that market forces are highly effective in quickly identifying and reabsorbing potential mispricing. This indicates that any inefficiencies that may arise are short-lived, reinforcing market efficiency in the long term.

Lu (2023) explored the global expansion of financial technology (fintech) and its influence on the digital economy and trade. The study defines fintech through key technologies such as AI, blockchain, cloud computing, and big data, and analyzes the business models of fintech, BigTech, and Metaverse firms. It also evaluates the competitiveness of major cities, such as New York, London, Paris, Shanghai, Dubai, and Mumbai, as emerging fintech hubs. Additionally, it presents case studies on two major areas of innovation: alternative finance platforms (e.g., virtual banks and P2P lending) and digital money (e.g., cryptocurrencies, stablecoins, and CBDCs).

Ayodeji et al. (2024) explored how digital technologies, such as AI, blockchain, big data, and cloud computing, are transforming the financial sector. This study highlights fintech innovations such as DeFi, digital payments, and robo-advisors, and emphasises the need for agility, regulatory compliance, and collaboration to ensure stability. It also underscores the importance of financial literacy and inclusion in shaping a secure, efficient, and customer-centric financial future for the country.

Han, Liu, and Wu (2023) examine how private money creation through money market funds influences cross-sectional stock returns. They find that the yield-accrual feature of these funds leads to speculative stockholders shifting toward safer assets at specific times, explaining stronger returns from long-short strategies on Thursdays and Fridays. The study shows that the FinTech-driven transformation of money market funds significantly amplifies this effect, especially for speculative stocks during periods of high volatility.

Financial research has mostly focused on the efficiency of the options market, and basic studies and contemporary assessments have provided an understanding of price dynamics and market behavior (Bossman & Agyei, 2022).

Black and Scholes (1973) developed a novel options valuation model that accurately approximated variations in U.S. stock returns. They find that the algorithm underprices low-variance stocks and overprices options for high-variance equities. Their efforts expanded the application of this concept to other corporate liabilities, including warrants, corporate bonds, and ordinary stocks (James & Menzies, 2023).

Elyasiani et al. (2021) introduce a skewness index for the Italian stock market (ITSKEW)and explore its connections with volatility and market returns, drawing comparisons with the US market. Although this study does not directly evaluate the Black-Scholes model, it assesses the efficiency of the Italian market from a different perspective. The study reveals that the skewness index serves as an indicator of market greed rather than fear in the US and Italian markets. The Granger Causality Test shows a significant association between increases in the skewness index and returns. (Elyasiani et al., 2021).

Zhang and Zhang (2024). Research on market efficiency using arbitrage pricing links has revealed complex dynamics in both internal and cross-market contexts. Studies examining the S&P 500 index options market have identified instances of mispricing, suggesting potential inefficiencies

Interestingly, while later studies indicate improved pricing efficiency within the options market itself, they do not find evidence supporting the increased cross-market arbitrage opportunities facilitated by the introduction of S&P Depository Receipts (SPRs) (Bali et al., 2022; Zhang & Zhang, 2024). This contradiction highlights the nuanced nature of market efficiency and the challenges in achieving perfect arbitrage across different but related financial instruments.

Aggarwal and Jha (2023) utilise GARCH to investigate the day-of-the-week effect in the Indian stock market from 1990 to 2022. The findings indicate that stock returns and volatility exhibit day-of-the-week effects, implying that the Indian stock market lacks efficiency. Aggarwal and Jha (2023) assert that traders can forecast future prices and achieve abnormal profits in the Indian stock market. This is in line with the proposition made by Jain et al. for potential opportunities for unusual profit.

P. K. Priyan and Debaditya Mohanti (2014) suggest that in the Indian options market, the weighted implied standard deviation (WISD) proves to be the most reliable measure for volatility estimation of underlying assets. The actual standard deviation measurement (HSD) weighted standard deviation (WISD), and standard deviation from the average implied volatility (AISD) are evaluated as volatility estimators. The analysis shows that the Black-Scholes pricing model works accurately in option value determination, and WISD demonstrates the best capability as a volatility measurement tool.

Galai (1977) applied the Black-Scholes model to evaluate the efficiency of the (CBOE) Chicago Board Options Exchange (CBOE). His tests on ex-post and ex-ante hedging show that the model and trading methods are consistent with each other. This was especially true for ex-post hedge returns, which shows the resilience of the model (Mittnik & Rieken, 2000) and examines the German DAX options market using simulated trading techniques. Despite the lack of definitive conclusions, their findings indicate potential breaches in market efficiency (McKenzie et al. 2007).

In conclusion, the research presented in the given papers, particularly Aggarwal and Jha (2023), supports Jain et al.'s findings on weak-form inefficiency in the Indian stock market. However, Chauhan et al. (2024) highlighted the influence of macroeconomic factors, suggesting that market dynamics are complex and not driven solely by historical price patterns. These findings have important implications for investors and portfolio managers in developing strategies for the Indian stock market.

With many studies examining price dynamics, market behaviour, and regulatory implications, options market efficiency has become a central focus of financial research (Bhatnagar et al., 2022). Building on fundamental models, such as Black-Scholes, more recent research has explored several facets affecting market efficiency, especially in India.

Furthermore, the competitive dynamics among Indian exchanges affect market efficiency. To attract businesses, the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) have developed new derivative products and lower transaction costs. With the notional number of derivatives traded at ₹8,737 trillion in March 2024, this rivalry significantly increased trading volumes. Although such an expansion indicates a strong market, it also calls for strong regulatory control to ensure that the quest for market share does not undermine market integrity.

Dealing with these issues mostly depends on regulatory actions. Raising the minimum contract size for derivatives and limiting multiple options contract strategies are two ways SEBI has suggested to reduce speculative trading. These programs seek to improve general market efficiency and reduce excessive risk-taking among ordinary investors. In addition, SEBI's plan to allow regular investors to use algorithmic trading is a balanced approach to both new ideas and investor safety. These will be subjected to strict approval and monitoring systems.

Despite the remarkable growth of the Indian options market, issues with market efficiency persist, particularly due to the involvement of retail investors and the impact of high-frequency trading. Constant regulatory initiatives are necessary to maintain a fairer trade environment and ensure that a wider range of players can benefit from the advantages of market expansion.

3. Research Methodology

3.1 Data Description

The Nifty50 Index is a benchmark for the Indian National Stock Exchange (NSE). The Nifty 50 is a diversified stock index of 50 stocks accounting for 13 sectors of the economy. It is used for various purposes, such as benchmarking fund portfolios, index-based derivatives, and index funds. The Nifty 50 Index represents approximately 55.48% of the free float market capitalisation of the stocks listed on the NSE as of 28 March 2025. European-style contracts settled in cash comprise 50 index options. For these options, the trading cycle consists of three-monthly expiry contracts and four weekly expiration contracts (apart from the monthly contracts). Monthly contracts expire on the last Thursday of each month, and weekly contracts conclude every Thursday. If the expiration date coincides with a trading holiday, the contracts expire the day before.

This study examines the periodic closing prices of Nifty 50 index options contracts and near-month closing prices of call and put options between 1 April 2022 and 31 March 2024. The National Stock Exchange of India (NSE) provided the data for this study. Next-month and far-month options were not considered because of their very low trading volumes. To estimate the risk-free interest rate, researchers used the yield from 91-day Treasury bills for the relevant time frame. This information was sourced from the Reserve Bank of India's (RBI) official website and subsequently converted into a continuous compound annual rate of return to obtain options and implied volatility (IV).

3.2 Evaluation of option pricing efficiency

This study investigates the efficiency of pricing in the Indian options market. The pricing of options is effective if there is a discrepancy between the market price and the theoretical price (model price). An arbitrage opportunity would be any significant difference from the theoretical price, which involves purchasing options that are priced below their value and selling those that are priced above their value. This is motivated by the fact that the theoretical value of such a pricing model equals (Black & Scholes, 1972, 1973; Galai, 1977) the option's fair value. In addition, there may be considerable discrepancies that indicate that the model may not have been specified correctly. However, as previous empirical research has found that the Black Scholes model adequately represents the pricing of options (Latane & Rendleman, 1976; MacBeth & Meerville, 1979; Manaster & Rendleman, 1982), it seems reasonable to conclude that any time series bias terms that may be present in the residual series of (1) will have a negligible impact on the pricing formula for European call options. As one of the most well-known options pricing models empirically, this study formulates theoretical option prices in this study by means of the Black-Scholes (1972) option pricing model.

Additionally, the Black-Scholes model is used for the National Stock Market (NSE) to calculate the theoretical value of options on the market, and it specifies the theoretical pricing of the call and puts options through the Black-Scholes equations:

$$C=S_0N(d_1) - Ke^{-rT}N(d_2); \; P=Ke^{-rT}N(-d_2) - S_0N(-d_1)$$

Where:

$d_1 = [\ln (S_0 / K) + (r + \sigma^2 / 2) T] / (\sigma\sqrt{T})$
$d_2 = d_1 - \sigma\sqrt{T}$
Variables Explanation:
C = Call option price
P = Put option price
S_0 = Current stock price
K= Strike price
T = Time to expiration (in years)
r = Continuously compounded risk-free interest rate
σ = Volatility of the underlying asset
N(x) = Cumulative standard normal distribution function

The cumulative probability distribution function describes the stock index price at the initial time, strike price, estimated standard deviation (volatility), continuously compounded risk-free rate (indicated by the 91-day Treasury bill yield), and duration until the option expiration.

3.3 Methods for Estimating Volatility

Asset valuation depends heavily on volatility, which exceeds the impact of price movement. Hull (2006) shows that the uncertainty of asset returns production drives the standard deviation measurements as a volatility indicator (Hull, 2006). There are two distinct methods for measuring the volatility of a stock.

1. Historical Standard Deviation (HSD)

2. Implied Volatility (IV)

Many real-world studies have shown that future volatility can be effectively forecasted using implied volatility (IV) (Chiras and Rendleman (1976; Chiras and Manaster, 1978). However, some studies challenge its predictive superiority, contending that past volatility retains significant information for anticipating future volatility (Canina, 1990; Lamoureux & Lastrapes, 1993). This study uses both historical standard deviation and implied volatility to determine theoretical option prices and how well they work in the Indian options market. There has been much academic discussion regarding both methods. The predictive effectiveness of the two techniques was assessed using a paired comparison t-test.

3.3.1 Historical Volatility

The most widely adopted method for assessing historical volatility is the standard volatility estimator. The Historical Standard Deviation (HSD) is calculated by determining the moving average of the standard deviation of the logarithmic changes in daily index values. During the study period, separate estimation windows of 7-day and 21-day moving averages were employed. To obtain an annualised volatility measure, the daily standard deviation is multiplied by 252, which is the average number of trading days in a year. The formula for estimating the HSD is as follows:

$$\sigma_{it} = \sqrt{\frac{1}{N}\ \sum_{i=1}^{N}(Xit\ -\ \mu)^{2}} * \sqrt{T}$$

$$X_{it} = ln(\frac{Si+1}{Si})$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} Xit$$

where μ represents the moving average of the logarithmic returns. N denotes the number of days used to calculate moving averages. T signifies the total number of trading days in a year.

Table 1: Outcomes of Option Pricing Mistakes Utilizing Historical Volatility

Observations		Market Price Mean	Model Price Mean	t-test
		Category A		
Call options	9716	66.09	74.67	-34.91
Put Options	9026	42.84	41.79	6.18*
		Category B		
Call options	9910	67.81	73.98	-22.98
Put Options	9332	42.74	39.72	15.01*

Notes: * denotes significant at 5% level

Category A: 21 days HSD; Category B: 7 days HSD

We then determine the theoretical option prices by applying the estimated HSD for two distinct periods of volatility, specifically the 7-day and 21-day volatilities of the moving average of returns, within the framework of the Black-Scholes model. The paired comparison t-statistics presented in Table 1 provide a comparative analysis of the discrepancies between market prices and model prices for call and put options across two categories: Category A (with a 21-day historical standard deviation) and Category B (with a 7-day historical standard deviation). This table is instrumental in assessing the pricing errors arising when historical volatility, rather than implied volatility, is used in the options pricing model.

In Category A, the mean market price for call options is ₹66.09, whereas the corresponding mean model price is significantly higher at ₹74.67. The negative t-test value of -34.91 indicates a statistically significant overvaluation of call options by the model, suggesting that using a 21-day historical volatility leads to systematic overpricing. In contrast, for put options within the same category, the market price average is ₹42.84, which is slightly above the model price of ₹41.79. The t-test statistic of 6.18*, which is significant at the 5% level, reveals that this difference, although numerically small, is statistically meaningful, implying a tendency of the model to modestly under-price put options when using longer historical volatility.

Turning to Category B, which uses a shorter 7-day historical volatility, the call options again show a discrepancy: the market price average is ₹67.81, whereas the model price is higher at ₹73.98. The t-test value of -22.98 reinforces the finding of consistent overvaluation by the pricing model, albeit to a slightly lower degree than in Category A. This suggests that even with shorter historical data, the model continues to overprice call options, but the magnitude of the error is somewhat reduced. The most striking result is seen in put options for Category B, where the market mean price is ₹42.74, and the model significantly underestimates this value at ₹39.72. The t-test statistic of 15.01* is highly significant, indicating a more pronounced and statistically robust underpricing of puts when the model is based on the 7-day volatility. Hence, the results highlight that relying solely on historical volatility, regardless of window size, introduces systematic biases in option pricing. Models tend to overprice call options and underprice put options, with the magnitude of these errors varying based on the volatility window used. These findings underscore the limitations of historical volatility in reflecting the forward-looking nature of market expectations and suggest the potential benefits of incorporating implied volatility or hybrid approaches into pricing models to enhance accuracy.

However, this does not imply that the Black-Scholes model is flawed or that the market lacks efficiency. The differences observed may stem from variations in the actual market trading structure, which the Black-Scholes model simplifies. For example, the model presumes trading symmetry, permitting both long positions and short selling to establish arbitrage-free prices, which may not consistently correspond with real-world market conditions. The Indian futures market has strict short selling restrictions that obstruct opportunities for risk-free arbitrage solutions. Governments' control of short selling produces market inefficiencies that specifically affect options valuation methods. If call options have low prices, arbitrageurs execute their standard practice of purchasing options and selling the underlying assets to gain risk-free profits. The inability to short-sell creates a situation in which this approach becomes impossible, resulting in a long-lasting price difference that weakens the worth of call options. These restrictions explain why put options remain costly, as market participants lack access to vital risk management strategies (Brenner & Galai, 1989; Chakrabarti & Sharma, 2018).

Our findings show that the Black-Scholes model is a pertinent framework for option pricing in the Indian market, especially considering trade asymmetries. Furthermore, we ascertain that the historical standard deviation (HSD) functions as a dependable metric of volatility for option pricing. A significant finding of our research is that an extended estimate window for an HSD enhances price precision. The 21-day HSD condition yielded fewer pricing errors than the 7-day HSD condition did. This corroborates the notion that extending the historical data window is useful for estimating volatility.

One might be able to reduce trading asymmetry if spot prices are substituted with futures prices, allowing trading in both directions. However, futures pricing does not significantly enhance efficiency. Notably, futures prices are used in this study to derive the t-statistics for call and put options compared to the spot prices. This implies that Indian investors do not appear to use futures as a delta hedge to replace the underlying asset. Futures trading is more complex and expensive than options trading (Basu et al., 1997). Moreover, the fees incurred while trading futures and options also diminish arbitrage opportunities, making option prices unequal.

3.3.2 Weighted Implied Volatility (WSIV)

Implied volatility, a critical factor in option pricing, represents the anticipated standard deviation of stock returns. We used the Black-Scholes model to make these predictions. This model determines an option's theoretical value based on factors such as volatility, exercise price, duration until expiration, and value of the underlying asset. However, computational techniques, often in MATLAB, solve the Black-Scholes model backwards from the observed price to determine the market volatility input.
The Black-Scholes model asserts that the volatility of an option remains unchanged throughout the term. The implied volatility changes with varying strikes and expiry dates. This variance produces patterns such as the "volatility smile" or "volatility smirk," in which implied volatility often decreases with increasing strike prices.
The volatility smile is a pattern in which the implied volatility is higher for deep-in-the-money and out-of-the-money options than for at-the-money options, forming a U-shaped curve. This occurs because markets expect extreme price moves more often than models such as Black-Scholes assume. It highlights the limitations of constant volatility models and shows why traders use more advanced models to price and hedge options.
Traders and analysts frequently need to calculate the average implied volatility for options that share the same expiration date but have different strike prices. Although one can apply a basic arithmetic average, also known as the average implied standard deviation (AISD), can be applied, a weighted method typically yields greater success. Some options trade more often than others, so their prices offer more consistent information. Therefore, the computation should weigh more heavily on actively traded options. Not all options respond to volatility changes in the same manner. Options with greater sensitivity to fluctuations, that is, at-the-money options, should influence the final weighted value. Considering these elements, a weighted standard implied volatility measure provides a more realistic picture of market expectations and a stronger basis for trading and risk management decisions. The formula for calculating the Weighted Standard Implied Volatility (WSIV) is as follows:

$$\text{WSIV} = \sum_{i=1}^{k} Wi.\sigma i$$

where k represents the strike price, Wi denotes the quantity of contracts traded at the strike price, and i denotes the implied volatility at the strike price k.

Table 2: Examination of Option Pricing Discrepancies Using Weighted Implied Volatility

	Total observations	Market Price Mean	Model Price Mean	t-test
Call options	9525	49.51	47.19	44.42*
Put Options	4630	78.85	41.81	53.38*

Note: * show 5% level of significance

Table 2 presents an analysis of option pricing discrepancies using weighted implied volatility instead of historical volatility. The findings indicate that when this more market-responsive measure is applied, the model's pricing becomes closer to actual market prices, particularly for the call options. For call options, the model slightly underprices compared to the market (mean market price: ₹49.51; model price: ₹47.19), with a significant t-test value of 44.42*, indicating a consistent but relatively smaller pricing gap. However, for put options, a substantial underpricing is observed as the market price averages ₹78.85, whereas the model price is only ₹41.81, with a very high and statistically significant t-test value of 53.38*. This large gap suggests that even with implied volatility, the model struggles to capture the pricing of put options accurately, likely because of the risk premiums embedded in these options during volatile or bearish conditions.

4. Results and Discussion

The comparison between Tables 1 and 2 offers a clear illustration of the impact of volatility estimation methods on option pricing accuracy. Table 1, which is based on historical volatility (21-day and 7-day windows), reveals systematic mispricing by the model. Specifically, call options were consistently overpriced by the model relative to their market prices, whereas put options were slightly underpriced. The magnitude and direction of these pricing errors are influenced by the length of the historical window, with longer windows producing larger discrepancies. This suggests that historical volatility, a backward-looking measure, fails to effectively reflect current market expectations. Conversely, Table 2 uses weighted implied volatility, a more forward-looking and market-sensitive measure. This adjustment leads to a noticeable improvement in the accuracy of the call option pricing. The model slightly underprices call options (market price mean: ₹49.51 vs. model price mean: ₹47.19); however, the gap is smaller than that in Table 1, indicating enhanced alignment with market valuations. However, for put options, the model continues to significantly underprice compared to the market (market price mean: ₹78.85 vs. model price mean: ₹41.81), with an even more substantial and statistically significant t-test result.
In summary, the shift from historical to implied volatility enhances the pricing precision for call options but does not fully resolve the discrepancies in put option valuation. This suggests that while implied volatility better captures market sentiment and expectations, additional model enhancements, such as incorporating volatility skew or stochastic volatility dynamics, may be required to address the persistent underpricing of put options. The findings underscore the critical importance of selecting appropriate volatility inputs in option pricing models and support the use of implied volatility for a more accurate and realistic valuation.

5. Implication

This study offers valuable insights for both financial market practitioners and regulators. By applying advanced arbitrage strategies and aligning regulatory frameworks with modern trading dynamics, market efficiency and stability can be significantly improved.

5.1 Implications for Practitioners

Practitioners can exploit various arbitrage opportunities to improve their risk-adjusted returns. Pair trading and statistical arbitrage help identify mispricing in correlated assets using historical and quantitative models. Cross-border arbitrage leverages pricing discrepancies in global markets, whereas synthetic positions via options and futures offer cost-efficient ways to replicate arbitrage strategies.

High-frequency trading (HFT) enables traders to act on fleeting inefficiencies at speed and scale. Fixed income arbitrage, including yield curve and swap spread trades, allows for the exploitation of interest rate anomalies. Additionally, merger arbitrage presents profitable strategies during corporate acquisition announcements by capturing the spread between the target's market price and the expected acquisition price.

5.2 Implications for SEBI and Policy Recommendations

To support efficient markets, SEBI could implement granular circuit breakers focused on specific stocks or sectors rather than broad market-wide halts. A tiered regulatory framework can provide differentiated oversight based on the size and risk of the participants.

The SEBI should also enhance cross-border regulatory coordination to address arbitrage flows involving international markets. Considering the rise in algorithmic trading, a robust framework for algorithmic and HFT should be established with mandatory testing, risk controls, and monitoring tools.

Revisiting short-selling regulations can promote liquidity while safeguarding market integrity. Encouraging innovation through regulatory sandboxes and faster approval of new products would support market development. Finally, real-time monitoring of large positions and improved disclosure of complex instruments would enhance transparency and reduce systemic risk.

6. Conclusion

This study evaluates the pricing efficiency of Nifty 50 index options on the National Stock Exchange of India from April 2022 to March 2024 using the Black-Scholes model. The findings reveal significant price discrepancies, with call options trading below their fair value and put options trading above their fair value, indicating market inefficiencies. These inefficiencies persist despite regulatory reforms due to short-selling constraints that hinder effective dynamic risk hedging. The use of futures prices in the valuation model fails to eliminate inefficiencies, suggesting that Indian investors rarely employ futures for delta-hedging purposes. The weighted implied volatility (WSIV) method yields a systematic underestimation of theoretical option prices, contrasting with the patterns observed in more developed markets. The persistent pricing inefficiencies are attributed to Indian investors' reliance on historical volatility for option valuation. This study has important implications for academic researchers, market practitioners, and regulators, providing insights into the applicability and limitations of the Black-Scholes model in emerging markets, identifying arbitrage opportunities, and highlighting the need to address structural issues and trading asymmetries to enhance market efficiency.

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