

**TESTING THE EFFICIENCY OF OPTION MARKET-THE
INDIAN MARKET EVIDENCE**

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

**in
COMMERCE**

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2026

DECLARATION

I, hereby declared that the presented work in the thesis entitled “**Testing the Efficiency of Option Market-The Indian Market Evidence**” in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is the outcome of research work carried out by me under the supervision of Dr. Mahesh Kumar Sarva, working as a Professor in Mittal School of Business of Lovely Professional University, Punjab, India. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or in full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled “**Testing the Efficiency of Option Market-The Indian Market Evidence**” submitted in fulfilment of the requirement for the award of the degree of **Doctor of Philosophy (Ph.D.)** in the Department of Commerce/ Mittal School of Business, is a research work carried out by Arun Kumar, Registration No.12207868, is a bona fide record of his original work carried out under my supervision and that no part of the thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

INTRODUCTION

Over the past two decades, India's financial markets have undergone significant transformations, characterised by increased sophistication, technological advancements, and regulatory reforms. Among the most dynamic segments of this transformation is the derivatives market, which has witnessed exponential growth in terms of volume, instrument diversity, and market participation. Within this domain, index options, particularly those linked to the Nifty 50 index, have emerged as one of the most actively traded and influential financial instruments on the National Stock Exchange (NSE).

This evolution has been driven by several, interrelated factors. The liberalisation of financial markets, improvements in trading infrastructure, enhanced regulatory oversight, and increased awareness among retail investors have all contributed to a broader and more engaged investor base in India. Furthermore, the proliferation of algorithmic and high-frequency trading, combined with the increasing use of derivatives for both speculative and hedging purposes, has led to a complex and dynamic market. Consequently, the Nifty 50 index options market now plays a crucial role in the price discovery process and the broader ecosystem of financial risk management in India.

The rapid expansion of this market segment also highlights several critical issues that warrant detailed academic enquiry. First, there is the question of pricing efficiency: Do the observed market prices of Nifty 50 index options accurately reflect their theoretical values, or do they exhibit consistent mispricings that could indicate inefficiencies in the market? Second, the challenge of volatility forecasting becomes particularly relevant in the context of options pricing because volatility is a key determinant of option premiums. Traditional econometric models, while widely used, may not fully capture the complex nonlinear patterns inherent in financial time series data, raising the need to explore modern forecasting techniques such as machine learning algorithms. Third, the behaviour of implied volatility (IV) across different strikes and maturities offers valuable insights into market sentiment, risk perception, and investor psychology, aspects that are often overlooked in standard models.

The importance of these questions is not limited to theoretical interests. Their answers have substantial implications for market participants, regulators, and policymakers. An efficient and transparent options market enhances investor confidence and market stability, whereas accurate volatility forecasts enable more effective trading and hedging strategies. Understanding the structure of implied volatility, including the presence of volatility smiles or skews, helps explain how information is processed and reflected in the market prices.

This study seeks to address these critical aspects by undertaking a comprehensive empirical investigation of the Nifty 50 index options market from April 2018 to March 2024. This time frame was selected to include a range of market conditions, including periods of normal volatility, extreme fluctuations such as those witnessed during the COVID-19 pandemic, and the impact of various regulatory interventions by bodies such as the Securities and Exchange Board of India (SEBI). This study aims to capture both the structural and behavioural dimensions of the Indian options market.

This study adopts a multifaceted approach, beginning with the evaluation of pricing efficiency using the Black-Scholes Option Pricing Model (BSOPM) as a benchmark. Despite its widespread acceptance, this model relies on assumptions that may not hold in real-world scenarios, such as constant volatility, frictionless markets, and the absence of transaction costs. This study incorporates real market frictions, including brokerage fees, Securities Transaction Tax (STT), service tax, and other levies, to assess whether observed pricing deviations are economically significant or merely artefacts of theoretical abstraction.

In the second part of the study, the forecasting performances of various volatility estimation models are examined. These include traditional time-series models such as the Auto-Regressive Integrated Moving Average (ARIMA), Generalised Auto-Regressive Conditional Heteroskedasticity (GARCH), and Exponential GARCH (EGARCH), as well as modern machine learning techniques such as Feedforward Neural Networks (FNNs). These models are evaluated using standard error metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), to determine their predictive accuracy and suitability in capturing real-world market dynamics.

The third component of the thesis explores the structure of implied volatility across varying levels of moneyness and time-to-maturity. The presence of phenomena such as volatility smiles and skews is investigated in depth, as these patterns have important implications for market

efficiency, investor behaviour, and model specification. The analysis extends beyond academic curiosity, offering actionable insights for traders, risk managers and regulatory authorities.

OBJECTIVES

1. To examine the market efficiency of Nifty index options.
2. To compare the forecasting performance of different volatility models for pricing Nifty index options.
3. To analyzing the structure of implied volatility vary across different time and moneyness levels of Nifty index options.

RESEARCH HYPOTHESIS

This study aims to fill this gap by evaluating the efficiency of Nifty 50 index options traded on the National Stock Exchange (NSE) of India. To guide this analysis and derive meaningful conclusions, a set of hypotheses was developed to test the presence or absence of market inefficiencies in the Indian index options segment. The null hypotheses for this study were as follows:

Ho1: After factoring in transaction costs, there is no significant frequency or magnitude of violations for both call and put Nifty index options when using the Black-Scholes model.

Ho2: There is no significant difference in the forecasting performance of different volatility models in pricing Nifty Index Options.

Ho3: The Indian options market makes a volatility smile.

RESEARCH METHODOLOGY

The research methodology adopted in this study is empirical and quantitative in nature, leveraging a comprehensive dataset of Nifty 50 index options traded on the National Stock Exchange (NSE) between April 2018 and March 2024. The data comprise over 900,000 raw option contracts, which were filtered to include 1,77,571 call options and 2,12,609 put options based on liquidity, pricing consistency, and maturity conditions. The study first applies the Black-Scholes Option Pricing Model (BSOPM) to calculate theoretical option values and compares them with market prices to assess pricing efficiency, incorporating realistic frictions such as transaction costs. For volatility forecasting, the research employs a comparative analysis of traditional econometric models ARIMA, GARCH, and EGARCH and machine learning models such as Feedforward Neural Networks (FNNs), evaluated using performance metrics such as RMSE, MAE, and MAPE. Implied volatility patterns are analysed across

moneyness levels and time to maturity to explore the volatility smile and skewness. Statistical techniques, such as the Mann-Whitney U-test and Kolmogorov-Smirnov test, were used to validate the significance of the observed deviations and model performance. This rigorous methodology ensures a robust and multidimensional analysis of pricing dynamics, forecast accuracy, and investor behaviour in the Indian index options market.

MAJOR FINDINGS

1. Market Efficiency

While there were frequent deviations between the observed and theoretical prices, most were economically insignificant once transaction costs were considered. This suggests a high degree of micro-efficiency in the Indian options market.

2. Volatility Forecasting

Feedforward Neural Networks (FNNs) consistently outperform traditional models, particularly in handling nonlinear market behaviour. Among traditional models, the EGARCH model stands out for its ability to capture asymmetric volatility clustering.

3. Implied Volatility Patterns

A clear volatility smile was observed: higher IV for deep in-the-money and out-of-the-money options and lower for at-the-money options, challenging the BSOPM assumption of constant volatility. This reflects the nuanced investor psychology and market sentiment.

CONCLUSION, IMPLICATION AND FUTURE SCOPE

This study provides strong evidence that while theoretical models, such as the Black-Scholes Option Pricing Model, offer a useful starting point, real-world factors, such as transaction costs, behavioural biases, and market frictions, play a critical role in shaping the actual pricing and dynamics of the Indian index options market. The analysis confirms that the Nifty 50 index options market demonstrates signs of micro-efficiency, particularly when practical trading costs are included. Moreover, a comparative study of volatility forecasting models reveals that machine learning approaches, especially Feedforward Neural Networks, significantly outperform traditional models in capturing the nonlinearities and complexities of financial data. The presence of volatility smiles and skews in implied volatility patterns further highlights how investor sentiment and demand for hedging shape market outcomes beyond what classical

models can explain. These findings have practical implications for traders, risk managers, and regulators: understanding volatility structures can improve hedging strategies, while evidence of efficiency supports regulatory efforts to maintain market integrity. For policymakers, insights into cost-driven inefficiencies can guide them to implement more effective reforms. Future research could explore deep learning methods or ensemble models to further enhance forecasting accuracy. Additionally, comparative studies across other emerging markets or asset classes could provide a broader perspective on how market maturity and structural differences impact pricing behaviour, ultimately contributing to a more inclusive understanding of global financial systems.

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CHAPTER 1

INTRODUCTION

1.1. Background

The economic condition of a nation is often reflected in its capital market performance (CM). Emerging economies such as India and China have demonstrated significant progress in their financial sectors. The importance of a capital market is assessed based on its impact on other economic entities. A strong and sustainable market signifies a progressive and resilient financial system crucial for attracting global investors. The liberalization, globalization, and deregulation strategies implemented in India in recent years have yielded substantial benefits for the economy. Foreign investment has increased, and local investor confidence has risen, as evidenced by capital market expansion.

In the ever-evolving landscape of global finance, derivatives have emerged as indispensable tools for risk management, investment, and improving market efficiency. Financial derivatives are contractual agreements whose value is derived from underlying assets, such as stocks, bonds, interest rates, or foreign exchange. Their introduction into financial systems worldwide has transformed the manner in which market participants manage uncertainty and volatility. In the context of the Indian capital market, equity derivatives, particularly futures and options, have contributed significantly to improving market stability and increasing investor confidence. These instruments have not only attracted foreign institutional investors but have also encouraged greater participation from domestic players, many of whom previously hesitated because of the inherent volatility of the market.

Futures and options are the cornerstones of derivative trading. A futures contract obligates the buyer and seller to transact an asset at a predetermined future date and price, whereas an option contract grants the right, but not the obligation, to buy or sell an asset under specified conditions. Options are further classified into call options (the right to buy) and put options (the right to sell) contracts. The flexibility and strategic value of these instruments make them particularly appealing to investors seeking to hedge against risks or pursue speculative profits.

The expansion of the derivatives market can largely be attributed to the growing need among risk-averse economic agents to safeguard their interests from unpredictable price movements.

Derivatives provide a crucial layer of financial protection by allowing hedging against potential losses from inventory holdings, financial exposures, or operational activities. These instruments not only smooth out the impact of price fluctuations on profitability and cash flow but also contribute to a more efficient and balanced risk distribution within the financial system. Additionally, by lowering the cost of capital and widening the array of available financial instruments, derivatives foster economic development and enhance market liquidity.

Over the last four decades, the global derivatives market has witnessed remarkable innovations and growth. The launch of index options on the Chicago Board Options Exchange (CBOE) in 1983 marked a pivotal moment in derivatives trading history. In particular, the cash settlement feature of index options has become a popular mechanism for managing systematic risk across diversified portfolios, enabling investors to maintain exposure while effectively controlling downside risk.

As global markets continue to integrate, derivatives serve as key instruments that bind the financial systems of various economies. Their ability to facilitate capital flows, hedge risks, and enhance liquidity underscores their growing relevance. This chapter sets the foundation for understanding the evolution, structure, and impact of financial derivatives, especially in the Indian context, and examines their role in shaping contemporary financial markets.

The derivatives market in India has expanded significantly since its inception in the early 2000s. The National Stock Exchange (NSE) launched index futures trading in June 2000 and updated it with index options in June 2001. The Bombay Stock Exchange (BSE) followed a month later by starting index options trading. Trading of stock options and single stock futures was introduced to the market in July and November, 2001. The derivative trading volume has experienced a major upward trend owing to market expansion. The expansion of derivative contract trading during the fiscal year 2023-2024 was substantial because the total traded contracts grew from 90,580 contracts in June 2000 to 32.9 billion contracts by March 2024. The market segment of index options gained 98.37% control over total derivative trading by the fiscal year 2023-24.

The Indian derivatives market is expected to experience vigorous growth in 2024. NSE and BSE trading data for the second quarter of 2024 demonstrated that equity index options reached 36.8 billion shares which was two times greater than the Q2 performance from the previous year. All futures and options transactions worldwide amount to more than two-thirds because

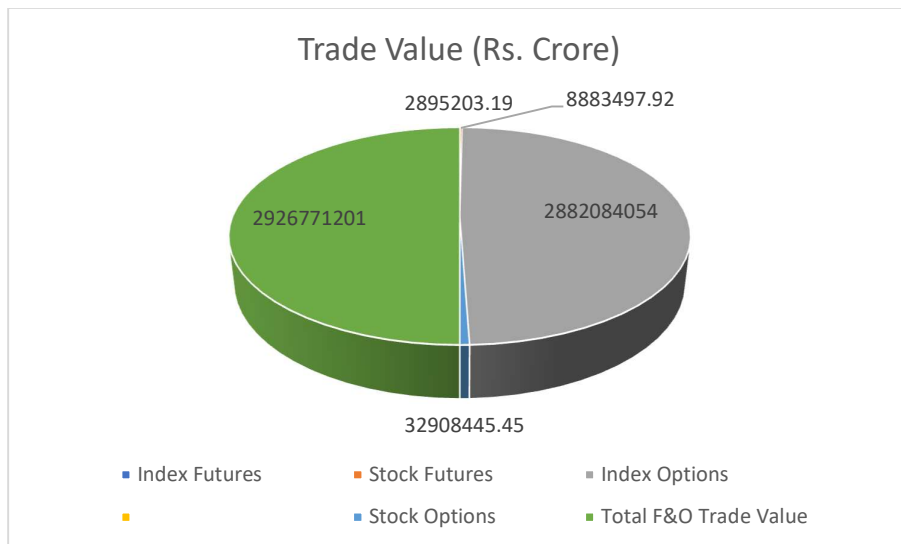
of the global operations. Changing demographics in retail investment circles are the main catalysts of market expansion.

Regulatory bodies have increased their inspection of the derivatives market because of its rapid growth to maintain market order and protect investor interests. The Securities Exchange Board of India (SEBI) enforced new measures in late 2024 to control excessive speculative trading in the derivatives markets. The regulators proposed two changes: limiting weekly options contracts to only one expiry date on each exchange and raising the minimum contract quantity to improve the market stability. The NSE, along with the BSE, plans to boost index futures and options lot sizes per SEBI instructions starting from November 2024.

Fig.1.1 Number of Contracts traded on F&O Segment (2001-2024)



Fig.1.2 Number of Contracts traded on F&O Segment (2001-2024)



1.2. Market Efficiency Test of Index Options

The "fair game" model from Eugene Fama (1970) interprets market efficiency through evidence by stating that financial security prices contain all the accessible market information. He established three separate versions of the Efficient Market Hypothesis (EMH): weak, semi-strong, and strong.

The weak-form EMH states that market prices fully absorb every piece of historical data, including price movements, volume trends, return data, block trades, insider dealings, and odd-lot transactions. According to the semi-strong form of the EMH, security prices incorporate all publicly available information, ranging from market data to non-market data, such as macroeconomic indicators, corporate reports, and investor performance indicators. Under the strong-form EMH, prices reflect every piece of information, including what is available to the public and what remains exclusively within the private sector. This means that an investor lacks full control over superior risk-adjusted returns. Thus, the strong form subsumes both weak and semi-strong forms.

Researchers evaluate market efficiency by studying whether trading strategies can result in predictable abnormal returns, although price adjustment tests are indirect. Market efficiency is questioned when systematic investment strategies consistently outperform market norms after factoring in trade expenses. When markets fail to produce excess returns, efficiency is the conclusion. According to Jensen (1978), market efficiency indicates that economic profits, which refer to net risk-adjusted returns minus all costs, must be equal to zero. According to this definition, persistent abnormal returns should not be possible for any trader to achieve. Separately, Ackert and Tian (2000) specified options market efficiency by examining the options price precision.

According to Fama (1970), transaction costs do not necessarily lead to market inefficiencies, although zero costs establish a sufficient condition for market efficiency. Asset prices maintain full information reflection when exchanges occur. According to West (1975), the high costs of transactions prevent arbitrage activities and disrupt information movement, resulting in price instability. Markets follow Fama's conditions of efficiency by remaining efficient, even with high transaction costs, as long as traders achieve returns that only match transaction expenses.

This study defines efficiency as the inability of traders to continuously yield abnormal returns beyond transactions expenses.

The Black-Scholes (1972) option pricing model provides theoretical prices for option testing, which are compared with current market rates to check market efficiency. Market inefficiencies provide traders with opportunities to engage in arbitrage through dynamic hedging strategies by simultaneously purchasing options and corresponding underlying shares.

The main barrier to using the Black-Scholes model for testing market efficiency is the volatility estimate, as volatility represents the only unobservable parameter. The main methods of volatility assessment involve computing the historical standard deviation of past returns, according to Taleb (1997), and extracting implied volatility from existing market option values, as explained by Latane and Rendleman (1976). Multiple scholars dispute the reliability and precision of volatility forecasting methods in academic research and commercial industry applications. Volatility estimation lacks a standard precise technique, which explains why option pricing retains artistic elements rather than scientific precision.

1.3. Relevance of Volatility

Volatility is a major risk factor and primary concern for those involved in finance or investing in the stock market and other financial instruments. Recently, the challenges posed by volatility has become increasingly critical for financial practitioners, market participants, researchers, regulators, and retail investors. Market participants are particularly concerned about volatility because investors always want to know the level of risk to which they are exposed; the more volatile a stock is, the riskier it is. Understanding a stock's volatility offers insights into its potential future value range, thereby enabling investors to make informed decisions. However, predicting the price of volatile stocks with certainty remains challenging. Generally, people dislike risk and prefer minimal or no risk when investing in stock. Additionally, volatility adversely affects the capital market and slows economic growth. Policymakers may perceive increased stock volatility as a threat to the viability of financial institutions and smooth operation of financial markets. Furthermore, volatility concerns regulators as it influences capital market functions. Excessive market volatility can deter small investors, strain market clearing and settlement obligations, erode investor confidence, and reduce participation and liquidity. Moreover, securities price volatility affects firms' decisions regarding capital issuance, the type of instruments used, and timing.

Economists generally view volatility from various perspectives. This results from new information entering the market, prompting participants to reassess the true value of the traded assets. In an efficient market, asset prices adjust quickly to reflect new information, resulting in high volatility. Thus, volatility indicates a properly functioning and information-efficient market. In this context, volatility is beneficial and somewhat desirable for investors. Additionally, if the market moves as expected, there is a potential for greater financial gain.

1.4. Determinants Impacting the Volatility

There are several factors that impact volatility.

Demand and Supply: Short-term fluctuations in share prices are largely governed by the immediate interplay of demand and supply in the stock market. When the demand for a particular stock increases, driven by factors such as investor sentiment, market expectations, company news, or macroeconomic events, its price typically rises. Conversely, an increase in supply without a corresponding increase in demand generally results in a price decline. In this context, price movements reflect the balance or imbalance between buyers and sellers at any given moment. When buying interest outweighs selling pressure, dealers may face stock shortages and respond by raising prices. Conversely, an excess of sell orders relative to buy orders usually drives prices downward. It is crucial to recognize that while the number of shares available for trading (i.e. the *float*) can fluctuate slightly because of market activity, the total supply of a company's issued shares does not adjust immediately in response to price changes. This inherent rigidity in supply further amplifies price sensitivity to short-term demand shifts.

Interest rates: Interest rates play a crucial role in shaping trends in securities markets. A reduction in short-term interest rates often stimulates speculative activity, as speculators are eager to capitalize on lower rates by borrowing money to invest in securities with higher yields. When money is abundant and inexpensive, share prices tend to rise and vice versa. Theoretically, there is an inverse relationship between interest rates and stock prices.

Political Conditions: The stock market is highly sensitive to political developments, and changes in the political landscape can immediately impact share prices. Shifts in power, party structures, or political leaders at the national or state level, or even changes in their portfolios, can lead to fluctuations in share prices as market operators quickly assess the implications of these changes.

Globalization: Globalization significantly affects the share prices. Bullish or bearish trends in major economies, such as the U.S. and Japan, often lead to similar movements worldwide. Markets anticipate that the global economy will be similarly impacted.

Inflation: Unexpected inflation increases may prompt the government or central banks to adjust fiscal or monetary policies. For instance, the government might impose price controls or alter tariff rates, potentially harming firms' profitability.

Foreign Institutional Investors: Since 1992, Indian stock markets have been open to foreign capital, enhancing liquidity as Foreign Institutional Investors (FIIs) can easily enter the market, driving stock prices up. However, when FIIs withdraw their funds, it can lead to significant market downturns and high volatility.

Fear Factor: The fear of financial losses plays a significant role in market volatility, as investors often strive to avoid potential setbacks. This anxiety can be sparked by the opinions of a few individuals, leading to a chain reaction of selling. As investors adopt a defensive posture owing to their fear of losses, they begin selling, which can prompt others to do the same, resulting in widespread market selloffs.

Information Boom: The rapid spread of information through media channels has intensified market volatility. The speed at which news travels from its source to the audience has increased significantly, accelerating volatility. Numerous business news outlets, such as Star News, Zee News, CNBC Asia, and Jain TV, offer continuous updates on stock movements, influencing share price fluctuations.

Sentiment: Investor sentiment significantly influences stock price movements. On a lacklustre trading day marked by downward trends, buyers may hesitate and refrain from making purchases, raising concerns about potential overnight changes in the company. This downward trend leads to more sellers than buyers, further driving prices down and setting new lows for stocks.

Understanding volatility is crucial for comprehending capital market dynamics. Investors who are well-versed in volatility can potentially achieve higher returns on their investments; otherwise, the risks associated with volatility may force them to exit the market.

Risk is an intrinsic part of investing and is closely tied to returns. While some investors may have a preference for or aversion to risk, risk is an unavoidable element of the investment process because of the positive correlation between risk and returns. As risk increases, so do

returns, and risk reduction generally results in lower returns. Investors strive to maximize returns while minimizing risks, making the investment process more engaging for investors. Various strategies exist to mitigate volatility risk and enhance returns, with investment portfolios and hedging techniques being among the most widely accepted risk management strategies.

Historically, volatility models have been widely used to evaluate stock price fluctuations in the global financial markets. However, the 1990s saw the emergence of innovative financial instruments known as derivatives, which were developed to mitigate risk. These derivatives, including forwards, futures, options, and swaps, are designed to facilitate hedging, protect against volatility, aid price discovery, and capitalize on arbitrage opportunities. While derivatives play a crucial role in transferring risk from one party to another, they do not remove volatility from the financial system. The underlying risks, especially those related to unpredictable price movements, continue to exist within the market. This means that volatility remains an inherent characteristic of financial markets, and participants must develop the ability to anticipate such fluctuations to make informed investment decisions. In this context, the ability to estimate future volatility is critical. Both individual and institutional investors rely on volatility forecasts to evaluate potential risks and returns, adjust their portfolios, and formulate strategies that align with their financial objectives. As market conditions evolve rapidly, timely and accurate assessments of volatility are essential tools for navigating uncertainty and enhancing decision-making in dynamic trading environments.

Before the advent of options trading, historical volatility was the only metric used to predict potential future volatilities. Volatility refers to the degree of price fluctuations of a financial instrument over time, serving as an indicator of uncertainty or risk based on the magnitude of changes in an asset's value. Typically, absolute volatility is expressed annually and can be quantified using statistical measures such as the standard deviation or variance of asset returns. Higher volatility suggests that an asset's value may fluctuate over a broader range. The standard deviation is widely recognized as an absolute measure of risk, capturing the overall variability in asset returns. However, even with the benefits of diversification, not all risks can be eliminated, particularly those tied to overall market movements. This market-related risk is known as beta, which quantifies an asset's sensitivity to changes in the broader market. A high beta indicates that the asset is likely to experience more significant fluctuations in response to market movements, whereas a low beta suggests relative stability.

When forecasting future volatility, many financial analysts caution against relying solely on historical volatility, as past market behaviour may not always be a reliable predictor of future trends. In this context, implied volatility (IV) derived from the pricing of options using models such as the Black-Scholes Option Pricing (BSOP) model has become an important tool. Unlike historical measures, implied volatility reflects the market's collective expectations of future price movements, as it is embedded in the prices investors are currently willing to pay for options. It captures investor sentiment and perceived risk in real time.

In option pricing, implied volatility represents the volatility level that would justify the current market price of an option, assuming that all other inputs are known. It is the volatility figure that, when input into the Black-Scholes model, produces a theoretical option value equal to its market price. However, implied volatility is not constant. It varies depending on the time to maturity and the strike price of the option. These variations create patterns known as implied volatility surfaces or volatility smiles.

The volatility smile, first observed in the aftermath of the 1987 stock market crash, shows that implied volatility tends to be higher for options that are deep in-the-money or far out-of-the-money and lower for those at-the-money, forming a 'U'-shaped curve across strike prices. This pattern is believed to reflect changes in investor behaviour and risk perceptions, particularly during times of market stress. For investors, the volatility smile is more than just a pricing anomaly; it offers valuable insights into market expectations. For instance, a steep smile may suggest a heightened demand for protective options or speculative bets, guiding investors toward potentially profitable positions and away from riskier ones.

1.5. Need for the study

This study is crucial for derivative markets in India, which have been the focus of much academic research recently, to achieve their intended purposes, that is, market efficiency and price discovery. One of the important aspects of options pricing is whether markets are efficient such that options reflect all available information. Most studies conducted so far have been on global markets, and there is a research gap in the Indian options markets, as evidenced by studies examining inefficiencies in the markets, suggesting deviations from theoretical pricing models, and the presence of arbitrage opportunities. Through the analysis of pricing efficiency in Nifty index options, this study seeks to contribute to the understanding of pricing quality, support regulatory decisions, and increase the confidence of investors in the growing derivatives market in India.

In addition, volatility dynamics should be well understood to price options correctly and to manage risk. While volatility forecasting models are crucial for forecasting price dynamics in financial markets, there is no agreement on the model that best captures volatility in Indian markets. Moreover, the distribution of implied volatility over different strikes and maturities frequently does not align with theoretical assumptions, forming obstacles for traders and investors. The implied volatility surface also assists in pricing by refining models, hedging, and trading. This study fills this gap by comparing the forecasting performance of various volatility models and examining the relationship between implied volatility and time and moneyness levels to provide a better structural relationship in the derivatives market in India.

1.6. Statement of the problem

Research on market efficiency has predominantly concentrated on developed markets, such as the US options and futures markets, and European options markets, which are renowned for their efficient trading mechanisms (Black and Scholes, 1972; Merton, 1973).

In contrast, Indian derivative markets are still evolving in terms of their trading volume. Nevertheless, since 2000, there has been a substantial increase in derivative trading volume, positioning the Indian derivatives market as an emerging one. The surge in trading within the Indian options market is notable, with the total number of derivatives contracts rising from 90,580 in June 2000 to 32.9 billion in 2023-24, and a significant portion of this trading, over more than 90 percent in 2023-24, occurring through index options. This underscores the necessity for the options market to operate efficiently. The effective functioning of financial markets is crucial for the orderly development of any economy, as they play a key role in risk hedging, price discovery, and asset allocation (Ackert and Titan, 2000). For the options market, a vital part of the Indian derivatives market, to function properly, it is essential that it operates efficiently. Market efficiency suggests that economic profits from trading are zero, meaning that risk-adjusted returns are net of all costs (Jensen, 1978), indicating that no trader can consistently achieve above-average returns. Ackert and Tian (2000) describe the efficiency of an options market as the accuracy of option prices, reflecting its effective performance in its designated roles.

Although the Indian derivative markets cannot match the US derivative markets in terms of high trading volumes, which provide ample arbitrage opportunities without risk, the issue of market efficiency is as significant in developing markets as it is in developed ones. Emerging

markets are more prone to market inefficiencies (Capelle-Blancard & Chaudhury, 2001). Therefore, it is crucial to regularly assess the efficiency of the Indian options market.

1.7. Research Motivation for the Study

The Nifty index options market has grown significantly in recent years and has become a cornerstone of the Indian financial ecosystem. However, several critical gaps and emerging trends necessitate further investigation into their efficiency, volatility forecasting, and implied volatility structures.

Market Efficiency of Nifty Index Options

Although derivative trading in India is becoming more voluminous and complex, the effectiveness of the Nifty index options market remains to be scrutinised. Recent patterns reveal a widening gap between theoretical pricing models and actual market actions, driven by elements such as sentiment-based trading and inherent market inefficiencies. For example, research indicates that sentiment analysis and news headlines can greatly influence market dynamics; however, their roles in efficiency assessments have not been fully explored. Determining whether the Nifty options market follows principles such as put-call parity or presents arbitrage opportunities is essential for enhancing price discovery processes.

Comparing Volatility Forecasting Models

Accurate volatility predictions are crucial for option pricing and risk management purposes. Although traditional models such as GARCH and ARIMA have been extensively utilised, recent progress in machine learning methods, including Gradient Boosting and Natural Language Processing (NLP), has shown potential in capturing intricate market behaviours. Furthermore, implied volatility (IV), derived from nifty options, has emerged as an important forward-looking indicator. However, its predictive effectiveness compared to historical volatility has not been thoroughly investigated. This study aims to evaluate these models to determine the most dependable method for forecasting volatility in the Indian equity market.

Implied Volatility Across Time and Moneyness Levels

The pattern of implied volatility (IV) in Nifty index options frequently displays characteristics such as volatility smiles or skews, which differ based on strike prices (moneyness), and time. Recently, IV levels for at-the-money (ATM) Nifty options have decreased to approximately 14%, indicating a lowered anticipation of major market events. However, this reduction

prompts enquiries about whether current pricing models effectively reflect risk perceptions across various timeframes and moneyness levels. Understanding these dynamics is crucial for traders and policymakers to accurately gauge market sentiments.

This study aims to address these gaps by examining the efficiency of Nifty index options, comparing advanced volatility forecasting models, and analysing the implied volatility structures across different dimensions. By integrating cutting-edge methodologies with practical insights from recent market trends, this study contributes to the academic literature and industry practices in India's dynamic derivatives market.

1.8. Research Objectives

1. To examine the market efficiency of Nifty index options.
2. To compare the forecasting performance of different volatility models for pricing Nifty index options.
3. To analyzing the structure of implied volatility vary across different time and moneyness levels of Nifty index options.

1.9. Research Hypothesis

Keane (1983) emphasized that regular market monitoring serves two essential purposes: it helps to consistently verify whether financial markets are functioning efficiently and ensures that any deviations from expected behavior are quickly detected and addressed. Despite the growing significance of derivatives in emerging economies, a close examination of the existing literature reveals a noticeable gap in studies focusing on the efficiency of Indian index options, particularly through the lens of no-arbitrage principles and hedging strategies. This study aims to fill this gap by evaluating the efficiency of Nifty 50 index options traded on the National Stock Exchange (NSE) of India. To guide this analysis and derive meaningful conclusions, a set of hypotheses was developed to test the presence or absence of market inefficiencies in the Indian index options segment. The null hypotheses for this study are as follows:

Ho1: After factoring in transaction costs, there is no significant frequency or magnitude of violations for both call and put Nifty index options when using the Black-Scholes model.

Ho2: There is no significant difference in the forecasting performance of different volatility models in pricing Nifty Index Options.

Ho3: The Indian options market makes a volatility smile.

1.10. Research Design

The research design acts as a blueprint that systematically guides the process of investigation, helping researchers align their methods and strategies with the intended objectives (Aaker et al., 2000). This study adopts a descriptive research design, a type of conclusive research approach that is particularly effective for portraying the features of a given market or population. In this case, a descriptive approach is applied to assess the characteristics of market efficiency in the Indian options market, with special attention to index options. This design enables the researcher to explore essential questions such as "what", "when", and "how", ultimately aiming to derive insightful and data-backed conclusions about market behaviour.

1.10.1 Scope of the Study

The concept of an efficient market was first introduced by Eugene Fama in 1970, marking a foundational moment in financial economics. According to Fama, competition among market participants drives prices to reflect all available information, thereby ensuring that securities are priced fairly. He organized a growing body of empirical studies into a structured framework known as the Efficient Market Hypothesis (EMH), grounded in fair game theory. This theory suggests that the expected return of a financial asset, once adjusted for risk, aligns with its current price because the price incorporates all relevant information.

Fama outlined three levels of market efficiency:

- The weak-form EMH suggests that prices fully reflect past market data, such as prices, trading volumes, and other historical trends.
- The semi-strong-form EMH posits that prices adjust rapidly to all publicly available information, including macroeconomic indicators and corporate disclosures.
- The strong-form EMH asserts that prices reflect all information, public and private, leaving no opportunity for any investor group to consistently achieve abnormal returns.

This study primarily focuses on testing weak-form efficiency in the Indian index options market by analyzing how well prices reflect historical information. Although this study employs dynamic hedging strategies using the Black-Scholes model, which some scholars, such as Cavallo and Mammola (2000), argue constitutes a slightly stronger test of efficiency, the core emphasis remains on the weak form of the EMH.

1.10.2 Why did choose Nifty50 index options?

1. Market Relevance and Popularity

- Nifty50 is the benchmark index of India, representing the top 50 highly liquid and large-cap stocks across major sectors in the country.
- It is widely tracked by institutional and retail investors, making it the most traded index in India.
- According to the NSE reports, the Nifty50 index options consistently account for the largest share of the total derivatives turnover in the Indian markets.

2. Liquidity and Depth

- Nifty50 options dominate in terms of liquidity, with high trading volumes, tight bid-ask spreads, and reduced market impact costs.
- Compared to stock-specific derivatives or other indices, Nifty50 has a deep open interest across multiple strike prices and expiries.
- High liquidity ensures reliable price discovery and lower chances of market manipulation, which is critical when performing empirical or quantitative analyses.

3. Regulatory and Structural Importance

- The NSE and SEBI often use Nifty50 derivatives as a benchmark when introducing regulatory or structural changes (e.g. contract size revisions, weekly options introduction, and margin framework updates).
- Therefore, Nifty50 is seen as a policy testing ground, making it the most academically relevant instrument to study.

4. Risk Management and Hedging Role

- Nifty50 options are the most widely used hedging tools by institutional investors managing large equity portfolios.
- Stock options and midcap indices may not provide the same diversified hedging benefits because they are narrower in scope.
- Nifty50 options serve as a proxy for Indian equity market risk, making them essential for risk management research.

5. Global Comparability

- Globally, most academic studies on options markets focus on benchmark index derivatives (such as S&P 500 options in the US and Euro Stoxx 50 in Europe).

- By selecting Nifty50, your thesis aligns with international research practices, allowing for easier comparison and contributing to the global literature.

6. Practical Feasibility

- The availability of extensive historical data on Nifty50 options (daily prices, volumes, and open interest) compared to many other derivatives.
- Stock-specific derivatives often face issues such as illiquidity, low open interest, or sudden delisting, making long-term studies difficult.

In 2023–24 alone, index options accounted for an overwhelming 98.48% of the total derivatives trading volume, as illustrated in Table 1.1.

Table: 1.1 Instrument-wise turnover of F&O segment of NSE (2023–2024)

Product	Trade Value (Rs. Crore)	Market Share of F&O Segments
Index Futures	2895203.19	0.09 %
Stock Futures	8883497.92	0.31 %
Index Options	2882084054	98.48 %
Stock Options	32908445.45	1.12 %
Total F&O Trade Value	2926771201	100.00 %

1.10.3 Ex-Post Efficiency Test

Market efficiency is typically assessed using two primary testing methods: ex-post and ex-ante. The ex-post approach involves analyzing market data that are already available at a given point in time (denoted as time t). Using this historical data, researchers design trading strategies and simulate positions as if trades were made at the same prices. In contrast, the ex-ante approach also formulates strategies using data from time t but assumes that trades are executed at a future time ($t + 1$) at prices that are not yet known when the strategy is formulated.

Most efficiency studies in the financial literature rely on ex-post testing. However, in practical terms, traders do not have the ability to execute trades precisely at observed prices during detected arbitrage opportunities. For this reason, such violations are often interpreted not as actionable trades but as signals that might inspire future trading strategies. However, it is important to recognize that the actual prices traders encounter in the market may differ from

those used in simulations, raising doubts about whether the profits observed in ex-post tests truly reflect inefficiencies or simply market timing mismatches.

Galai (1978) criticized the reliance on ex-post evaluations, advocating instead for ex-ante testing. He argued that only ex-ante strategies can realistically reflect the conditions that an arbitrageur would face. Because ex-post methods do not outline a replicable trading path, any strategy developed after the fact lacks practical relevance. Additionally, strategies designed based on past violations may lead to negative returns when applied to real-time market conditions.

A key concern in ex-ante testing is the risk of delayed execution, often referred to as the immediacy risk. As Kamara and Miller (1995) pointed out, this risk arises from the possibility of price movements between the identification of a trading signal (at time t) and the actual execution of the trade (at $t + I$). This timing gap introduces a layer of uncertainty that must be accounted for when assessing the viability of any arbitrage strategy.

Because the study relies on daily closing prices, there is an inherent minimum one-day delay in the execution. To date, no prior research has explored market efficiency using closing data with at least a one-day lag, as market anomalies based on no-arbitrage conditions are generally expected to dissipate rapidly, often within a few minutes. Consequently, this study is retrospective, as it does not propose a strategy to capitalise on mispricing signals (Trippi, 1977; Chiras and Manaster, 1978). In a retrospective analysis, the trading strategy is formulated using prices at time (t) and is presumed to be executed at the same time (t).

1.11. Outline of the Chapters

Chapter 1: Introduction

Chapter 2: Indian Index Options Market

Chapter 3: Literature Review

Chapter 4: Test of Market Efficiency of Indian Nifty 50 Index Options

Chapter 5: Forecasting Volatility in Indian Index Options Market

Chapter 6: Implied Volatility structure by Indian Nifty 50 Index Options

Chapter 7: Findings, Conclusion, and Recommendations

CHAPTER 2

INDIAN INDEX OPTIONS MARKET

2.1. Introduction

The wave of liberalization worldwide developed the economies of different nations, leading to a common stage of economic development. This has resulted in a massive increase in international trade and business volume. The growing number of financial transactions has also led to the emergence of new financial instruments at the national and global levels. Interest rates, exchange rates, equities, and other financial market prices have undergone significant volatility, increasing the financial risks for individual and institutional investors. In some cases, adverse changes in these variables have created existential threats to companies. However, risk still exists, creating the need for new financial instruments called financial derivatives.

A financial derivative is a type of financial instrument whose value is derived from another asset. Typically, the prices of traded financial instruments constitute the fundamental assets of derivatives. A stock option is a derivative whose value depends on the price of a specific stock. These tools derive their value from their connection to underlying assets and have no inherent value. These instruments make assertions that enable the owner to exchange or possess financial instruments and assets. Butter, which comes from milk, is a basic analogy; hence, the availability and demand for milk determine its price. In Section 2(ac) of the Securities Contract Regulation Act (SCRA) of 1956, a derivative is defined as a security formed from a debt instrument, share, loan (either secured or unsecured), or a risk instrument. Financial derivatives contracts, whose values are determined by the prices or price indices of the underlying securities.

Derivatives may be traded on over-the-counter (OTC) markets or arranged exchanges or through other means. A derivative exchange is a marketplace in which traders with standardized contracts are established through exchanges. Such interactions have long been present; for example, the Chicago Board Options Exchange (CBOE) was founded in 1848 to enable the uniform trading of grain between merchants and farmers in Chicago. Not all derivative trading occurs on exchanges. Regarding trading volume, the OTC market is a major substitute that has exceeded the exchange-traded markets. Securities that do not fit the exchange listing criteria

are exchanged directly between brokers or dealers in the OTC market using computer networks and phone conversations.

Derivatives can be classified into four main types: forwards, futures, options, and swaps. Futures and options are actively traded on exchanges, whereas forwards, swaps, and other options are mostly traded in over-the-counter (OTC) markets. A forward contract is a derivative deal in which an item is bought or sold at a predefined future date and price. Financial institutions and business customers typically negotiate agreements with banks to obtain loans. While one party adopts a short position by consenting to sell the underlying asset, the other adopts a long position by agreeing to purchase it.

A **futures contract** is a standardized agreement between two parties to buy or sell a specific quantity of an asset at a predetermined price on a specified future date. These contracts are facilitated through organized exchanges, which play a central role in ensuring transparency and reducing counterparty risk by acting as intermediaries between buyers and sellers. Futures are designed to serve the needs of a wide range of market participants, including traders, investors, and hedgers. Their standardization and high liquidity make them more accessible and easier to trade, especially for those seeking quick entry and exit from the market.

In contrast, **forward contracts** are private agreements made directly between two parties, allowing for complete customization of terms, such as quantity, price, and settlement date. This flexibility makes forwards particularly useful for businesses that require tailored hedging strategies, especially in markets such as commodities or foreign exchange, where price fluctuations can significantly affect profitability. However, because forwards are traded over the counter (OTC), they carry a higher counterparty risk and lack the transparency associated with exchange-traded contracts.

Options contracts offer a different type of financial instrument. Unlike futures and forwards, which obligate both parties to fulfil the contract terms, options provide the buyer with the right, but not the obligation, to buy or sell an underlying asset at a predetermined price within a specified timeframe. There are two main types of options.

- A **call option** grants the right to purchase an underlying asset.
- A **put option** grants the right to sell.

This asymmetry, where the buyer has a choice but the seller has an obligation, sets options apart as unique tools for hedging or speculation. Investors often use options to limit potential

losses while maintaining upside opportunities, making them appealing in volatile market conditions.

Each of these derivatives serves a distinct purpose: forwards are ideal for customized hedging needs, futures for standardized and transparent trading, and options for flexible risk-management strategies.

A swap is another useful derivative product that allows two people to trade the cash flows of financial instruments depending on predefined terms. Rather than being traded on exchanges, swaps are OTC products that banks usually create. Hedging risks include changes in interest rates and foreign exchange rate volatility, which mostly involve swap transactions. The first known swap transaction is said to have occurred between the World Bank and IBM in 1981. Since then, corporate treasury operations have extensively embraced swaps as risk control strategies.

2.2. Origin of Derivatives Market

The history of derivative markets in India can be traced back to the late 19th century, with the establishment of the Bombay Cotton Trade Association in 1875, marking the beginning of organized futures trading in India. However, in 1952, the Indian government-imposed restrictions on cash settlements and options trading, forcing derivative trading in informal forward markets. The revival of financial derivatives began with the Securities Laws (Amendment) Ordinance of 1995, which lifted the ban on options in the securities markets. The early 2000s saw a resurgence in futures trading across various commodities and the creation of National Electronic Commodity Exchanges. A crucial milestone was reached in June 2001 when SEBI granted final approval for trading derivatives.

In response to the L.C. and based on the recommendations of the Gupta Committee, the Securities and Exchange Board of India (SEBI) granted permission to the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) to offer derivative trading. The initial phase of trading began with index futures contracts linked to stock market indices, including the S&P CNX Nifty and Sensex. Subsequently, options for both indices and individual stocks were introduced into the market. Key events in the evolution of India's derivatives market include the introduction of index futures trading on the NSE on June 12, 2000, followed by index options trading on June 4, 2001. Stock options trading commenced on 2 July 2001 and

single-stock futures became available on 9 November 2001 in the KOSDAQ market. The Nifty 50 index forms the basis for NSE index futures and options contracts.

Currently, India's derivatives market has outpaced its securities market in terms of volume and transaction counts. As the second-largest emerging market after China, India boasts a market capitalisation of over \$1 trillion. India has a significant position in the exchange-traded derivatives market among developing countries. By 2011, India ranked third globally in derivative contracts, with the NSE claiming the second spot in stock index options trading. The NSE has continually expanded its derivative offerings, including currency and interest rate products, further cementing India's position in the global derivatives market. In the past two decades, India's derivatives market has experienced remarkable growth and evolution, making it one of the most dynamic derivatives markets in the world. By 2023, Indian exchanges, notably the National Stock Exchange (NSE) and the BSE, led the global derivatives trading.

In the second quarter of 2024, equity index options trading on the NSE and BSE experienced continued growth, with volumes exceeding 32.8 billion, more than doubling the previous year's figures for the same period. This represented over two-thirds of the global futures and options trading at that time. To address the rapid growth of the derivatives market, the SEBI implemented stricter regulations to protect investors and maintain market stability. Starting 20 November 2024 SEBI limited the number of weekly options contracts per exchange and raised the minimum trading amount to 1.5-2 million rupees to mitigate the risks associated with increased retail investor participation in derivatives trading.

Subsequently, the NSE eliminated weekly derivative contracts on several indices, including Bank Nifty, Nifty Financial Services, and Nifty Mid-Cap, while maintaining those linked to the Nifty 50 index. Despite market expansion, several issues have arisen. From March 2021 to March 2024, retail traders suffered net losses of 1.81 trillion rupees (\$21.67 billion) in futures and options trading, with only 7.2% of individual traders reporting gains, underscoring the inherent risks of trading derivatives. Additionally, early 2025 saw a decline in Indian stocks, with the NSE Nifty 50 index experiencing its longest streak of losses since 1996. The index fell by 15% from its September high, resulting in a \$1 trillion decrease in investor wealth. This downturn was attributed to poor earnings, continued foreign outflows, and uncertainty regarding U.S. tariffs. NSE has continually expanded its derivative product offerings to meet diverse investor needs. As of 31 December 2024, the NSE had 2,671 listed companies, with 2,084 on the main board and 587 on the SME platform, NSE Emerge. In 2024, the NSE

facilitated 268 IPOs, raising approximately Rs 1.67 lakh crore (US\$19.5 billion), marking a significant milestone in global equity markets. The exchange offers a wide range of equity derivatives, including contracts on major indices such as Nifty 50, Nifty Bank, and individual securities.

2.3. The Impact of Derivative Markets on the Economy

India's economic liberalization has created a substantial demand for derivative products to assist investors in risk management. The introduction of financial derivatives in India began in 1995 with the introduction of index futures. The Reserve Bank of India (RBI) authorized the trading of forward rate agreements (FRA) and interest rate swaps (IRS) in the over-the-counter (OTC) derivatives market in June 1999, thereby expanding the range of financial risk management instruments available to market participants. Since then, derivative trading in India has experienced significant growth, characterized by higher trading volumes and increased participation in the market. These financial instruments provide risk-averse investors with a means to safeguard themselves against price fluctuations, foster price stability, and decrease their investment volatility. Furthermore, derivatives aid in price discovery by aligning futures prices with underlying asset values as contracts approach settlement, thereby enabling more accurate valuations.

The increasing significance of derivative markets has resulted in heightened trading activity, particularly in highly volatile asset classes. Regulatory bodies, such as the Securities and Exchange Board of India (SEBI) and RBI, have adopted a balanced yet progressive approach to introducing new derivative instruments while implementing measures to prevent excessive speculation and market manipulation. The continuous expansion of derivatives, including currency, commodities, and interest rate futures, has reinforced India's position as a significant player in the global financial markets. With the National Stock Exchange (NSE) consistently ranking among the world's top exchanges in terms of derivatives trading volume, these markets are anticipated to enhance investor confidence, promote capital formation, and contribute to long-term economic growth by offering improved risk management and investment opportunities for investors.

2.4. Options Contracts, Mechanism, and Characteristics

An option is a financial contract between two parties: the buyer (also called the holder) and the seller (known as the writer). This contract gives the buyer the right but not the obligation to buy or sell a specific asset at an agreed-upon price (the strike price) on or before a predetermined future date. In exchange for this right, the buyer pays the seller a fee, known as the premium. If the buyer decides to exercise the option, the seller is required to fulfil the contract terms.

There are two main types of options.

- A call option allows the buyer to purchase an underlying asset.
- A put option allows the buyer to sell an underlying asset.

Options are commonly traded on regulated exchanges, where standardized contracts promote liquidity and transparency. However, a significant number of options trades still occur outside these exchanges through over-the-counter (OTC) transactions. These privately negotiated contracts allow parties to customize the terms to better suit their specific hedging or investment needs. The OTC market for options existed long before formal exchanges were established.

The creation of the first organized options exchange in 1973, the Chicago Board Options Exchange (CBOE), initially drew much of the trading away from OTC markets because of the benefits of standardized and regulated contracts. However, in recent years, OTC options have regained popularity, particularly among corporations and financial institutions that require more tailored risk management tools than those provided by exchange-traded options.

The fundamental principles of option pricing and usage remain consistent, regardless of the trading venues. Many options of interest involve the purchase or sale of financial assets, such as stocks or bonds. However, options also exist for futures contracts, metals and foreign currency. Various financial arrangements, such as credit lines, loan guarantees, and insurance policies, can be considered. Furthermore, stocks can be viewed as options for a company's assets.

Call Options

A call option is a financial instrument that confers the holder with the right, but not the obligation, to purchase an underlying asset at a predetermined price (strike price) within a specified period (expiry date). These derivative contracts are available for diverse asset classes,

including equities, fixed income securities, futures contracts, commodities, and foreign exchange. Moreover, financial instruments such as lines of credit, loan guarantees, and insurance policies operate similarly to options. Even owning stocks can be viewed as an option for a company's asset.

Let us consider a scenario in which an investor trades a call option for an XYZ Corp. On 1 January 2024 multiple exchanges offered call options for the XYZ stock. A specific call option had a strike price of ₹50 and expired on 16 February 2024. At that time, the XYZ stock was valued at ₹48 per share. The individual who purchased this option gained the right to buy XYZ stock at ₹50 per share at any point until 16 February. The party that issued (wrote) the option was obligated to sell the stock at a specified price if the option holder exercised it. The buyer paid the writer a premium of ₹2.50 per share for this right.

What motivates both parties to enter into such agreements? The call option buyer anticipated that the XYZ stock would surpass ₹50 before the expiration date. In contrast, the call writer expects the stock to remain below this price. The ₹2.50 premium reflects market expectations and associated risks. If the XYZ stock value increases shortly after the purchase, the call option becomes more valuable as the strike price remains fixed, whereas the stock price appreciates. Consequently, comparable options with identical terms would trade at higher premiums. Conversely, if the stock price declines, the value of the call option decreases.

A call option is categorized based on its relationship with stock prices.

- In-the-money (ITM): The stock price is higher than the strike price.
- At-the-money (ATM): The stock price is equal to the strike price.
- Out-of-the-money (OTM): The stock price is lower than the strike price.

It is important to note that ITM calls should not always be exercised before expiration because their market value may exceed their immediate intrinsic value.

Put Options

A put option is a financial derivative instrument that confers the holder with the right, but not the obligation, to sell an underlying asset at a predetermined price within a specified time frame. Similar to call options, put options are available for various asset classes, including equity and futures contracts.

Consider a scenario in which an investor acquires a put option for XYZ Corp. stock on 1 January 2024 with a strike price of ₹50 and an expiration date of 16 February 2024. At the time of acquisition, the XYZ stock traded at ₹48 per share. The put option allowed the holder to sell the XYZ stock at ₹50 per share until 16 February. The buyer paid a premium of ₹3.00 to the put writer, who committed to purchasing the stock at ₹50 per share if the put was exercised.

The put buyer anticipated a further decline in the stock price, whereas the put writer expected it to remain at or above ₹50. If the XYZ stock fell to ₹45, the put option would increase in value as the holder could sell the stock at ₹50 while acquiring it in the market for ₹45. Conversely, if the stock price rises above ₹50, the put would decrease.

Put options are classified based on their relationship with the stock prices.

- In-the-money (ITM): The stock price is lower than the strike price.
- At-the-money (ATM): The stock price is equal to the strike price.
- Out-of-the-money (OTM): The stock price is higher than the strike price.

As with call options, the early exercise of ITM puts may not always be advisable, as their market value could exceed their intrinsic value.

2.5. Market Structure and Options Trading at National Stock Exchange

2.5.1. Derivative Market Structure

The derivatives market is broadly categorized into two main segments: exchange-traded and over-the-counter (OTC) derivatives.

Exchange-traded derivatives are traded on formal platforms, similar to stock or commodity exchanges, and follow standardized contracts. These are transparent, regulated, and backed by clearinghouses, which significantly reduces counterparty risk. Products such as equity options, equity futures, currency futures, and interest rate futures are actively traded on major Indian exchanges, such as the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). Likewise, commodity futures are primarily traded on platforms such as the National Commodity & Derivatives Exchange (NCDEX) and the Multi Commodity Exchange (MCX).

In contrast, OTC derivatives are private contracts negotiated directly between two parties and are often tailored to meet specific hedging or trading needs. These include forward contracts in currencies, commodities, and interest rates, as well as currency options, interest rate options,

and currency swaps. Since OTC markets lack centralized exchanges, the risk of counterparty default is higher, and the terms are more flexible than those of standardized contracts.

For example, currency forwards are typically initiated between banks and their clients. The bank quotes a forward rate for the contract, and in most cases, the client is required to demonstrate an existing exposure that they wish to hedge. Banks may also request clients to maintain a margin or deposit funds to support the contract. Meanwhile, brokers usually facilitate currency options, interest rate options, and swaps, connecting buyers and sellers, often with a bank acting as the counterparty.

2.5.1.1. Listing Requirements

Options exchanges play a crucial role in defining the assets eligible for options trading. In the case of stock options, exchanges lay down specific listing criteria that a stock must meet before options can be traded. Historically, these criteria were quite strict, allowing only the stocks of large and well-established companies to qualify. However, in recent years, these rules have been relaxed to permit options trading on the stocks of smaller companies. Beyond the initial listing, exchanges also enforce maintenance requirements to ensure that a stock remains eligible for options trading. These ongoing conditions are generally similar to those required for the initial listing but slightly less demanding. Nevertheless, exchanges reserve the right to make exceptions when adding or removing stocks from the list. Within the options market, all options of a specific type, either call or put for a particular stock, are grouped into what is known as an option class. For example, all Nifty call options belong to one class, whereas Nifty put options form a separate class. Within each class, options are further categorized into option series, which include all contracts with the same exercise price and expiration dates. For instance, the Nifty September 27.5 call options form a distinct series, as do the Nifty 25 October call options.

It is worth noting that the decision to list a stock for options trading lies entirely with the exchange, not with the company itself. This framework has also been adopted internationally, with several exchanges, such as those in China, listing options on various stocks across multiple platforms in recent years.

2.5.1.2. Contract Size

A standard exchange-traded stock option contract typically exposes 100 shares of an underlying stock. This arrangement confers the right to purchase or sell 100 shares upon the acquisition of a one-option contract. In Indian derivative markets, the minimum contract value is two lakhs. Deviations from the standard contract size occur in instances of corporate actions, such as stock splits or dividends, which necessitate adjustments in contract specifications and its original value.

2.5.1.3. Exercise Prices

In organized options markets, exercise prices, also known as strike prices, are standardized to streamline trading and ensure liquidity. These predetermined prices are established by the exchange and dictate the levels at which investors can buy or sell options contracts for the underlying stock. Traders must choose from the listed strike prices when placing trades rather than setting their own. This differs from the over-the-counter (OTC) market, where two parties can freely agree on any strike price that suits their individual needs, offering greater customization but less transparency and liquidity than the options market. Exchanges typically focus on listing options with strike prices that are close to the current market value of the underlying asset, as most of the trading volume tends to cluster around these levels. For example, if Reliance Industries is trading at ₹2,430, the exchange may list call and put options at strike prices of ₹2,400, ₹2,420, ₹2,440, and ₹2,460. If the stock price shifts significantly, the exchange updates the list of strike prices to keep them relevant to market conditions.

To ensure consistency, exchanges follow a tiered structure when determining the spacing between the strike prices. For instance, options on stocks priced below ₹50 usually have ₹2.50 intervals. Stocks priced between ₹50 and ₹100 have ₹5 intervals, whereas those priced between ₹100 and ₹250 have ₹10 intervals. From ₹250 to ₹1,000, the interval is typically ₹20, and for stocks traded above ₹1,000, strike prices are usually spaced by ₹50. For example, if Reliance Industries is trading above ₹2,400, options might be listed at every ₹50 increment, such as ₹2,400, ₹2,450, and ₹2,500. This systematic approach allows efficient price discovery and orderly trading.

2.5.1.4. Expiration Dates

The expiration or exercise date of an options contract is generally defined as the month in which the option terminates. For instance, a January call option on Tata Limited signifies a contract that gives the holder the right to buy Tata shares before or on the expiration date in January. Exchanges are responsible for clearly specifying the exact expiry date, last trading day, and final deadline for exercising the option. In Indian stock exchanges, options typically expire on the last Thursday of the month. If this Thursday is a trading holiday, the expiry is shifted to the previous trading day. Stock options in India follow a rolling three-month trading cycle, covering the current (near), next, and far months. For example, in January, options are available with expiry dates of January, February, and March. As the January contract expires, the April contract is introduced, thereby maintaining a three-month forward window for hedging and speculation. Similarly, stock index options are categorized into regular and long-term categories. Regular index options follow the same monthly cycle as stock options, while long-term index options are structured around quarterly expiries in March, June, September, and December and half-yearly expiries in June and December, offering more extended planning horizons for long-term investors.

2.5.2. Operations of Derivative Exchange

Three primary operations are essential in any derivative exchange: trading, clearing, and settlement. To ensure the smooth functioning of an exchange, it is imperative to develop an efficient trading system that enables traders in futures and options markets to enter positions with ease. Furthermore, the exchange must establish a mechanism to ensure that traders fulfil their obligations when required and that the calculation and delivery of cash and goods are executed accurately and promptly. The subsequent section elucidates the trading, clearing, and settlement systems implemented by the NSE. Notably, other exchanges employ comparable systems.

2.5.2.1. The Trading System

All major exchanges in India have adopted fully automated, screen-based trading platforms that enhance investor safety, accessibility, and convenience across the country. These platforms rely on modern computerized infrastructure built around an order-driven market model. At the National Stock Exchange (NSE), the futures and options (F&O) segment operates through a

sophisticated trading system that enables seamless, screen-based trading nationwide without the need for a physical trading floor. This system incorporates real-time monitoring and surveillance features to ensure market integrity and prevent market manipulation. The trading process is entirely transparent; orders submitted by investors are instantly time-stamped and assessed for possible matches. If no immediate match is found, the orders are stored in an electronic order book. The order book organizes pending orders based on a price-time priority system, where orders are first prioritized by the most competitive price and then by the time at which they are entered. This efficient and fair system has significantly improved market operations, allowing for orderly execution and increased investor confidence in the market.

2.5.2.2. Types of Orders

The various types of orders utilized in Indian derivative exchanges are as follows:

Indian derivative exchanges accommodate a wide range of order types to suit the diverse strategies and risk appetites of the market participants. One of the most common types is the market order, which seeks immediate execution at the best available prices. For example, if a sugar producer wants to lock in prices by entering into a sugar futures contract and places a market order, the trade will be executed promptly at the prevailing market price. While the key benefit of this order is assured execution, the downside is the uncertainty of the final transaction price until the order is completed.

Another widely used order is the limit order, where a trader specifies a maximum (for buying) or minimum (for selling) price, referred to as the limit price, at which the trade can be executed. For instance, if a trader sets a buy limit order at ₹500, the order will only be executed if the market price is ₹500 or lower. Likewise, a sell-limit order at ₹500 will only be executed if the market price is ₹500 or above. This type of order offers control over the execution price, although it may remain unfilled if market conditions do not meet the specified criteria.

A stop-loss order enables traders to manage risks by specifying a stop price. Once the market hits this price, the order is transformed into a market order and executed immediately. However, if the stop price is not triggered, the order remains dormant.

Immediate or Cancelled (IOC) orders require prompt execution. If the order cannot be filled in full or in part instantly, the unfilled portion is automatically cancelled. Similarly, Good Till Day (GTD) orders must be executed on the same day; if they are not, they are cancelled at the end of the day.

More persistent are Good till Cancelled (GTC) orders, which stay active until the trader manually cancels them, and Good till Date (GTD) orders, which remain valid until a predetermined expiration date. If not executed by then, they are automatically cancelled.

Finally, a spread order is a sophisticated strategy in which the trader enters two linked orders involving the same underlying asset. In the futures market, these orders have different maturity dates, whereas in the options market, they may vary by maturity or strike price. This helps traders capitalize on the price differences across contracts.

2.5.2.3. Order Matching Rules

The system facilitates pairing the most advantageous buy order with the most advantageous sell orders. The orders may be partially matched, resulting in multiple transaction records. When matching orders, the system considers the highest- and lowest-priced sell orders to be optimal. This approach is predicated on the system's perspective, which evaluates buy orders from the seller's viewpoint and sell orders from the buyer's standpoint. Consequently, a seller inherently prefers to sell at the highest available buy price in the market at any moment. Therefore, the optimal buy order is characterized by the highest price, and the inverse is true for sell orders.

Users can actively input orders into the system, which remain visible until the entire quantity is matched by one or more opposing orders, culminating in a trade. Alternatively, users can respond to existing orders by submitting matching orders. In the trading system, orders that do not find an immediate match are classified as passive orders, whereas those that match existing orders already in the system are known as active orders. When a trade occurs, it is always executed at the price of a passive order. This mechanism ensures fairness and transparency by prioritizing orders that are placed earlier. In essence, the system operates on a price-time priority basis, first giving preference to the best price and then to the earliest time of order entry. This structured approach helps maintain order in the market and encourages traders to enter competitive bids and offers.

2.5.2.4. The Clearing and Settlement System

In financial markets, the clearing process ensures accurate documentation of transactions. Settlements, which are the resulting cash and delivery arrangements, are executed when traders close their positions. This clearing and settlement procedure is generally uniform across exchanges, with each having a subsidiary clearing corporation to manage its operations.

The clearing and settlement system is the foundation of any derivative exchange. It was designed to accurately record the derivative contract orders of traders in the trading system. Furthermore, when contracts expire or traders' close their positions, the system ensures that no defaults occur and that traders receive their profits. This critical process is overseen by a clearing corporation, which is typically a subsidiary of the derivatives exchange. For India's National Stock Exchange (NSE), the National Securities Clearing Corporation Limited (NSCCL) functions as a clearing and settlement agency for all derivatives (futures and options) transactions.

2.5.2.5. The Members of the Clearing House

In derivative markets, the role of the clearing house is vital for ensuring that trades are settled smoothly and with minimal counterparty risk. The clearing house functions through designated members known as clearing members (CMs) who are authorized to clear trades executed by trading participants. A trade on the derivatives exchange is only considered valid once it is cleared by a recognized clearing member. Exchange participants are generally categorized into two groups: Clearing Members (CMs) and Trading Members (TMs).

Trading Members are authorized to execute trades and match buy and sell orders for futures and options contracts. However, they do not have the authority to independently clear trades. The clearing and settlement of all transactions executed by Trading Members must be processed through a Clearing Member, typically under the oversight of the National Securities Clearing Corporation Limited (NSCCL) in India. CMs are responsible for three main functions: (1) **clearance**, which involves determining the obligations of each TM under their purview by calculating net positions; (2) **settlement**, which refers to executing the financial settlement of trades (only fund settlement is currently permitted for index and stock futures and options contracts); and (3) **Risk Management**, which includes setting position limits for TMs based on upfront margins or deposits and continuously monitoring exposure to ensure market stability.

Clearing Members are further classified based on the scope of their permitted activities. A Trading Member/Clearing Member (TM/CM) is a participant who both trades for themselves or clients and is authorized to clear and settle trades for themselves as well as for other TMs. Professional Clearing Members (PCMs), such as banks and custodians, are not allowed to trade but are authorized to clear trades for other TMs. Self-Clearing Members (SCMs) can trade and

are permitted to clear and settle only their own trades and those of their clients; however, they cannot clear trades executed by other TMs.

To qualify as a Clearing Member under NSCCL norms, participants must meet specific financial requirements. A trading or clearing member must have a minimum net worth of ₹30 million, while Self-Clearing Members are subject to a lower net worth requirement of ₹10 million. Additionally, all clearing members are required to deposit ₹50 million with the NSCCL, which serves as their Base Minimum Capital. For every additional TM whose trades are cleared, an extra deposit of ₹1 million must be provided to the NSCCL. These criteria are set to ensure the financial robustness of clearing members and enhance the credibility and integrity of the clearing and settlement processes in India's derivatives market.

2.5.2.6. The Clearing Mechanism

The primary role of a clearing house in the derivatives market is to ensure the smooth and secure execution of all contracts initiated by traders on exchanges. This is accomplished by positioning the Clearing Member (CM) as the central counterparty to every trade, thereby guaranteeing the fulfilment of contractual obligations by both the buyer and the seller. Essentially, the clearing corporation interposes itself between the two parties in a trade, enhancing trust and minimizing counterparty risks.

To facilitate this process, the clearing corporation aggregates and monitors the open positions of each Clearing Member. These open positions are derived from the trading activity of Trading Members (TMs) and custodial participants associated with a CM. When placing orders through the trading system, TMs must identify the nature of the trade using the "Pro/Cli" indicator. This designation distinguishes whether the order is proprietary (executed for the TM's account) or client-based (executed on behalf of a customer).

Open positions are computed differently for proprietary and client orders. For proprietary trades, positions are calculated on a net basis, meaning that buy and sell transactions offset each other within the same TM account. For example, if a TM buys and sells equal quantities of a contract, the position is effectively neutralized. In contrast, for client trades, positions are computed on a gross basis for each client; individual buy and sell trades for each client are tallied without being offset by trades from other clients. This method ensures accountability at the client level and enhances risk-tracking.

A CM's total open position is determined by consolidating the open positions of all affiliated TMs and custodial participants who clear through them. This includes both proprietary positions and all client positions from the TMs. Because the clearing corporation assumes counterparty risk, it carefully monitors these aggregate exposures to enforce margin requirements and position limits, thereby preserving the overall stability of the derivatives market.

2.5.2.7. Margin and Margin Accounts

CMs are obligated to deposit a specified sum, referred to as a margin, for all trades cleared through them. The margin was computed based on the value of cleared contracts. The exchange maintains a margin account for each CM, indicating all positions held and the amount of exposure. This account is updated daily using the settlement price to reflect the daily profit and loss of the CM. If the margin balance falls below a critical level—commonly referred to as the variation margin threshold due to adverse market movements—the exchange issues a margin call. This requires the CM to promptly replenish the margin account by depositing the additional funds. The required margin for each derivative contract is determined by factors such as contract size and volatility of the underlying asset, as these influence the potential for price fluctuations and, hence, financial risk.

To meet margin requirements, exchanges often allow CMs to deposit not only cash but also approved alternative securities, such as government bonds, Treasury bills, or highly liquid instruments. These non-cash margins are subject to a discounting mechanism (called a haircut) to account for potential changes in market value. This margin system ensures financial stability in the derivatives market by managing counterparty risk and maintaining the discipline of traders.

2.5.2.8. The Settlement Process

Settlement refers to the completion of contractual obligations by the parties involved. Futures contracts involve two settlement types: daily mark-to-market and final settlement. Daily mark-to-market settlement results from the daily margin and mark-to-market requirements of futures contracts. The final settlement occurs on the expiration date of the contract. For contracts with physical delivery, the final settlement requires one party to provide the asset while the other party supplies the agreed-upon funds. In cash-settled contracts, the losing party pays the winning party. All transactions are handled through an exchange-clearing corporation, which

allocates funds to the appropriate party. The amount an external party owes to the exchange is called the pay-in, whereas the amount of exchange that is disbursed is termed the pay-out.

2.5.2.9. Risk Management Strategies

The main risk faced by derivative exchanges is the potential default of Clearing Members (CMs) on their obligations. In such cases, the exchange must still fulfil its contract commitments, potentially resulting in losses. To address this risk, derivative exchanges implement a comprehensive risk containment system. This system is built on an online position monitoring and margin system that operates intraday. The National Securities Clearing Corporation Limited (NSCCL) uses the Standard Portfolio Analysis of Risk (SPAN) system to calculate the margin requirements. SPAN determines margins based on the volatility of the underlying asset, with more volatile assets requiring higher margins.

Clearing Members (CMs) are mandated to submit daily reports that detail the margins collected from and owed by all traders whose trades have been cleared through them. These reports provide the clearing corporation with crucial insights into the financial standing of each participant. To ensure market stability, the positions of all CMs are continuously monitored to verify compliance with the regulatory limits set by the exchange.

For real-time risk surveillance, the National Securities Clearing Corporation Limited (NSCCL) utilises a Parallel Risk Management System (PRISM). This advanced system allows for the continuous tracking of the financial exposure of both Trading Members (TMs) and CMs. It evaluates trading activities in real time and issues alerts or automatic disablement messages if any participant breaches the assigned risk or position thresholds.

This proactive risk-monitoring infrastructure helps mitigate systemic threats and maintain orderly market functioning. In instances where participants violate margin or position limits, the exchange enforces strict penalties, which may include monetary fines, restrictions on trading activities, or even suspension from the exchange. This comprehensive and dynamic framework underscores the importance of maintaining discipline and accountability in the derivatives market.

2.5.2.10. Online Trading

Numerous brokerage firms offer clients access to online trading platforms. To utilise these services, customers must register with the company, which provides software that enables them to execute trades through the broker's network. This software allows clients to submit orders to

buy or sell derivative contracts on the exchange. Once a suitable counterparty is identified for the contract, the broker initiates the transaction clearing process.

2.5.2.11. Derivatives Trading Regulation in India

In India, three regulatory bodies oversee derivative trading: the SEBI, the RBI, and the FMC. The Securities and Exchange Board of India (SEBI) is responsible for equity derivative contracts, whereas the Reserve Bank of India (RBI) manages interest rates and currency derivatives. Commodity derivatives fall under the purview of the Forward Market Commission (FMC). According to regulatory guidelines, all contracts, whether exchange-traded or over-the-counter (OTC), must be approved by the appropriate regulatory authority before being introduced into the market. These organizations also monitor exchange operations, the structure of the Clearing Corporation, and the risk management strategies implemented through exchanges to ensure the efficient functioning of the derivatives market.

2.6. Conclusion

Since its inception in the late nineteenth century, the Indian derivatives market has experienced substantial expansion since the late 19th century. A period of rapid growth occurred in the early 2000s following the reintroduction of financial derivatives. India holds a prominent position in global derivatives trading, with the NSE and BSE ranking among the leading exchanges worldwide, particularly in options trading. Despite these challenges, the Indian derivatives market continues to play a crucial role in the country's financial ecosystem by providing risk management tools, contributing to price discovery, and improving market efficiency. Its ongoing expansion and innovation, in conjunction with regulatory oversight, have established India as a significant global player. As the market evolves, it is imperative to maintain an equilibrium between growth, investor protection, and market stability. The future trajectory of India's derivatives market is likely to be influenced by technological advancements, regulatory modifications, and evolving investor requirements, ensuring its continued significance in the global financial landscape.

CHAPTER-3

LITERATURE REVIEW

3.1. Introduction

This chapter critically examines existing scholarly work that informs and contextualizes the present study. A comprehensive literature review not only demonstrates the depth of understanding of the chosen topic but also identifies theoretical foundations, methodological trends, empirical findings, and gaps that justify further investigation.

This chapter begins by outlining the historical evolution and conceptual frameworks related to the study's core themes. It then reviews key empirical studies, focusing on both global and regional contexts, and evaluates the methodologies adopted by previous studies. Emphasis is placed on identifying patterns, contradictions, and limitations in existing research, which serve to highlight the contribution and relevance of this study.

This chapter situates the research within a broader academic discourse and provides the necessary theoretical grounding. It also establishes the rationale for the research questions, hypotheses, and methodological choices adopted in subsequent chapters.

3.2. Literature Review related Market Efficiency of Index Option

Black and Scholes (1972) used a dynamic hedging methodology to evaluate the level of market efficiency in the US over-the-counter stock options market. Their methodology included computing the theoretical valuation of options using a model that relied on historical stock-price volatility. They observed a notable level of instability in the stock on which options were based, resulting in undervalued options. Conversely, options with low instability are overvalued. To take advantage of these discrepancies, they develop a delta-neutral hedge. Nevertheless, transaction costs eradicate exceptional earnings from this study. Hence, they deduce that while the options market may seem inefficient when transaction costs are disregarded, these inefficiencies are probably not susceptible to exploitation by other traders.

3.2.1. Dynamic Hedging Tests

Dynamic hedging is a fundamental concept rooted in the Black-Scholes model's theoretical foundation. According to this model, a risk-neutral, continuously rebalanced portfolio

consisting of a derivative (such as an option) and its underlying asset can be constructed to replicate the payoff of an option. The key idea is that if such a portfolio is formed correctly, its return over a very brief time interval will closely mirror the return on a risk-free asset. This strategy leads to the creation of what is known as a hedge-replicating portfolio.

However, in practical markets, a portfolio's risk-neutral state does not persist indefinitely. The no-arbitrage condition holds true only for an infinitesimally short period due to constant changes in the market price of the underlying asset. Therefore, to maintain a risk-free position over time, the portfolio composition must be continuously adjusted or rebalanced. This ongoing rebalancing process is essential for preserving the hedge and is known as the dynamic hedging strategy.

This concept was empirically explored by researchers such as Nandi and Waggoner (2000), who demonstrated how dynamic hedging could be implemented in real-world conditions despite transaction costs and market frictions. Their work highlights both the potential and limitations of continuous rebalancing, providing critical insights into the practical viability of the Black-Scholes framework in derivative markets.

Black-Scholes Model

The assumptions underlying the original Black-Scholes option pricing model are as follows:

- Stock prices follow a log-normal distribution with constant volatility.
- Short selling is allowed with the full use of sale proceeds.
- There are no transaction costs, taxes, or divisible securities.
- The underlying asset pays no dividends during the life of the option.
- No arbitrage opportunities exist in this market.
- Securities can be traded continuously, without restrictions.
- The risk-free interest rate is constant for all maturities.

Based on the assumption above, the Black-Scholes option pricing formulae for call and Put option can be written as

European Call Option:

$$C = SN(d_1) - Xe^{-rT} N(d_2)$$

European Put Option:

$$P = Xe^{-rT} N(-d_2) - SN(-d_1)$$

$$d_1 = \frac{\log(s/x) + (r + \sigma^2/2)t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

Where:

- C = Price of the call option (the cost to buy the right to purchase the asset)
- P = Price of the put option (the cost to buy the right to sell the asset)
- S = Current market price of the underlying stock or asset
- X = Strike (exercise) price of the option—the predetermined price at which the asset can be bought or sold
- T = Time to expiration, expressed in years (e.g., 3 months = 0.25 years)
- r = Continuously compounded annual risk-free interest rate applicable over the period T
- σ (sigma) = Annualized volatility of the asset’s return (a measure of how much the price fluctuates)
- N (•) = Cumulative distribution function of the standard normal distribution (i.e., the probability that a value from a standard normal distribution is less than or equal to a given number)

3.2.2. Why Use the Black–Scholes Model for Option Pricing?

The **Black–Scholes model (1973)** remains the most widely used framework for evaluating the theoretical price of European options because of its balance of analytical tractability, intuitive economic assumptions, and historical significance in financial theory. The key reasons for its adoption are as follows:

1. Closed-Form Solution

- Black and Scholes provide a closed-form formula for European call and put options.
- This makes option pricing computationally efficient and analytically transparent, unlike simulation-based or lattice models (for example, Monte Carlo and binomial trees), which are more computationally intensive and less elegant for theoretical exposition.

2. Foundational Role in Finance

- It is the first widely accepted no-arbitrage model for derivative pricing.

- The model introduced the concept of risk-neutral valuation, which underpins nearly all modern option pricing and risk-management techniques.
- For a thesis, using Black–Scholes provides a rigorous theoretical foundation and allows the results to be benchmarked against a globally recognised standard.

3. **Simplicity and Parsimony**

- Despite assuming idealised conditions (constant volatility, frictionless markets, lognormally distributed asset prices), the model is mathematically elegant and easy to implement.
- Other models (e.g. Heston’s stochastic volatility model and Merton’s jump-diffusion model) relax these assumptions but add complexity that may not be necessary for a baseline analysis.

4. **Benchmarking and Comparability**

- Black and Scholes serve as the industry benchmark, deviations from it highlight real-world effects such as volatility smiles, stochastic volatility, or market frictions.
- Using it in research ensures comparability with prior studies and allows for extensions (e.g. implied volatility analysis) that build on its framework.

3.2.3. **Why Not Another Model?**

- **Binomial/Trinomial Trees:** Flexible and intuitive, but computationally heavier for large steps and less elegant for deriving analytical insights.
- **Monte Carlo Simulation:** Useful for exotic or path-dependent derivatives, but unnecessary for plain European options where Black–Scholes suffices.
- **Advanced Models (Heston, Merton, Bates):** Capture market imperfections (e.g., stochastic volatility, jumps), but their additional parameters require extensive calibration and may obscure rather than clarify the theoretical discussion.
- **Black–Scholes as a Baseline:** These alternative models are typically judged relative to Black–Scholes; thus, omitting it risks losing the benchmark perspective.

3.2.4. **Forecasting the Expected Volatility of the Underlying Asset**

One of the major difficulties in evaluating market efficiency in the options market using the Black-Scholes model lies in estimating the volatility of the underlying asset until the contract’s expiration. Unlike other components of the model, such as the stock’s closing price, which is observable, the risk-free interest rate, which can be derived from government securities with similar maturity, the time to maturity, which is easily calculated, and the strike price, which is

predefined, volatility is not directly available from published sources or databases. Instead, it must be estimated using a different approach. As Black and Scholes (1972) themselves pointed out, accurately estimating volatility is crucial to the model's effectiveness, stating, "If the model has an accurate estimate of the variance, it works very well... More work must be done to predict variances using the information available." This highlights the importance of forecasting volatility to determine the theoretical value of an option. However, because volatility is inherently unstable and varies over time, achieving a precise estimate remains a complex and ongoing challenge for researchers and practitioners.

According to Hull (2006), volatility is a measure of the unpredictability of an asset's return. In statistical terms, volatility is identified as the standard deviation of the asset's returns from the spot date to the expiration date of the options contract. There are two primary methods to estimate volatility: one involves calculating the standard deviation of historical returns (HSD) over a recent period (Taleb, 1997), and the other involves determining implied volatility (IV) (Latane and Rendleman, 1976) using the observed spot option prices and solving the Black and Scholes pricing model. The concept of implied volatility is based on the premise that the current option price reflects all available market information, making the volatility implied by the current observed option price a reliable indicator of the expected volatility of an underlying asset (Fontanills, 2003). Nonetheless, the accuracy of these volatility estimation techniques (HSD and IV) in predicting theoretical option prices remains a contentious issue in practice and academic circles.

3.2.5. Implied Volatility

In real-world trading, options are often priced using a metric called *the implied volatility* (IV). This form of volatility is not directly observed but is derived from the current market price of an option. Essentially, implied volatility is the level of volatility that, when input into the Black-Scholes model, results in a theoretical option price equal to that currently observed in the market. However, the challenge lies in the fact that the Black-Scholes formula is not algebraically invertible to directly solve for implied volatility. This means that there is no straightforward way to isolate volatility as a function of known variables such as the option's market price, current stock price, strike price, risk-free interest rate, and time to expiration. To tackle this, traders and researchers use iterative numerical techniques, such as the Newton-Raphson method. With tools such as RStudio, this process becomes manageable: the method is used to iteratively feed different volatility values into the Black-Scholes equation until the

model's output matches the actual market price of the option. Thus, the implied volatility is effectively "back-calculated", making it a crucial tool for option valuation.

According to the **Black-Scholes model**, the implied volatility for a class of options should remain constant at any specific moment. Nonetheless, in reality, implied volatility often fluctuates with varying strike prices and expiration dates for the same assets. This variation presents a significant challenge in estimating implied volatility, commonly referred to as the "implied volatility smile." In this context, a "sneer" is observed because the implied volatility consistently decreases as the strike prices and maturity increase (Dumas et al., 1998).

Tan (1990) employed the Black-Scholes call option pricing model, incorporating the Merton dividend adjustment, to examine market efficiency. Their findings indicate that while above-normal returns can be achieved in the absence of transaction costs, these returns are eliminated and turn negative once bid-ask spread costs are considered. The study concludes that no significant inefficiencies exist in the options market, specifically within the European Options Exchange, and that potential excess returns are effectively offset by transaction costs, such as bid-ask spreads.

Pope et al. (1999) This study identifies a common component in the return volatilities of the S&P 100 and S&P 500 indexes and leverages this relationship by trading the volatility spread between tick-by-tick OEX and SPX call options listed on the CBOE. The findings suggest that the OEX and SPX options markets are not jointly efficient, as consistent profits can be earned from volatility spread trading, even after accounting for transaction costs.

Ackert et al (1999) The authors investigate the efficiency of the S&P 500 index options market by testing theoretical pricing relationships derived from no-arbitrage conditions. Additionally, they examine the impact of a tradable stock basket, Standard and Poor's Depository Receipts (SPDRs), on the pricing link between the index and its options. The results support the efficiency of the index options market under no-arbitrage conditions and suggest that the presence of stock baskets, such as SPDRs, enhances pricing efficiency across markets.

Poon and Pope (2000) reveal the existence of a common component in the return volatilities of the S&P 100 and S&P 500 indices. By exploiting this shared volatility factor, the authors implement a trading strategy based on the volatility spread between tick-by-tick OEX and SPX

call options listed on the CBOE. The results demonstrate that such strategies yield significant profits, indicating exploitable inefficiencies in the joint behaviour of these options markets.

Ackert & Tian (2000) This paper provides new insights into index option pricing by analyzing arbitrage strategies that do not require trading the underlying stock index and by exploring pricing relationships that remain valid regardless of the underlying asset's value. The findings reveal that index options are often mispriced in the market; however, the authors caution that such mispricing does not inherently imply market inefficiency.

Capelle-Blancard et al. (2001) investigate the efficiency of the French options market by analyzing transaction data on CAC 40 index options from 2 January 1997 to 30 December 1999. The findings reveal a low frequency of arbitrage violations on the MONEP exchange, although no definitive evidence of improved market efficiency was found. These results raise concerns regarding the profit potential of arbitrage opportunities, particularly for low-cost institutional traders.

Ackert et al. (2001) The authors examine the efficiency of the S&P 500 index options market by testing theoretical pricing relationships derived from no-arbitrage conditions. Their analysis indicates that pricing efficiency in the index options market has improved over time. However, they find limited evidence to support the notion that the introduction of stock baskets, such as SPDRs, significantly enhances arbitrage opportunities across related market segments.

Torricelli and Brunetti (2004) adopted a model-free approach to test strategies involving only options, using a high-frequency dataset spanning from 1 September to 31 December 2002. The results provide evidence supporting the efficiency of the Italian index options market. Additionally, this study complements previous studies on cross-market efficiency, further validating the findings.

Hou and Muñoz Luengo (2004) examine the market efficiency of the Swedish OMX options market and find no evidence of systematic abnormal returns, supporting the hypothesis of no arbitrage opportunities and overall market efficiency. The results confirm that the OMX options market operates efficiently, with no significant mispricing or exploitable opportunities.

Brunetti & Torricelli (2007) investigate the internal efficiency of the Italian index options market using a model-free approach and assess its consistency with cross-market efficiency. The findings indicate that the Italian market exhibits a high degree of internal efficiency, with fewer arbitrage violations than in North American markets.

Narayana Moorthy and Sehgal (2007) assess the applicability of the Black-Scholes model to the Indian options market and find that both call and put options are fairly priced, provided the trading asymmetry condition in the spot market holds. The results indicate that historical volatility serves as an effective input for option pricing in the Indian context, whereas the use of weighted implied volatility results in significant pricing errors.

Sanjay Sehgal and Vijayakumar. N (2009) delves into assessing the pricing efficiency of the Indian index options market, focusing on the applicability of the Black and Scholes model within the Indian context. By analyzing data from the S&P CNX Nifty index options over a specific period, this study contrasts the use of historical volatility and weighted implied volatility in the Black and Scholes model. The findings suggest that while historic volatility aligns option prices well with market conditions, weighted implied volatility tends to underestimate option values, leading to significant pricing errors. This study not only sheds light on the efficiency of option pricing in India but also contributes to the options market literature for emerging markets, offering valuable insights for academics, market participants, and financial regulators.

Doidge and Wei (2009) examined the efficiency of the Toronto 35 index options market by employing a delta-neutral straddle trading strategy. The results show that while trading profits can be generated when mispricing is identified and trades are initiated using same-day (ex post) prices, these profits are eliminated once the transaction costs are accounted for. Overall, the findings support the efficiency of the Toronto 35 index options market, with no evidence of abnormal profits after the costs.

P. Srinivasan, K. Srinivasan and Malabika Deo (2009) investigates spot market volatility impact after futures and options trading introduction in India using EGARCH (1,1) model. Data from the NSE website included daily closing prices of the S&P CNX Nifty spot index from January 1996 to March 2009. The findings indicate that futures and options trades reduce spot market volatility. The results show no asymmetric effects in the Indian spot market, suggesting

that the Nifty spot index was not affected by noise trading. The introduction of futures and options improved the information flow in the spot market, enhancing market depth and liquidity while reducing informational asymmetries and spot market volatility.

Han et al. (2011) investigates the impact of market friction on efficiency by testing the martingale restriction for the KOSPI 200 index options market, one of the most liquid and active options markets globally. The findings reveal substantial arbitrage opportunities, as the martingale restriction is violated, indicating that market efficiency is not supported in the KOSPI 200 options market, and the market is inefficient.

Hou et al. (2012) evaluate the efficiency of the OMXS30 Index options market and demonstrate that the AJD model significantly outperforms other models in forecasting option prices and trading strategies. The results show no significant abnormal returns, thereby supporting the hypothesis of market efficiency in the OMXS30 options market.

Guo et al. (2013) examine the effect of market frictions on the KOSPI 200 index options market, one of the most liquid and active options markets globally, by testing martingale restriction. The findings reveal substantial arbitrage opportunities, with the violation of the martingale restriction indicating market inefficiency in the KOSPI 200 options market.

Jarrow (2013) The authors demonstrate that risk-neutral valuation, the standard method for pricing derivatives, holds true only if the market for the underlying asset is efficient with respect to the information set that drives the evolution of the price process. This highlights the fact that market efficiency is crucial for valid derivative pricing. Additionally, the study emphasizes that new methods have improved testing for both market efficiency and options pricing.

P. K. Priyan, Debaditya Mohanti (2014) This study provides evidence on the market efficiency of S&P CNX Nifty index options traded on the National Stock Exchange (NSE) of India, utilizing the Black-Scholes model and a dynamic hedging strategy. The results show that market prices are closely aligned with those predicted by the Black-Scholes model. Furthermore, transaction costs eliminate any abnormal profit opportunities in options trading, supporting market efficiency.

Priyan and Mohanti (2014) The Black-Scholes model is an effective predictor of option prices in the Indian options market, even when accounting for trading asymmetry. This consistency

highlights the model's robustness in the Indian context, where market conditions may differ from those in more developed markets. Furthermore, the weighted implied standard deviation (WISD) volatility measure is the most accurate estimator of the underlying asset volatility in the Indian options market. The WISD volatility measure outperforms other volatility estimation methods, providing a more reliable input for option pricing and reinforcing the accuracy of the Black-Scholes model in this market segment.

Shivam Singh, Vipul (2015) used the two-scale realized volatility measure (TSRV) as the volatility estimator to ensure efficient volatility estimation, without forecasting error. Ex post TSRV used for efficient volatility estimation - Tick-by-tick data used for price comparisons. A negative pricing bias indicates inadequacy of the BS model. Further exploration of volatility estimation methods is required. The B-S model shows a significant negative pricing bias for options. - Pricing bias depends on option moneyness and the underlying volatility.

Priyan & Mohanti (2015) In this study, the authors assess the internal market efficiency of Indian index options by testing the S&P CNX Nifty index options using a box-spread arbitrage strategy. The results reveal that while some instances of mispricing are observed, most of these violations are deceptive, arising primarily due to low liquidity in certain contracts. Despite the presence of mispricing, the Indian index options market demonstrates efficiency, as the majority of these violations are not exploitable in practice. Furthermore, when transaction costs are considered, the potential for arbitrage profits is effectively eliminated, underscoring the market's efficiency in real-world conditions.

Mohanti and Priyan (2015) investigate the cross-market efficiency of Indian index options, futures, and the cash market by testing the S&P CNX Nifty index options through the Put-Call Parity condition, using spot index values and futures prices. The findings reveal traces of inefficiency in the Indian index options market, with certain violations of the Put-Call Parity condition. However, the majority of these inefficiencies are not exploitable because transaction costs significantly erode the potential for arbitrage profits. This suggests that while there may be occasional mispricing, the market operates efficiently when transaction costs are factored in, limiting arbitrage opportunities.

Tanuj Nandan, Puja Agrawal (2016) the authors attempt to determine the method of volatility estimation that prices the CNX Nifty Index options closest to the theoretical price as computed

by the Black-Scholes (1973) model. Limited studies prove the superiority of historical volatility as a forecaster. - Few volatility estimation methods have been reviewed for pricing efficiency. Historical Volatility (HV) is used for volatility estimation. - EGARCH with generalized error distribution (GED) innovations. Evaluated alternative volatility measures for pricing efficiency. - Implied volatility shows mixed performance in forecasting.

Vaibhav Kaushik (2017) conducted a comprehensive study to evaluate how effectively the Black-Scholes option pricing model predicts option prices in the context of Indian stock exchanges. For this analysis, a dataset comprising the market prices of option contracts traded between 2008 and 2015 was used. This study incorporated three different volatility measures—historical, actual, and implied—to test the robustness of the model. To assess the statistical validity of the Black-Scholes framework, we employed regression techniques, including logit and probit models. The findings revealed that the Black-Scholes model exhibited considerable pricing errors when it was applied to the Indian market. Moreover, alternative pricing models demonstrated superior accuracy, suggesting that the Black-Scholes model may not be the most reliable option pricing tool under Indian market conditions.

Sonali Jain, Jayanth R. Varma and Agarwalla (2019) conducted an insightful study on the pricing behaviour of equity options in India, which is recognized as one of the largest options markets globally. Their research provides evidence in favour of market efficiency, revealing that a streamlined, smile-adjusted version of the Black model closely aligns with observed option prices. Furthermore, the study found that implied volatility (IV) reflects current market conditions and has additional predictive value for forecasting future volatility. Interestingly, the researchers observed that the risk premium embedded in the IV of Single Stock Options in India is comparatively higher than that typically found in other international markets. This implies that even in a highly liquid market with active global institutional investor involvement, certain structural elements can lead to consistent deviations from fully rational market behaviour, despite the market still displaying characteristics of micro-level efficiency.

Kalak and Hudson (2020) examine the cross-market efficiency of the FTSE/MIB index options contracts traded on the Italian derivatives market (IDEM) during a period that includes the financial crisis, from 1 October 2007 to 31 December 2012 using daily option prices. The results show that the Italian index options market exhibits cross-market efficiency throughout the study period. Notably, the frequency of violations of pricing conditions decreased

significantly after the financial crisis compared to the crisis period itself. This suggests that the market became more efficient post-crisis, likely due to improved market conditions and adjustments in market dynamics following the crisis.

Jiang, Durieux, and K.V. (2022) introduced a novel approach by developing classification models that integrate outcomes from the Quasi-Reversibility Method (QRM), which is used to solve the Black-Scholes equation for predicting option prices one day ahead. Their methodology combines the QRM minimizer with machine-learning classification techniques to determine whether the value of an option is likely to rise or fall. By categorizing options in this manner, this study explored how different trading strategies could be applied to potentially enhance the predictive performance of the QRM model. To validate the effectiveness of their framework, the researchers used a dataset of 23,548 real-world options contracts. These data, along with the QRM minimizer outputs, were used to construct decision trees and random forest models. These models were then evaluated based on their accuracy, precision, and recall, with the aim of refining the predictive capabilities and practical relevance of QRM-enhanced option pricing strategies.

Hoque et al. (2023) evaluated the efficiency of Shanghai 50 ETF index options and found that the market operates efficiently when both call and put options are at-the-money. However, inefficiencies emerge when the call option is in the money and the put option is out of the money, leading to mispriced options. The findings indicate that the SSE 50 ETF index options market demonstrates efficiency when options are at-the-money, but market inefficiencies become apparent when the options are deep in-the-money or out-of-the-money, resulting in significant mispricing. These inefficiencies could provide potential opportunities for arbitrage but also highlight areas where the market may not fully reflect underlying asset prices under certain conditions.

Brunetti (2023) This study employs a statistical arbitrage strategy to assess the efficiency of the index options market, utilizing 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.

Singh & Kumar (2024) The research has evaluated the application of deterministic option pricing models to Nifty and Bank Nifty index options, with particular attention to the performance of the Black–Scholes framework and its variants. The results indicate that modified versions of the Black–Scholes model tend to outperform the original formulation in capturing option prices more accurately. An important contribution of this study is the recognition of liquidity as a decisive factor influencing pricing efficiency. Specifically, contracts with higher trading volumes—most notably at-the-money (ATM) and out-of-the-money (OTM) options—exhibited greater pricing accuracy. These findings are consistent with broader strands of the literature which emphasize that, beyond model specification, market microstructure conditions such as liquidity play a central role in determining the reliability of option valuation models.

Hsu et al. (2024) The researcher investigates the relationship between options trading and firm-level investment efficiency. Evidence suggests that active options trading contributes to improved investment efficiency in firms with listed options. This effect is shown to operate through the mitigation of information asymmetry and the reduction of uncertainty in the market. Notably, the influence of options trading on investment efficiency appears to differ from that observed in equity markets. The positive impact is found to intensify in contexts characterized by overinvestment tendencies, higher levels of risk-taking, and stronger incentives for organizational learning.

3.3. Literature on the forecasting ability of Implied Volatility

Latane and Rendleman (1976) investigate the link between implied and actual stock return volatility by analyzing the closing prices of stocks and options for twenty-four companies listed on the CBOE. They introduced the weighted average implied standard deviation (WISD), calculated using implied standard deviations derived from the Black-Scholes Option Pricing model, as a forward-looking volatility measure. This was compared with three backward-looking measures: historical volatility over a four-year span and realized volatility over the same period as the WISD. By conducting a cross-sectional correlation analysis among these four metrics, they found the strongest relationship between the WISD and realized volatility. They concluded that WISD, which reflects market expectations, offers a more accurate prediction of future volatility than historical data alone.

Chiras and Manaster (1978) explored the comparative value of the Weighted Implied Standard Deviation (WISD) versus historical volatility, using data from the Chicago Board Options Exchange (CBOE) for the period between June 1973 and April 1975. Their findings revealed that the WISD provides a better estimation of actual volatility than historical measures. This study advances earlier research by Latane and Rendleman (1976) in two major ways: it incorporates dividend effects using Merton's (1973) dividend-adjusted Black-Scholes model and employs multiple regression models instead of simple correlation analysis. Their analysis demonstrated that the WISD carries more relevant information for predicting market behaviour.

Beckers (1981) examined how well implied volatility could predict future stock-price volatility. Drawing on daily data from individual stock options traded on the CBOE from 1975 to 1977, he tested three different estimation methods, including a modified version of Latane and Rendleman's approach and a new method that assigned more weight to at-the-money options. His research indicated that all three models of implied volatility were more effective in forecasting cross-sectional stock volatility than quarterly historical data. Among these, the at-the-money implied volatility proved to be particularly informative, although the study also concluded that implied volatility is not a completely unbiased or efficient predictor.

Gemmill (1986) focused on the predictive power of implied volatility in the UK market. His findings showed that options which are in-the-money or at-the-money reflect implied volatility more accurately. Simultaneously, historical volatility appeared to outperform implied volatility when forecasting future market movements. This led to the conclusion that implied volatility lacks information efficiency and does not fully incorporate historical data insights.

Day and Lewis (1992) conducted a detailed analysis of implied volatility as reflected in S&P 100 index options from November 1983 to December 1989, encompassing the infamous 1987 market crash. Their study compared implied volatility with predictions made by the GARCH and Exponential GARCH models. While they found that implied volatility contains useful information, the volatility models offered more accurate forecasts, indicating that implied volatility may not be the most reliable tool for predicting future market behaviour.

Canina and Figlewski (1993) tested the informational efficiency of implied volatility derived from S&P 100 index call options between 1983 and 1987. Their regression analysis compared implied, historical, and realized volatilities but found no meaningful correlation between

implied and realized volatility. They concluded that implied volatility is not a reliable predictor of future market fluctuations.

Gemmill (1993) revisited this question by examining the FTSE options market. By comparing implied volatility with forecasts from an autoregressive random variance (AR-RV) model, he concluded that implied volatility generally provides more complete information than historical models, indicating its effectiveness in forecasting realized volatility.

Lamoureux and Lastrapes (1993) analyze implied volatility using the stochastic volatility model developed by Hull and White (1987). Using data from the CBOE for ten non-dividend-paying stocks from 1982 to 1984, they found that historical volatility added meaningful information to implied volatility forecasts. Although informative, implied volatility was found to be biased, and the study's findings were somewhat limited by overlapping sample periods and timing mismatches between implied and realized volatilities.

Jorion (1995) shifted the focus to currency options traded on the Chicago Mercantile Exchange, covering major currencies such as the Deutsche Mark, Yen, and Swiss Franc. He concluded that the Implied Standard Deviation derived from these options served as an unbiased predictor of currency movements, reinforcing the relevance of implied volatility in forecasting.

Vasilellis and Meade (1996) compared implied volatility with forecasts from time-series models over a three-month investment horizon using data from 12 UK firms. Their results indicate that implied volatility generally produces better forecasts than models, including GARCH, highlighting its practical utility.

Fleming (1998) used transaction-level data for S&P 100 index options from 1985 to 1992, excluding the 1987 crash, to study the predictive performance of implied volatility (IV). He estimated the implied volatility using a binomial model and applied the Generalized Method of Moments (GMM) to avoid regression biases. Although the study found that implied volatility held more information than historical or GARCH-based forecasts, it also noted that implied volatility was not biased.

Christensen and Prabhala (1998) aimed to address sample overlap issues in earlier studies by creating non-overlapping datasets that matched implied volatility with single, realized outcomes. Focusing on at-the-money S&P 100 options from 1983 to 1995, they found that

implied volatility was a biased estimate, likely due to measurement errors, but still contained useful predictive content.

Gwilym and Buckle (1999) analyzed options on the London International Financial Futures Exchange (LIFFE) using Mean Square and Absolute Error metrics. Their research suggested that historical volatility offers better forecast accuracy than implied volatility, although the results may have been influenced by a low adjusted R^2 and possible model misspecification.

Hansen (2001) extended Christensen and Prabhala's sampling approach to the less liquid Danish options market. Using data from 1995 to 1999, he found that implied volatility was both biased and inefficient when ordinary least squares regression was used. However, after correcting for measurement errors using instrumental variables, implied call option volatility emerged as a reliable predictor, whereas implied put volatility remained inferior to the historical estimates. This study recommends combining call and put data to create a more robust implied volatility metric.

Christensen and Hansen (2002) analyze both call and put implied volatilities using data from S&P 100 index options between 1993 and 1997. Their findings show that implied volatilities are generally unbiased and efficient predictors of future volatility, with call options performing slightly better than put options. They used full-information maximum likelihood estimation to confirm these results and accounted for potential measurement errors, ultimately reinforcing the predictive validity of implied volatility.

Shu and Zhang (2003) examined the link between realized and implied volatility by analyzing daily closing prices of at-the-money S&P 500 index options from the CBOE for the period spanning January 1995 to December 1999. Using a non-overlapping sampling method, following the recommendation of Christensen and Prabhala (1998), they explored how measurement errors affect the consistency of this relationship. They utilized four different methods for computing realized volatility: the standard deviation of daily returns, the Parkinson (1980) high-low range estimator, Yang and Zhang's (2000) estimator, and Andersen's (2000) intraday return squares. Implied volatility was derived from the Black-Scholes and Heston stochastic volatility models. Regression analyses revealed that implied volatility consistently outperformed historical volatility in predicting future volatility across all approaches. The authors concluded that implied volatility is not only a better predictor but also absorbs the informational content of past volatility, thus rendering historical volatility less effective in predicting future volatility.

Szakmary et al. (2003) investigated thirty-five futures options markets across eight exchanges to assess the predictive strength of implied volatility using both standard regression techniques and GARCH models. Their findings confirmed that, although implied volatility tended to be biased, it provided better forecasts of future volatility than did historical volatility. The study highlights that the information content embedded in option prices makes implied volatility a superior indicator.

Claessen and Mittnik (2004) focused on DAX index options to evaluate various volatility estimation techniques. Their findings align with prior studies in that implied volatility contains more forward-looking information than historical volatility models such as GARCH. However, they acknowledged the presence of bias in implied volatility despite its overall predictive strength.

Koopman et al. (2004), who analyzed several volatility types as realized, historical, and implied. Contrary to dominant findings, their empirical study suggests that historical volatility may offer better predictive capability than implied volatility under certain conditions.

Rao (2005) focused on the Indian options market by analyzing S&P CNX Nifty call options. This study aimed to identify the inherent bias in implied volatility and evaluate how the time to maturity affects forecasting accuracy. Using data from April to August 2002, Rao found that the predictive power of implied volatility diminished with longer maturities. Possible reasons include market inefficiencies, mis-specified valuation models, or limitations in long-term market information.

Maheshwaran and Ranjan (2006) expanded the regional scope by comparing the Nifty index with indices from Hong Kong, Korea, and Taiwan. They used regression models to test the forecasting power of implied volatilities. While implied volatility was a poor and biased predictor for India and South Korea, it showed statistical significance and a better predictive ability for Hong Kong and Taiwan.

Becker, Clements, and Curchin (2007) explored whether implied volatility held more informative content than econometric models such as GARCH. Using CBOE S&P 500 option data from 1990 to 2003, they concluded that while both models contained useful information, implied volatility did not consistently show superiority over econometric forecasts.

Mixon (2007) analyzed the implied volatility surface of at-the-money call options to test the expectations hypothesis. The results suggest the limited forecasting ability of implied volatility

slopes for short-term forecasts. This was attributed to the absence of proper adjustments for risk premiums embedded in the option prices.

Mohan and Chaturvedi (2008) assessed the Indian Market Volatility Index (IMVI) derived from Nifty options between 2001 and 2005. Their findings showed that the IMVI lacked predictive strength for realized volatility, largely due to insufficient liquidity in the Indian options market. Unlike developed markets, where volatility indices are robust indicators, the Indian market displays weaker links.

Kumar (2008) conducted a comparative study of historical and implied volatilities using simple regression methods. The research confirmed that implied volatility, especially from call options, was a more accurate predictor of future realized volatility than historical measures, and in this case, also appeared unbiased and efficient.

Devanadhen and Rajagopalan (2009) examined data from 2002 to 2008, focusing on nifty index options. Their study concluded that implied volatility, despite being upwardly biased, has greater informational efficiency than historical volatility. Both call and put option-derived implied volatilities outperform historical measures, with call option data offering slightly better forecasts.

Dixit Alok et al. (2010) explored the informational efficiency of implied volatility in the Indian Nifty index options. By comparing implied volatility with GARCH and EGARCH models from 2001 to 2007, they concluded that implied volatility did not fully incorporate all the information available in historical volatility, suggesting inefficiencies in the Indian options market.

Chalamandaris and Tsekrekos (2010) utilized OTC currency options from 25 currencies to evaluate the predictive power of the implied volatility surface. Employing vector autoregression (VAR), they found that implied volatility significantly aided portfolio optimization and short-term risk management, effectively capturing systematic movements.

Wang et al. (2010) assessed the comparative efficiency of exchange-traded and OTC options in Hong Kong and Japan. Their findings revealed that OTC-derived implied volatility was more informative than historical volatility in Japan, whereas exchange-traded options were more effective in Hong Kong, indicating market-specific dynamics in the two countries.

Amadori (2011) investigates the informational efficiency of European stocks, options, and credit default swaps (CDS). Using data from 1999 to 2005 for 100 firms, the study applied a

two-step regression analysis and found that implied volatility is a strong predictor of CDS spreads, highlighting the deep interconnections between derivatives markets.

Cheng and Fung (2012) focused on model-free implied volatility (MFIV) and compared it with Black-Scholes and historical volatility estimates in Hong Kong's futures and options markets. They concluded that implied volatility from the Black-Scholes model retained more information than the MFIV and historical measures. However, its forecasting ability weakened as the options neared maturity.

Okumu and Nilsson (2013) analyzed data from the S&P 500 and OMXS30 indices between 2007 and 2013 to determine whether implied or historical volatility better predicts future realized volatility. Their results favored implied volatility, confirming it as a stronger predictor and showing that it encompassed much of the information held by historical measures.

Kourtis et al., (2016) compares the performance of different volatility forecasting models in equity index with respect to their varying factors of influence like country, the horizon of the forecast, market state and accuracy of statistics. The Heterogeneous Autoregressive model (HAR) has been labelled as the most accurate in producing a one-day forecast, whereas an implied volatility model which factors in the volatility risk premium is more appropriate for a monthly forecast. The results indicate that international portfolios have tremendous potential to be diversified using implied volatility-based forecasts, as opposed to historical procedures. This implies that investors have the opportunity to manage risks better and deliver returns using these forecasts in their investment plans.

Kambouroudis et al., (2016) confirms that the information of the implied volatility (IV) forecasts provides more information about the future volatility of the stock index returns than GARCH and realized volatility (RV) forecasts. The implication of this is that investors will find a good use of the IV in their forecasting models. It also reflects that the realized volatility compiled using the high-frequency data casts a more accurate measure of real volatility when compared to daily returns. This justifies the impetus that intraday data improves forecasting accuracy.

Metaxoglou and Smith (2017) conclude that State Prices of Conditional Quantiles (SPOCQ), which are implied by option prices, are strong predictors of future returns of the U.S. equity market, especially in their ability to capture market risk preferences and relative aversion. Although the measures of volatility aversion have very weak predictive capability, the inclusion

of the SPOCQ in the models of asset pricing has potential benefits in both predictive accuracy and investment and risk management.

Sadik et al. (2019) found that the sentiment scores of the news contribute considerably to better volatility prediction by the news-augmented GARCH (NA-GARCH) model compared to conventional models such as GARCH and EGARCH models. It works well to capture volatility spikes and shows that news, or more precisely negative news, also drives volatility in the market. NA-GARCH is an excellent contribution to risk management and investment strategy, given its high predictive power, computational efficiency, and practical applicability to investment tools such as Value at Risk and volatility swaps.

Shi et al., (2020) makes findings that realized measures (RMs) and implied volatility (IV) are both distinctive in their individual analysis of the upcoming volatility in the market, however, their predictive powers may be asynchronous and subjective to the evolving market. This study shows an increase in and consistent performance forecasting due to extending the empirical similarity approach by adding both RMs and IV. This indicates that a concerted effort that takes advantage of both will improve the precision and stability of volatility forecasts, thus providing a valuable tool for financial analysts and risk managers.

Kambouroudis et al., (2021) concludes that implied volatility (IV) plays a crucial role in predicting the realized volatility, the HAR-IV model supersedes the models that do not incorporate IV in most global markets. Although enhancements involving overnight returns can make things more accurate in most cases, other measurements, including realised volatility and leverage effect, do not have a significant positive contribution. This suggests that flexible, tailored modelling strategies are essential and confirms that IV can be included in the volatility forecast to better understand VaR and more efficient financial risk management efforts.

Yfanti and Karanasos (2021) found that the combination of the option-implied volatility with the macroeconomic uncertainty leads to a considerable improvement in the forecasting of the volatility of the financial markets, which is evident in the newly proposed AIM-HEAVY model. The model's ability to capture asymmetries and high-frequency macro-financial interactions provides superior insights into volatility dynamics during periods of pronounced uncertainty, including the COVID-19 crisis. These results highlight the importance of enriched models in enhancing risk assessment, policy formulation, and financial stability.

Chen et al., (2022) concludes that nonlinear three-regime realized GARCH model and Bayesian MCMC yield significant volatility and risk predictions compared to other standard

volatility models and especially in cases of extreme market events like during COVID-19 pandemic. Having been able to capture favoured regime variability, indicating a higher level of performance compared to that of the traditional models based upon quantile forecasting and backtesting, the model is powerful enough to show regime shifts and perform best to forecast the value at risk (VaR) and expected shortfall (ES) in real-world financial models.

Chen & Li, (2023) reports that contrary to the findings of Chen, Lee, and Martin, (2022), the option-implied volatility is a significant predictor of the realized volatility on all time horizons through the information it provides, about the timing and influence of both scheduled and unscheduled news announcements, particularly of the fundamental nature. Implied volatility serves as a measure of market sentiment in general and as a prospective means of predicting volatility driven by news. Thus, it has practical utility for traders and risk managers in gauging near-future market trends.

Gunnarsson et al., (2024) concludes that the memory-based neural networks such as LSTM and GRUs as one of the AI and machine learning technique suggests better performance than the old models in predicting the realized and implied volatility. Nevertheless, classical econometric tools can be useful, and their integration with contemporary ML might improve the effectiveness of predictions. This study also highlights the importance of increased use of XAI to enhance the explainability of models and the future prospects of greater investigations of probabilistic ML and the associated effort to quantify uncertainty in volatility forecasting.

3.4. Literature related to the structure of the implied volatility function

Black (1975) made a seminal observation about the nature of option volatilities, emphasizing that volatility is not static and can differ across options with different expiration dates. His research introduced the idea that extremely high or low volatility levels are often temporary, with a tendency to revert over time to a more normal range—a concept known as "mean reversion." This insight helps explain the observed term structure of implied volatility, where the shape of the volatility curve across different maturities reflects market expectations of future volatility levels reverting to the mean level.

Merton (1976) extended the foundational work of Black and Scholes by incorporating jump processes into the traditional log-normal asset return model. He employed simulation techniques to quantify the impact of such model misspecifications on option pricing. Merton found that inaccuracies in modelling the stochastic behaviour of underlying asset returns,

particularly the omission of sudden jumps, could lead to pricing errors. These errors might arise due to short-lived market imbalances in supply and demand, often triggered by changing economic conditions or fluctuations in investor sentiment and capitalisation rates.

MacBeth and Merville (1979) undertook a year-long study of call options between the end of 1975 and 1976. By comparing observed market prices with those generated by the Black-Scholes Option Pricing (BSOP) model, they uncovered structural patterns in implied volatility. They found that volatility levels varied significantly with moneyness (the relationship between the strike price and underlying asset price) and time to maturity. For example, in-the-money (ITM) options nearing expiration tend to exhibit higher implied volatilities, whereas this pattern is reversed for out-of-the-money (OTM) options. Their work highlighted the complex, non-linear relationship between an option's characteristics and implied volatility.

Geske and Roll (1984) addressed a limitation in prior research by focusing on American-style call options, which can be exercised early. They explored how features such as dividend payouts and interest rates affect early exercise probabilities and, in turn, influence implied volatility patterns. Their findings show that during periods when early exercise is unlikely, implied volatility decreases with higher exercise prices. However, when the chances of early exercise increase, implied volatility tends to increase alongside the exercise price. This dynamic explains the inconsistencies observed in earlier studies and reinforces the importance of accounting for early exercise features in pricing models.

Rubinstein (1985) conducted an empirical analysis using call option data from the Chicago Board Options Exchange (CBOE) covering the period from August 1976 to August 1978. He tested a range of alternative pricing models, such as the Pure Jump, Displaced Diffusion, Constant Elasticity of Variance, and Mixed Diffusion-Jump models, against the standard Black-Scholes framework. These alternative models have been generally successful in explaining some of the biases observed in the traditional Black-Scholes model. Rubinstein discovered that implied volatility was particularly high for short-term options, especially at-the-money options, during the latter half of the study period. In contrast, during the earlier half, options with lower strike prices tended to show higher implied volatility. These findings suggest a shifting volatility structure over time, likely driven by changing market conditions and investor behaviour.

Poterba and Summers (1986) explored how stock market volatility influences equity prices by examining the time-series properties of volatility in the S&P stock index from 1928 to 1984.

Their research found that the autocorrelation of estimated volatility provides limited evidence that changes in volatility significantly affect stock prices. They suggested that volatility shocks tend to be short-lived and do not reflect sustained changes in investor sentiment regarding volatility. The study also assessed option-implied volatility from the CBOE index for the years 1979–1984 and concluded that these volatility shocks were not persistent. These findings challenge the belief that fluctuations in volatility significantly affect stock prices through variations in risk premiums.

Shastri and Wethyavivorn (1987) examined the implied volatility patterns for currency options on the Yen, Franc, and Deutsche Mark traded on the Philadelphia Stock Exchange during 1983–1984. They categorized the data based on the time to maturity and the ratio of the spot price to the strike price. Using the Black-Scholes-Merton model, they estimated implied volatilities and found a U-shaped pattern with respect to the moneyness ratio, particularly for options with shorter maturities. However, for options with more than 220 days to expiration, this pattern was not observed, indicating variability in the implied volatility behaviour across different option characteristics.

Stein (1989) analyzed how implied volatility behaves across option maturities using data from S&P 100 index options between 1983 and 1987. He found that short-term implied volatility levels were generally higher than long-term ones and that longer-dated options appeared to overreact to short-term volatility changes. These reactions exceeded the levels predicted by rational expectations models, although their practical significance was limited in this study. Stein concluded that long-dated options could be subject to pricing errors due to this overreaction and the neglect of mean-reverting behaviour in volatility.

Fung and Hsieh (1991) performed an extensive analysis of implied volatility across futures options on stocks (S&P 500), bonds (T-bonds), and currencies (Deutschemark) over the period from 1983 to 1989. They observed distinct patterns, such as volatility smiles and sneers, when plotting implied volatility against the strike price. For instance, in the case of S&P 500 and T-bond futures options, implied volatility generally declines as the option moves away from being at-the-money. Meanwhile, Deutschemark options exhibit more pronounced smile patterns, highlighting the differences in volatility structures across asset classes.

Sheik (1991) applied Rubinstein's (1985) non-parametric approach to S&P 100 index call options from 1983 to 1985. His findings show significant deviations from the pricing behaviour observed in individual stock options. Notably, implied volatilities across strike prices often

form a smile pattern, which is attributed to the market's incorporation of changing volatility expectations for the underlying index. These patterns varied across sub-periods, underscoring the dynamic nature of the market expectations.

Duque and Paxson (1994) focused on call equity options traded on the London International Financial Futures and Options Exchange (LIFFE). By analyzing European-style options with a reasonable time to maturity, they identified consistent volatility smile patterns. Their results suggest that the Black-Scholes model's assumption of constant volatility fails to capture real market dynamics. Specifically, they observed higher implied volatility for in-the-money options and noted unusual patterns, such as a "wry grin" or "reverse grin" in the volatility surface.

Bates (1996) reviewed various theoretical models that aimed to explain implied volatility structures across different maturities and strike prices. He argued that the biases observed in implied volatility cannot be solely explained by assumptions about the underlying asset distributions. Instead, he advocated models that incorporate time-varying skewness, which could improve the accuracy of time-varying volatility models and better reflect market behaviour.

Bakshi et al. (1997) compared multiple option pricing models, including those with features such as stochastic volatility, interest rates, and jump processes, against the standard Black-Scholes framework. Their dataset covered the period from 1988 to 1991. Their analysis showed that models accommodating these additional features performed better in pricing and hedging, particularly in capturing the volatility smile. They emphasized that the traditional Black-Scholes model's volatility estimates, especially for near-month options, exhibit clear U-shaped smile patterns across different moneyness levels.

Brown and Taylor (1997) investigated pricing errors in the SPI futures options market using the Asay model between 1993 and 1994. They found systematic mispricing in call and put options, especially for at-the-money and out-of-the-money contracts. For call options, the model tended to underprice in-the-money options and overprice out-of-the-money options, whereas the reverse was true for puts. These discrepancies align with the presence of a volatility smile and highlight the limitations of using a single model input.

Dumas et al. (1998) explored the shape of the implied volatility surface using S&P 500 index options data. Before the 1987 market crash, implied volatility exhibited a "sneer" pattern, with a steady decline in volatility as strike prices moved further out of the money. This pattern was

particularly evident for put options, which tend to increase in value during the market downturns. The researchers linked this behaviour to a perceived higher probability of market decline, which in turn led to higher demand and implied volatility for out-of-the-money put options. They concluded that such patterns result in negatively skewed implied volatility distributions, reflecting investors' concerns about downside risk.

Brown (1999) investigates the behaviour of implied volatility for options on SPI 200 index futures traded on the Sydney Futures Exchange (SFE) between June 1993 and June 1994. By applying the Asay (1982) model—a modification of Black's (1976) futures options model—Brown analyzed thousands of calls and put options. The study revealed a clear volatility skew, where in-the-money calls carried higher implied volatility than their out-of-the-money counterparts, a trend that was reversed for put options. This behaviour mirrored the skew patterns observed by Dumas et al. (1998) for S&P 500 index options following the 1987 market crash.

João Duque (1999) explored the implied volatility smile using data from nine liquid stock options traded on the LIFFE exchange from 1990 to 1991. This study focuses on how smiles evolved with option maturity and underlying asset volatility. Employing cubic B-splines to estimate implied volatilities for unavailable strike prices, Duque found that the smile effect was most intense for short-term options and under high market volatility, indicating a strong relationship between market sentiment and the shape of the implied volatility curve.

Pena et al. (1999) extended the analysis to options on Spain's IBEX-35 index, spanning 1994 to 1996. Using both simple and advanced causality models, they uncovered a seasonally influenced volatility smile, which was particularly sharper at the end of the week. Interestingly, when macroeconomic variables were introduced, seasonality faded. The study concluded that transaction costs played a key role in shaping the smile and that market conditions, rather than the time to maturity, significantly influenced its structure.

Hafner and Wallmeier (2000) focused on the German DAX options market from 1995 to 1999. Through spline regression and weighted least squares, they model the implied volatility surface more effectively than traditional quadratic models. Their findings show that moneyness alone can explain up to 95% of the cross-sectional variation in implied volatility, highlighting its dominant role in volatility modelling.

Beber (2001) examines the drivers of implied volatility using data from 1995 to 1998. A notable “smirk” in the implied volatility was observed across moneyness. Factors such as time to maturity, transaction volume, and past volatility have been shown to impact the smile. Although some nonlinear relationships were detected, portfolio insurance activity did not significantly explain the observed volatility patterns in the cryptocurrency market.

Dennis and Mayhew (2001) focused on single-stock options in the U.S., identifying those stocks with higher beta values exhibited steeper volatility skews. Their study indicated that firm-specific factors, rather than systematic ones, were crucial in explaining smile asymmetries, a conclusion that challenges the notion that market-wide factors are the primary influencers.

In the Indian context, Varma (2002) conducted the first major study on implied volatility in the NSE options market. Using the Black-Scholes model and the Breeden-Litzenberger framework, the study found volatility smiles in Indian options markets, although the market was characterized as “immature” due to inefficiencies and a lack of awareness about downside risk protection.

Amadeo Alentorn (2004) contributed a model for real-time estimation of implied volatility for FTSE options, finding that quadratic regression provided the best fit for capturing both the smile across moneyness and the term structure across different maturities.

Bollen and Whaley (2004) analyzed individual stock options traded on the CBOE and found that implied volatility formed a “smile” pattern—especially for deep in-the-money and out-of-the-money options. In contrast, index options show a monotonic decline in implied volatility across delta values.

Cassese and Guidolin (2005) investigated MIBO options from Italy and found that the quality of the pricing data heavily influenced the volatility surface. Their work highlights the importance of accurate data for effective volatility modelling.

Gonçalves and Guidolin (2005) analyzed S&P 500 index options and found time-varying characteristics on the volatility surface using vector autoregression. This dynamic behaviour underscores the non-static nature of implied volatility patterns and their sensitivity to evolving market conditions.

Misra et al. (2006) studied Nifty options in India and confirmed a U-shaped smile, consistent with early observations in U.S. markets pre-1987. This pattern was especially pronounced in deep in- and out-of-the-money options.

Vijayakumaran and Sehgal (2008) explored the Nifty options market and identified the time to maturity and historical volatility as the primary factors influencing the smile's asymmetry. The authors' use of both linear and nonlinear models adds depth to the analysis of market behaviour.

Kotze and Joseph (2009) built an implied volatility surface for Alsi index options, using quadratic regression. Their results indicated a U-shaped surface that varied with time to maturity, echoing the findings in more developed markets.

Vagnani (2009) linked the implied volatility smile to investors' beliefs and subjective risk perceptions. He suggested that U-shaped volatility curves often arise in markets where investors rely heavily on personal judgment rather than objective market indicators.

Similarly, Reddy and Arora (2011) applied volatility surface modelling techniques to the Indian options market using principal component analysis. Their findings favoured quadratic models and provided insights into the market's risk structure.

Jin Zheng and Yan Cai (2013) revisited the U.S. market using S&P 500 data and found that implied volatility is indeed a function of moneyness rather than a constant. Their results highlight the complexity of the volatility surface, suggesting broader implications for risk management and exotic option pricing.

Abdullah et al. (2014) Researcher studies on the implied volatility structure of index options reveal distinct patterns across moneyness and maturity dimensions. For at-the-money contracts, implied volatility typically exhibits a relatively flat profile. In contrast, across maturities, implied volatility tends to rise as the time to expiration shortens, indicating a pronounced term structure effect. Furthermore, when moving along the moneyness spectrum, implied volatility generally declines from deep in-the-money to deep out-of-the-money options. These patterns capture important aspects of market dynamics and are frequently interpreted as evidence of investor expectations, risk perceptions, and market imperfections embedded in option pricing.

Marks & Simon (2017) Scholars have explored an intermediate case by analyzing options written on sector exchange-traded funds (ETFs). Since the underlying asset of a sector ETF is a portfolio of stocks drawn from a specific industry, the associated volatility risk exhibits both systematic and sector-specific characteristics. While part of the variance reflects broader market movements, a substantial industry component introduces dynamics that resemble single-stock idiosyncratic risk rather than pure market-wide risk. This dual nature of volatility risk positions sector ETF options between index options and individual stock options in the broader option pricing literature.

Pathak & Mitra (2017) Study the implied volatility structure of index options is frequently characterized by a volatility smirk, where out-of-the-money put options exhibit higher implied volatilities than at-the-money call options. This generates a negatively skewed volatility curve, widely regarded as evidence of investors' heightened concern about downside market risk. The phenomenon contrasts with the flat implied volatility surface predicted by the Black–Scholes model, highlighting a well-documented anomaly in option pricing theory. In the broader literature, this “volatility smile” or “smirk” has been interpreted as capturing factors such as crash risk, asymmetric investor demand for portfolio insurance, and deviations from the assumptions of lognormal return distributions. As such, the volatility smirk remains a central feature linking empirical market behavior to theoretical refinements in option valuation models.

Branger et al. (2018) has examined the volatility-of-volatility (VVIX) term structure, demonstrating that it conveys information beyond that captured by the traditional VIX term structure. The analysis identifies several key drivers, including the continuous component of volatility-of-volatility, the presence of variance jumps, and the role of a lower bound element. Collectively, these factors shape market perceptions of uncertainty and exert a measurable influence on option returns.

Dash (2019) A strand of research has concentrated on modeling the implied volatility surfaces of Nifty index options, which serve as forward-looking measures of market expectations regarding future volatility as inferred from option prices. These studies underscore the importance of accurately capturing the shape and dynamics of volatility surfaces, given their critical role in informing trading strategies, risk management practices, and the calibration of option pricing models.

Shi et al. (2019) Empirical studies on the term structure of implied volatility in index options reveal an upward slope with increasing maturity, accompanied by a negative curvature that produces a hump-shaped pattern. To capture these dynamics, researchers have applied the Nelson–Siegel (N–S) framework, demonstrating its effectiveness in modeling and forecasting the evolution of implied volatility over different maturities.

Madan & Wang (2020) Research on the term structure of implied volatility has also compared the CBOE Skew Index with parametric measures of skewness. Findings indicate notable discrepancies between the two approaches, largely attributable to strike price discretization. To address these limitations, the literature suggests employing interpolation and extrapolation techniques for implied volatilities, thereby enhancing the accuracy and consistency of skew estimates.

Ait-Sahalia et al. (2021) research has focused on implied stochastic volatility models, which establish a direct link between the observed features of the implied volatility surface and the underlying coefficients of stochastic volatility frameworks. Such models allow for both parametric and nonparametric estimation approaches, offering flexibility in empirical implementation. By doing so, they provide an effective means of capturing the complex structure of implied volatility in index options, addressing limitations of traditional option pricing models.

Stahl (2022) studies have examined structural limitations in the construction of the VIX Index, showing that it tends to underestimate model-free implied volatility. This bias arises because the VIX methodology does not extrapolate the volatility smile in the tails of the distribution. To address this issue, researchers have proposed a model-independent correction based on the asymptotic properties of the volatility surface, which requires only option prices at the two outermost strikes.

Ulrich et al. (2023) study on the construction of single-stock volatility surfaces, based on an extensive dataset of nearly half a billion option prices, evaluates the effectiveness of various estimation techniques. The findings demonstrate that a refined one-dimensional kernel smoothing approach delivers superior performance in terms of both accuracy and robustness when compared to alternative methods. This methodological advancement has important

implications for option pricing, risk management, and the broader functioning of financial markets, as it enhances the reliability of volatility surface estimation in practice.

Friz (2023) research has addressed the pricing of index options that are particularly sensitive to implied volatility by extending traditional frameworks to account for non-Markovian dynamics and rough volatility. These extensions provide a richer representation of market behavior, as rough volatility fundamentally alters the shape of implied volatility surfaces and challenges standard correlation assumptions embedded in option pricing and hedging strategies. By incorporating these features, the literature highlights the need for more sophisticated models to capture the empirical characteristics of volatility observed in financial markets.

Rolloos (2024) research proposes a methodology to de-correlate instantaneous volatility from underlying price processes within stochastic volatility models. This approach facilitates the symmetrization of implied volatility skews and enables the extraction of realized volatility moments directly from index option prices. Such innovations not only refine the interpretation of option-implied information but also provide deeper insights into the structural determinants of the implied volatility surface.

3.5. Conclusion

Based on the literature review above, it appears that there were opportunities for abnormal profits in these options markets. Nevertheless, some research suggests that these profits vanished entirely when transaction costs were factored in. Consequently, the hypothesis that markets are efficient cannot be dismissed. However, this conclusion from previous studies does not eliminate the necessity for further investigation, especially in emerging markets such as India. Keane (1983) highlighted the significance of consistently examining financial markets for efficiency.

CHAPTER 4

TEST OF MARKET EFFICIENCY OF INDIAN NIFTY50 INDEX OPTIONS

4.1. Introduction

Financial derivatives are specialized financial contracts whose value is derived from underlying assets, such as equities, bonds, interest rates, or foreign currencies. In India, equity derivatives play a pivotal role in stabilizing capital markets. They have helped reduce market volatility, thereby encouraging participation from both domestic and international investors, who may have previously hesitated due to unpredictable market conditions. Among these, futures and options are the most widely used. A futures contract obligates the buyer and seller to transact an asset at a predetermined price on the future date. By contrast, an options contract provides the holder with the right, but not the obligation, to buy or sell an asset at a specified price within a defined period. Options are further classified into call options, which allow the purchase of assets, and put options, which allow sale.

The rise in the derivatives market is largely driven by growing demand among market participants to manage price volatility and hedge against uncertain financial outcomes. These instruments are specifically designed to mitigate the risks associated with fluctuations in asset values, whether related to inventory, financial transactions, or business operations, over time. By enabling investors to lock prices in advance, derivatives help safeguard returns and ensure predictable cash flows, especially for risk-averse investors. In addition to risk management, derivatives support more efficient capital allocation by offering issuers and investors a wider array of financial tools. This contributes to reducing the overall cost of raising capital, enhancing the financial system efficiency, and stimulating economic development.

As global financial systems have become increasingly integrated, derivatives have played an essential role in connecting markets, improving liquidity, and facilitating seamless trade and capital flow. Over the last 40 years, the evolution of the derivatives market has been profound, particularly in its ability to provide robust risk-management strategies and attractive investment alternatives. A major milestone in this journey was the launch of index options on the Chicago

Board Options Exchange (CBOE) in 1983. These instruments have gained rapid traction due to their cash settlement feature, which offers a streamlined method for managing systemic risk in diversified portfolios. Their growing popularity reflects the vital function derivatives that serve in modern financial markets.

The derivatives market in India has expanded significantly since its inception in the early 2000s. The National Stock Exchange (NSE) launched index futures trading in June 2000 and updated it with index options in June 2001. The Bombay Stock Exchange (BSE) started index options trading a month later. Trading of stock options and single stock futures was introduced to the market in July and November, 2001. The derivative trading volume has experienced a major upward trend owing to market expansion. The expansion of derivative contract trading during the fiscal year 2023-2024 was substantial because the total traded volume grew from 90,580 in June 2000 to 32.9 billion by March 2024. The market segment of index options gained 98.48 % control over total derivative trading by the year 2023-24.

The Indian derivatives market is expected to experience vigorous growth in 2024. NSE and BSE trading data for the second quarter of 2024 demonstrated that equity index options reached 36.8 billion shares which was two times greater than the Q2 performance from the previous year. All futures and options transactions worldwide amount to more than two-thirds because of the global operations. Changing demographics in retail investment circles are the main catalysts of market expansion. During the first nine months of the 2024–2025 fiscal period, the National Stock Exchange reported 107 million separate investors and 15 million new investors in its system.

Regulatory bodies have increased their inspection of the derivatives market because of its rapid growth, to maintain market order and protect investor interests. The Securities Exchange Board of India (SEBI) enforced new measures in late 2024 to control excessive speculative trading in the derivatives markets. The regulators proposed two changes: limiting weekly options contracts to only one expiry date on each exchange and raising the minimum contract quantity to improve the market stability. The NSE, along with the BSE, plans to boost index futures and options lot sizes per SEBI instructions starting from November 2024.

4.2. Research Methodology

4.2.1. Data Description

This study examines the periodic final values of Nifty 50 index options contracts between 1 April 2018 and 31 March 2024. The National Stock Exchange of India (NSE) provided the data for this research. We also acquired relevant data for Nifty 50 index futures contracts from the NSE website. To estimate the risk-free interest rate and evaluate the lower boundary condition of the Black-Scholes model, researchers used the yield from 91-day Treasury bills for the relevant timeframe. 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.

This study is based on the Black-Scholes model. This model posits that it is possible to create a short-term portfolio by combining a hazardous asset with an option on that asset, which yields a return that is roughly equivalent to the risk-free rate. This study utilized a dynamic hedging test to take advantage of the possible differences between market pricing and theoretical option prices calculated using the Black-Scholes model. This approach, referred to as volatility trading, is based on predicting the future volatility of an underlying asset (Cavallo & Mammola, 2000). When the anticipated future volatility exceeds (falls short of) the current market-implied volatility, the approach entails purchasing or selling options with the expectation of increasing (decreasing) option prices.

4.2.2. Forecasting Volatility

A crucial challenge in assessing the market efficiency of the options market using the Black-Scholes model is accurately estimating the volatility of the underlying asset until the options contracts mature. This is because, unlike other key factors in the Black-Scholes model, the volatility of the underlying asset is not directly observable; therefore, it must be forecasted to determine the option's theoretical price.

Upon reviewing the literature, it becomes apparent that most volatility estimation methods lack theoretical support; thus, they will not be included in this study for estimating volatility. Nonetheless, the Weighted Implied Standard Deviation (WISD) estimator has been frequently

employed in past research as a volatility estimation technique. Consequently, WISD estimators were selected for the current study.

$$\mathbf{WISD} = \sum \mathbf{ISD}_j (\delta \mathbf{W}_j * \mathbf{v}_j / \delta \mathbf{v}_j * \mathbf{W}_j) / \sum (\delta \mathbf{W}_j * \mathbf{v}_j / \delta \mathbf{v}_j * \mathbf{W}_j) \quad \text{Equation (4.1)}$$

where N is the number of options recorded under an option class on a given date, W_j is the current option price of the index, ISD_j is the implied standard deviation of option j, and $(\delta W_j * v_j / \delta v_j * W_j)$ is the price elasticity of option j with respect to its implied standard deviation (v_j).

The first step in computing the Weighted Implied Standard Deviation (WISD) is to determine the implied volatility (IV), which reflects the market's expectations of future price fluctuations. Implied volatility is not directly observable, but is inferred from the current market prices of options. Essentially, the value of volatility, when input into the Black-Scholes pricing model, aligns the theoretical price with the actual market price of the option.

However, a major complication in this process is that the Black-Scholes formula does not allow for a straightforward calculation of implied volatility; it cannot be algebraically inverted to solve IV. In other words, implied volatility is a function of several variables, including the market price of the option (call or put), the current stock price (S_0), the strike price (K), the risk-free interest rate (r), and the time to maturity (T).

To overcome this, the **Newton-Raphson** iterative method can be used, which is typically implemented in statistical computing software, such as RStudio. This numerical method starts with an initial guess for volatility and repeatedly adjusts it until the theoretical price produced by the Black-Scholes model closely matches the observed market price. By iterating in this way, RStudio helps reverse engineer the implied volatility with a high degree of accuracy, making it possible to calculate WISD as part of broader options analysis.

According to the Black-Scholes model, the implied volatility of a class of options should remain constant at any given moment. However, in reality, implied volatility often varies with different strike prices and expiration dates for the same assets. This variation presents a significant challenge in estimating implied volatility, a phenomenon referred to as the "implied volatility smile." In this context, a "sneer" is observed because the implied volatility decreases consistently as the strike prices and maturities increase (Dumas et al., 1998). Nonetheless, this issue can be addressed by averaging the implied volatilities across various strike prices and

expiration dates. In this study, the method employed for estimating implied volatility is the Weighted Implied Standard Deviation (WISD), as illustrated in the equation above.

After estimating the volatility, we can proceed to determine the theoretical price of options using the Black-Scholes model for call and put options, as outlined in Equations (4.2) and (4.3), respectively, for a specific day.

Black-Scholes Model

The assumptions underlying the original Black-Scholes option pricing model are as follows:

- Stock prices follow a log-normal distribution with constant volatility.
- Short selling is allowed with the full use of sale proceeds.
- There are no transaction costs, taxes, or divisible securities.
- The underlying asset pays no dividends during the life of the option.
- No arbitrage opportunities exist in this market.
- Securities can be traded continuously, without restrictions.
- The risk-free interest rate is constant for all maturities.

Based on the assumption above, the Black-Scholes option pricing formulae for call and Put option can be written as

European Call Option:

$$C = SN(d_1) - Xe^{-rT} N(d_2) \quad \text{Equations (4.2)}$$

European Put Option:

$$P = Xe^{-rT} N(-d_2) - SN(-d_1) \quad \text{Equations (4.3)}$$

$$d_1 = \frac{\log(s/x) + (r + \sigma^2/2)t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

Where:

- C = Price of the call option (the cost to buy the right to purchase the asset)
- P = Price of the put option (the cost to buy the right to sell the asset)
- S = Current market price of the underlying stock or asset

- X = Strike (exercise) price of the option—the predetermined price at which the asset can be bought or sold
- T = Time to expiration, expressed in years (e.g., 3 months = 0.25 years)
- r = Continuously compounded annual risk-free interest rate applicable over period T
- σ (sigma) = Annualized volatility of the asset's return (a measure of how much the price fluctuates)
- $N(\cdot)$ = Cumulative distribution function of the standard normal distribution (i.e., the probability that a value from a standard normal distribution is less than or equal to a given number)

4.2.3. Creating Delta-Neutral Portfolios

Traders predominantly use the delta (Δ) hedging approach to attain risk neutrality in their option portfolios (Andersson, 1995). Delta measures the sensitivity of an option's price to fluctuations in the price of the underlying asset. The option value behaviour towards underlying asset price fluctuations is expressed through delta computation. The delta value establishes the necessary underlying asset quantity for each option to build risk-neutral portfolios using delta-hedging procedures.

Delta for call options: $\delta=N(d1)$

Delta Formula for Put Options: $\delta=N(d1) -1$

To find, $d1 = (\ln(S/K) + (r + \frac{\sigma^2}{2})t) / \sigma \sqrt{t}$

Where:

- K as strike price
- N as Normalized function
- r as risk-free rate.
- σ as volatility.
- S as Spot price
- t as time to maturity

The value of Delta (Δ_c) remains positive for call options, indicating that their prices typically mirror the price movements of the underlying asset. The price of put options moves opposite

to the underlying assets because they carry negative delta (Δ_p) values. The explanation remains brief, omitting the specific equations required to compute delta in call and put option calculations.

4.2.4. Utilizing WISD Volatility and Identifying Deviations

This study employs the WISD volatility estimator to determine the theoretical option prices for every sample. Mohanti and Priyan (2014) consider WISD volatility to represent the top volatility estimating technique for Black-Scholes framework assets. We examined the variations between the model prices developed from theory and the prices that the markets actually charged. The examination of discrepancies between option market prices and calculated model prices leads to trading decisions regarding option purchases and sales.

4.2.5. Developing a Delta-Neutral Hedging Strategy

We utilized delta-neutral hedging to detect recognized changes to develop a theoretical risk-free portfolio. For call options, delta hedging entails holding a long position in the underlying asset that corresponds to the delta ($N(d_1)$) for each option sold. Conversely, when an option is bought, a corresponding short position of equal size ($N(d_1)$) is taken in the underlying asset. Delta hedging in this scenario requires taking a long position in the underlying asset for each put option bought, with a magnitude of $N(d_1)$, or taking a short position for each put option sold, with a magnitude of $N(d_1)$ because of the negative delta of the put options.

4.2.6. Ex-Post Analysis and Short Selling Constraints

It is critical to recognize that this study is ex-post, meaning that it does not present a trading strategy in real time to take advantage of potential mispricing. We devise and presume the execution of the trading strategy based on the prices obtained at a given time point (t). To conduct an ex-post test of market efficiency using the delta-neutral hedging approach, mispricing must be identified first. We promptly implement a hedging strategy upon identifying discrepancies between the model and the prevailing market prices.

Nevertheless, this analysis does not consider delta-neutral hedge techniques that involve shorting the underlying asset because of substantial limitations on short-selling in the Indian capital market. Therefore, this study examines mispricing scenarios in which the market price

of a call option exceeds its model price and the market price of a put option is lower than its model price (Mohanti & Priyan, 2014), as demonstrated by the following equations:

$$\lambda_C = C_{\text{Market}} - C_{\text{Model}} \quad \text{Eq. 4.4.}$$

$$\lambda_P = P_{\text{Model}} - P_{\text{Market}} \quad \text{Eq. 4.5.}$$

This study defines anomalous profits (λ_C and λ_P) as the absolute discrepancy between the market price (C Market and P Market) and the matching model prices (C Model and P Model) of the put and call options. Values of 'C' and 'P' greater than zero would suggest that call and put options are mispriced (Mohanti & Priyan, 2014).

4.2.7. Delta-Neutral Hedging Strategy and Dynamic Simulation

The dynamic hedging simulation considers two possibilities for delta-neutral hedging:

- **Short Call Option:** For sold call option, the investor maintains a long position $N(d1)$ in the underlying asset.
- **Long Put Option:** For each put option acquired, the investor maintains a long position of $N(d1)$ in the underlying assets.

As previously stated, delta hedging guarantees risk neutrality for a short duration only. Consequently, to maintain a risk-free condition, portfolios require ongoing rebalancing during ownership. We use a dynamic hedging simulation to determine whether the observed discrepancies between the model and market prices yield tangible profits. In general, a delta-neutral hedging portfolio can be unwound under three typical scenarios: (i) when the market price of the option realigns with its theoretical value, as predicted by the pricing model, (ii) when the observed mispricing in the option is corrected, or (iii) when the option contract reaches its expiration date. In this study, the hedge position is maintained until the option's maturity, at which point the delta-neutral portfolio is closed out. This approach allows for a consistent assessment of performance over the full life cycle of the option.

This study focuses on market efficiency and the expenses incurred during the transactions. The theory of market efficiency posits that if all risks and costs are considered, it is not possible to consistently achieve returns that are higher than the average through trading (Jensen, 1978).

Transaction costs can eliminate any perceived profits. Hence, this study computes net profits by including transaction expenses to ascertain exceptional profit gain.

4.2.8. Measurement of Transaction Costs

Options trading incurs transaction expenses, including brokering commissions, securities transaction tax (STT), and service tax on brokerage. It is crucial to emphasize that the Securities Transaction Tax (STT) is applicable exclusively to the seller's portion of derivative transactions, in contrast to equity transactions, where both parties are subject to the tax. This study includes the costs associated with broking fees, service tax on broking, and Securities Transaction Tax (STT) when calculating transaction costs for the trading strategy. Nevertheless, accurately determining transaction expenses, particularly brokerage fees, is challenging. The exact trading strategy and transaction size also influence brokerage fees, which vary over time and across businesses. We performed dedicated research on transaction costs because this factor strongly affects the exploitation of market inefficiency. Brokerage costs were estimated using substantial information obtained from interviews with brokerage house members. These figures are consistent with those of prior studies on the Indian futures market (Dixit et al., 2009, 2011; Vipul, 2008).

In addition, this study classifies arbitrageurs into two distinct groups based on disparities in transaction costs: retail and institutional investors. Typically, broking fees for individual investors, who are often general participants, amount to approximately 0.05% of the strike price, in addition to the option premium. In contrast, institutional investors benefit from reduced expenses, which are specifically calculated at 0.03% of the strike price, in addition to the option premium. This benefit arises from the possibility of not having to pay broking fees (if the institutional investor is a broking house) or having considerably lower fees as a result of engaging in large-scale trading. Both futures contracts and stock transactions exhibit similar pricing differences, with institutional investors regularly facing lower transaction costs.

4.2.9. Challenges in Data Synchronization

This study relies on daily closing prices for index options, futures, and the underlying spot index, which can give rise to synchronization issues due to different trading times across these markets. Ideally, intraday data would provide a more accurate alignment; however, this analysis utilizes index futures along with spot index values to construct hedge arbitrage portfolios aimed

at evaluating the efficiency of the options market. Previous research by Granath and Krisell (2004) show that index futures tend to align more closely with options markets than spot indices, particularly in the case of the OMX Swedish derivatives market. This insight is especially relevant to the Indian derivatives landscape, in which both options and futures are traded on the same exchange platform and follow uniform settlement procedures and expiration cycles. Such structural consistency helps reduce timing mismatches and enhances the reliability of using futures data instead of spot prices for efficiency assessments.

4.2.10. Data analysis and the examination of empirical evidence.

After collecting the data, we executed a filtering procedure that considered liquidity and maturity. This study exclusively analyzes options contracts with a minimum of one trade. We focused on contracts that were in close proximity to near the month (NTM), next the month (NXTM), and far the month (FTM) (Mohanti & Priyan, K.,2014). Due to insufficient liquidity, the NSE excluded long-term options contracts launched after 2008 from its trading system. Furthermore, a standard "pure arbitrage test" (Jensen, 1978) excludes any choices that violate the lower boundary conditions (LBC). Galai (1977) argues that a market cannot simultaneously exhibit inefficiency under weak conditions, as shown by the LBC test, and efficiency under stronger assumptions, such as model-based testing. Table 1 shows the total number of observations retained after applying filters.

Subsequently, we calculated the theoretical value of options using the Black-Scholes model with WISD volatility, which we found to be the most accurate predictor of the volatility of the underlying asset based on our previous study (Mohanti & Priyan, K.,2014). However, historical option prices determine volatility; therefore, we cannot directly use them to calculate the current model price. To address this issue, we used the volatility from the preceding day as a proxy for the anticipated volatility (Mohanti & Priyan, P. K.,2014). To calculate the model price for the current day, we used the Black-Scholes approach. We computed the option prices using the model.

The data shown in Table 4.1 demonstrate that the Black-Scholes model, when utilizing WISD volatility, resulted in pricing discrepancies of approximately 28% and 80% for call and put options, respectively, compared to market prices.

This result provides evidence against semi-strong form market efficiency, suggesting that the market is not fully efficient in the short term. For the entire study period, statistical research reveals evidence of pricing efficiency in the Indian options market. Although discrepancies exist between model and market prices, it remains unclear whether these inconsistencies can be effectively capitalized. Can the potential profits from exploiting these variances outweigh the costs associated with the implementation of dynamic hedging strategies? We created a dynamic hedging simulation to investigate this question and evaluate the undervalued options. In this simulation, we establish a hedge by acquiring a long position in a specific quantity of the underlying asset, as determined by the delta hedge ratio. We subjected the long position to daily rebalancing.

To investigate this further, we analyze deviations for a larger sample of 49,827 call and 1,70,049 put options, as shown in Table 4.1. We delve deeper into the nature of the Black-Scholes model violations to assess their potential for exploitation, which is a key factor in market inefficiency.

4.3. Results & Interpretation

Table:4.1 Deviations of the Black-Scholes Model

Particular	Call options	Put options
Total number of observations	1,77,571	2,12,609
Total number of ex-post Black-Scholes violations observed	49,827 (28%)	1,70,049 (80%)

Note: Author's Work

Tables 4.2, 4.3, and 4.4 analyze these violations in relation to liquidity, maturity, and moneyness. Because mere mispricing does not guarantee exploitability, we aimed to understand how these factors influence the observed violations. We categorized liquidity into three tiers: thinly traded (less than 100 contracts daily), moderately traded (100–500 contracts daily), and highly traded (more than 500 contracts per day). We divided the time to maturity into four ranges: 0-7 days, 8-30 days, 31-60 days, and 61-90 days. Moneyness, defined as the current index price divided by the strike price, was categorized into call and put options. Following Rubinstein (1985), we classified call options into five categories: deep-out-of-the-

money (DOTM, 0.75-0.85), out-of-the-money (OTM, 0.85-0.95), at-the-money (ATM, 0.95-1.05), in-the-money (ITM, 1.05-1.15), and deep-in-the-money (DITM, 1.15-1.25). To gain a more nuanced understanding, we further classified violations by moneyness. This comprehensive sensitivity analysis allows us to draw insightful conclusions regarding the exploitability of these violations.

Table 4.2. Deviations Associating to the Three Tiers of Liquidity

	Call options	Put options
Low traded options	21,331 (43%)	56,711 (33%)
Medium traded options	8,829 (18%)	27,988 (16%)
High traded options	19,667 (39%)	85,350 (51%)
Total	49,827	1,70,049

Note: Author's Work

The analysis in Table 4.2 reveals that deviations from theoretical pricing occur across all liquidity tiers, indicating that market inefficiencies are not limited to illiquid contracts. For call options, the highest share of deviations (43%) is found in low-traded options, suggesting that thin trading contributes to the mispricing. In contrast, put options show the most deviations (51%) in highly traded contracts, possibly because of increased speculative activity or volatility during bearish market conditions. This divergence highlights that liquidity does not guarantee pricing efficiency and that deviations persist even in actively traded segments, emphasizing the need for tier-specific strategies in efficiency analysis.

Table 4.3. Violations Associating to the Maturity of Options Contract

	Call options	Put options
0 - 7days	15,844 (32%)	6,582 (4%)
8 - 30 days	22,855 (46%)	62,882 (37%)
31 - 60 days	9,091 (18%)	68,737 (40%)
61 - 90 days	2,037 (4%)	31,848 (19%)
Total	49,827	1,70,049

Note: Author's Work

The analysis in Table 4.3 shows that violations in option pricing are significantly influenced by the maturity of contracts, with different trends for call and put options. For call options, most violations (46%) occur in the 8–30 days maturity range, followed by short-term contracts (0–7 days) at 32%, indicating that mispricing is more prevalent in near-term calls, likely due to time decay and speculative trading. In contrast, put options show the highest violations (40%) in the 31–60 days range, followed closely by 8–30 days (37%) and 61–90 days (19%), whereas very short-term puts (0–7 days) show minimal violations (4%). This suggests that put-option mispricing becomes more pronounced in medium- to long-term maturities, possibly due to volatility expectations and hedging complexities. Overall, maturity plays a crucial role in pricing deviations, with short-term calls and medium-term puts being more susceptible to it.

Table 4.4. Violations Associating to the Five Levels of Moneyness

	Call options		Put options
Deep out of the money (< 0.90)	13,416 (27%)	Deep out of the money (1.10<)	23,453 (14%)
Out of the money (0.90 to 0.95)	8,001 (16%)	Out of the money (1.05 to 1.10)	29,314 (17%)
At the money (0.95 to 1.05)	11,016 (22%)	At the money (0.95 to 1.05)	91,031 (54%)
In the money (1.05 to 1.10)	7,492 (15%)	In the money (0.90 to 0.95)	19,148 (11%)
Deep in the money (1.10 <)	9,902 (20%)	Deep in the money (< 0.90)	7,103 (4%)
Total	49,827	Total	1,70,049

Note: Author’s Work

Table 4.4 highlights the clear patterns in violations across moneyness levels for call and put options. Put options show the highest number of violations at the at-the-money (ATM) level, accounting for 54% of all cases, indicating that these options are more prone to pricing inefficiencies, likely due to their sensitivity to volatility and heavy trading. For call options, most violations occur in deep out-of-the-money contracts (27%), possibly because of the challenges in pricing low-premium options. In contrast, deep in-the-money puts have the fewest violations (only 4%), suggesting relatively accurate pricing for these options. Overall, put options exhibit far more violations than calls, indicating potential inefficiencies or market asymmetries. These trends imply that pricing accuracy and by extension, market efficiency–varies significantly with the level of moneyness.

Table 4.5. Descriptive Statistics of the Absolute Magnitude of Violations at Various Liquidity levels

Liquidity	Mean		Standard Deviation		Minimum		Maximum	
	Call	Put	Call	Put	Call	Put	Call	Put
Low traded options	34.10	344.82	58.65	235.33	0.0001	0.0007	947.49	1091.38
Medium traded options	23.02	325.76	51.31	231.51	0.0051	0.0038	602.71	1097.45
High traded options	19.88	314.68	49.20	226.24	4.78	0.0013	580.69	1130.34

Note: Author's Work

Table 4.5 presents the descriptive statistics of the absolute magnitude of pricing violations across different liquidity levels for call and put options. The analysis shows that low-traded options exhibit the highest average violation for both calls (34.10) and puts (344.82), along with the widest variability (highest standard deviations and maximum values), indicating significant mispricing in illiquid contracts. As liquidity improves, both the mean and standard deviation of violations decrease; medium traded options show reduced means (23.02 for calls, 325.76 for puts), and high traded options show the lowest mean violations (19.88 for calls, 314.68 for puts). This trend suggests a clear inverse relationship between liquidity and pricing error magnitude, affirming that higher liquidity is associated with more accurate option pricing and a lower risk of mispricing.

Table 4.6 presents the descriptive statistics of absolute pricing violations across various option maturity levels for call and put options, revealing a clear pattern of increasing mispricing with longer maturities. For both option types, the mean and standard deviation of the violations grow significantly as maturity increases. Call options show an increase in mean violations from 12.75 (0–7 days) to 58.23 (61–90 days), whereas put options rise dramatically from 51.22 to 515.07 over the same range. The standard deviation also increases, reflecting greater uncertainty and variability in pricing for longer dated contracts. Minimum violations remain small across all groups, but the maximum values peak sharply for longer maturities, especially for puts (up to

1130.35). This trend suggests that pricing efficiency deteriorates as the time to maturity increases, likely due to compounded volatility expectations and the difficulty in accurately modelling long-term risk.

Table 4.6. Descriptive Statistics of the Absolute Magnitude of Violations at Maturity levels

Maturity	Mean		Standard Deviation		Minimum		Maximum	
	Call	Put	Call	Put	Call	Put	Call	Put
0 - 7 days	12.75	51.22	29.16	81.91	7.32	0.001	792.79	603.78
8 - 30 days	24.54	145.46	41.43	134.59	4.79	0.0007	534.84	734.24
31 - 60 days	48.42	431.24	84.92	167.35	0.005	0.015	713.63	951.80
61 - 90 days	58.23	515.07	95.74	215.96	0.007	0.0182	947.50	1130.35

Table 4.7 Descriptive Statistics of the Absolute Magnitude of Violations at Various Moneyness levels

Moneyness	Mean	SD	Min	Max	Moneyness	Mean	SD	Min	Max
	Call options					Put options			
Deep out of the money (< 0.90)	8.22	29.88	7.32	567.81	Deep out of the money (1.10<)	51.83	64.92	0.0007	483.60
Out of the money (0.90 to 0.95)	12.30	47.15	0.0009	576.30	Out of the money (1.05 to 1.10)	142.07	116.91	0.0013	617.22
At the money (0.95 to 1.05)	41.40	74.04	0.0016	947.50	At the money (0.95 to 1.05)	449.86	194.92	0.006	1130.34
In the money (1.05 to 1.10)	38.68	52.88	0.011	713.63	In the money (0.90 to 0.95)	415.87	164.33	0.010	973.14
Deep in the money (1.10 <)	37.10	49.81	4.79	792.79	Deep in the money (< 0.90)	174.03	115.39	0.101	633.50

Note: Author's Work

Table 4.7 presents the descriptive statistics of absolute pricing violations across different moneyness levels for call and put options, revealing that mispricing severity increases as options approach or move deeper into the money. For call options, violations are lowest in deep out-of-the-money contracts (mean: 8.22) and highest at-the-money (mean: 41.40), with elevated deviations persisting in the in-the-money and deep in-the-money categories. Put options exhibit a sharper rise, with mean violations peaking at-the-money (449.86) and in-the-money (415.87), indicating that these contracts are most prone to pricing inefficiencies. Standard deviations and maximum violations follow similar trends, reinforcing that options near or in the money, especially puts, are more sensitive to valuation complexities. This suggests that moneyness significantly affects pricing accuracy, with ATM and ITM options being the most mispriced.

However, the interpretation of the above results should be approached with caution, as an important factor in real-world trading transaction costs has not yet been considered. Transaction costs play a crucial role in the arbitrage mechanism and can significantly impact the feasibility of exploiting pricing violations (Baesel et al., 1983; Phillips & Smith, 1980). To gain a clearer understanding of the actual magnitude of the violations identified using the Black–Scholes model, this study incorporates transaction costs from both retail and institutional investor perspectives. Specifically, the analysis considers brokerage fees, service tax on brokerage, and the Securities Transaction Tax (STT) as part of the total transaction cost in the trading strategy.

Table 4.8 Deviations of Black-Scholes model after incorporate transaction cost

Particulars	Call options	Put options
Total sample ex-post violation after transaction cost (retail investors)	3323 (1.87%)	57,117 (27%)
Total sample ex-post violation after transaction cost (institutional investors)	3387 (1.91%)	24078 (11%)

Note: Author’s Work

Table 4.8 shows the deviations in the Black-Scholes model after incorporating the transaction costs. For call options, deviations are minimal for both retail (1.87%) and institutional investors (1.91%), indicating that the model remains efficient in this segment. However, for put options, retail investors face a significantly higher deviation rate (27%) than institutional investors

(11%). This suggests that the model is less effective in pricing put options, particularly for retail participants, possibly because of limited resources, higher costs, or information asymmetry. These findings highlight the importance of accounting for investor type and transaction costs when evaluating options pricing efficiency.

Table 4.9 Descriptive Statistics of the Absolute Amount of the Violations of Black Scholes Model after Transaction Cost

Descriptive Statistics	Before Transaction cost		Retail Investors		Institutional Investors	
	Call	Put	Call	Put	Call	Put
Mean	26.52630	326.5587	51.68899	504.4234	99.658229	516.76264
Std. Dev.	54.20891	230.5682	95.34701	157.8493	120.23060	154.89051
Minimum	4.78609	0.0007178	0.0350505	76.049350	0.1496904	58.775101
Maximum	947.4959	1130.347	947.4959	1086.3299	658.854988	1130.34745

Note: Author’s Work

Table 4.9 shows that after incorporating transaction costs, the absolute violations of the Black-Scholes model increase notably, especially for the put options. The average deviation is the highest for institutional investors in puts (516.76), followed closely by retail investors (504.42), indicating significant mispricing. Call option violations are lower in comparison, with retail and institutional means at 51.69 and 99.66, respectively, respectively. The high standard deviations and maximum values suggest a large variation and the presence of outliers. Overall, the model performs less effectively for put options, and both investor types face notable pricing inefficiencies in the market.

While the previous analysis identified potential violations, a more complete picture requires consideration of transaction costs, a crucial element in arbitrage strategies (Baesel 1983; Phillips and Smith 1980). This study integrates transaction costs relevant to both retail and institutional investors to assess their influence on the degree of violations of the Black-Scholes model. Broking fees, broking service tax, and security transaction tax (STT) are all components of transaction costs. Table 9 presents the findings after accounting for the transaction expenses. The occurrence rate of exploitable violations for call options decreases to approximately 1.87% of all observations, particularly for retail investors. This percentage increases to 1.91% for

institutional investors. Similarly, for put options, the occurrence of exploitable violations decreases to 27% and 11% for retail and institutional investors, respectively. It is important to recognize that when transaction costs are considered, the number of exploitable infractions decreases significantly. The decline is significant, as call option violations have dropped from 28% to less than 4% (combining both retail and institutional investors), and put option violations have decreased from 80% to 38%.

4.4. Conclusion

The findings of this study offer a comprehensive view of pricing efficiency in the Indian options market, specifically focusing on Nifty 50 index options over the period from April 2018 to March 2024. Initially, the analysis of ex-post violations using the Black-Scholes model indicates significant mispricing in both call and put options. Approximately 28% of call options and 80% of put options exhibit deviations from theoretical prices, suggesting notable inefficiencies in the options market.

A deeper investigation into the nature of these violations, categorized by liquidity, maturity, and moneyness, reveals that mispricing is influenced by various structural and trading characteristics. For call options, the highest percentage of violations occurred in low-traded and near-term contracts, whereas for put options, violations were more common in highly traded and medium- to long-term maturities. The moneyness analysis showed that at-the-money (ATM) options, especially puts, exhibited the most frequent and severe deviations, reflecting the complexity of pricing options with high sensitivity to volatility.

However, when transaction costs were incorporated into the analysis—factoring in brokerage fees, service taxes, and securities transaction tax (STT)—the number of exploitable violations decreased significantly. For call options, the occurrence of pricing violations fell to 1.87% for retail investors and 1.91% for institutional investors. Similarly, for put options, violations are reduced to 27% for retail and 11% for institutional investors. This sharp reduction highlights that while theoretical mispricing exists, actual arbitrage opportunities diminish significantly once trading frictions are considered.

The descriptive statistics of the absolute magnitude of the violations also corroborate this finding. The mean magnitude of violations of post-transaction costs remained the highest in put options for both investor types; however, their exploitability is limited because of increased

costs and potential slippage. Additionally, higher liquidity and shorter maturity are associated with lower deviations, suggesting better pricing efficiency in those segments.

In conclusion, while raw Black-Scholes deviations initially suggest a lack of pricing efficiency, a more practical interpretation that accounts for transaction costs supports the notion that the Indian options market is largely efficient, especially in the case of call options. The remaining inefficiencies in put options, particularly for retail investors, may stem from information asymmetries, behavioural biases, or execution constraints. Therefore, although some inefficiencies persist, particularly in certain market segments, the broader picture affirms that the market exhibits a reasonable degree of efficiency when viewed through a real-world lens.

CHAPTER 5

FORECASTING VOLATILITY IN THE INDEX OPTION MARKET

5.1. Introduction

Financial markets across the globe comprise a diverse set of participants, including individual investors, fund managers, Foreign Institutional Investors (FIIs), Foreign Portfolio Investors (FPIs), Domestic Institutional Investors (DIIs), and policymakers. A common objective among these participants is to anticipate market fluctuations to make informed investment decisions that generate positive returns.

Volatility is a key element in understanding and predicting market behaviour. Volatility refers to the degree of variation in the returns of financial instruments, such as stocks, indices, and commodities. It is a critical metric in financial analysis because it provides insights into both the current state of the market and its potential future movements. Typically, volatility is quantified using the standard deviation of the logarithmic returns.

Numerous methods have been developed to estimate the historical volatility. While the conventional close-to-close method is widely used, advanced estimators such as Garman-Klass, Rogers-Satchell, Parkinson, and Yang-Zhang provide improved efficiency by incorporating additional price information, such as high, low, and open prices. These methods attempt to capture market dynamics more accurately by reducing estimation errors.

The success of a volatility estimation approach is often determined by its accuracy. Accurate volatility forecasting plays a pivotal role in various financial applications, including risk management, derivative pricing, portfolio optimisation, and trading strategy development. In this context, time-varying models are frequently used to forecast the volatility. Among the most prominent are the autoregressive integrated moving average (ARIMA), generalised autoregressive conditional heteroskedasticity (GARCH), Exponential GARCH (EGARCH), and Neural Networks with a feedforward architecture.

Each volatility estimator has unique characteristics, and its performance may vary depending on market conditions and the forecasting model used. Therefore, it is essential to assess and compare their forecasting capabilities. In this study, the performance of different models is evaluated based on a set of error metrics, including Mean Error (ME), Mean Absolute Error

(MAE), Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE), Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE), and Autocorrelation of Forecast Errors at Lag 1 (ACF1).

The empirical analysis is conducted using time-series data from the Nifty 50 Index, a key benchmark index of the National Stock Exchange (NSE) of India. The Nifty 50 Index encompasses 50 actively traded stocks from 22 different sectors of the Indian economy, providing a comprehensive representation of the Indian market. Owing to its high liquidity and broad sectoral coverage, Nifty 50 is an ideal choice for studying volatility dynamics and forecasting accuracy.

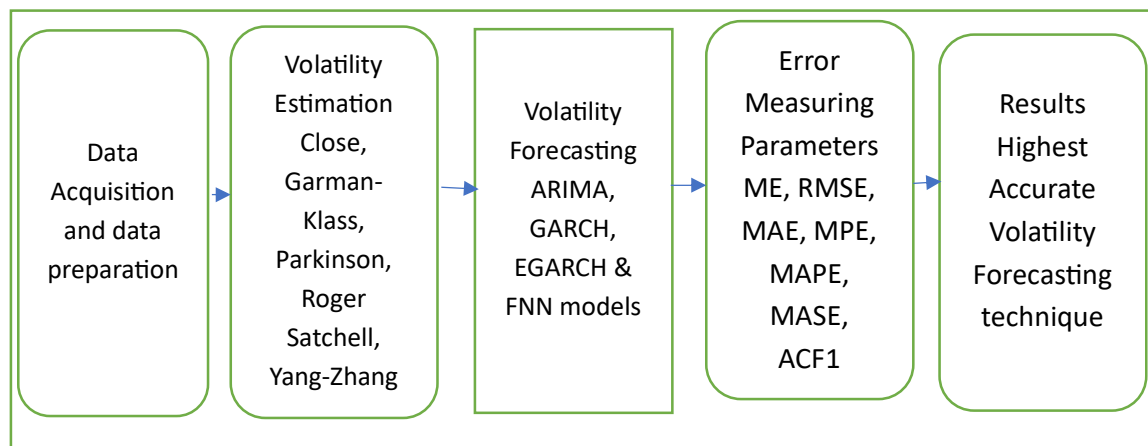
5.2. Research Methodology

5.2.1. Data Description

This study is based on historical stock market data for the Nifty 50 Index of the National Stock Exchange (NSE) of India, covering the period from 1 April 2018 to 31 March 2024 a span of six years. The Nifty 50 Index comprises 50 large-cap companies from 22 sectors, offering a representative view of the Indian equity markets.

The data, sourced from the NSE’s official website, consist of end-of-day trading information, including the opening, high, low, and closing prices for each trading day. The dataset includes 1,488 observations, corresponding to the number of trading days (approx. 21days in months) during the specified period. The data points were arranged chronologically. To obtain the best estimate and accuracy of all models in forecasting, estimation and implementation were conducted in RStudio.

Table 5.1 The pictorial table representation of methodology



5.2.2. Data Preprocessing

Before conducting any analysis, the following preprocessing steps were performed.

- Data Cleaning: Removal of non-trading days or missing values.
- Transformation: Calculation of log returns for volatility estimation using

$$R_t = \ln(P_t / P_{t-1})$$

Stationarity Check: The Augmented Dickey-Fuller (ADF) test was used to ensure stationarity.

5.2.3. Volatility Estimators and formulas

In this study, historical volatility was estimated using five distinct methods. A common practice in financial analysis is to compare implied volatility with historical volatility in order to assess whether an asset might be undervalued or overvalued. The five estimators chosen for this analysis each provide a different lens through which to evaluate market behaviour.

1. Close-to-Close

This approach calculates volatility based on the standard deviation of an asset's daily closing price over a given period. It assumes a zero average return, meaning that it does not account for any upward or downward trend in the price series. The formula used for this method is as follows:

$$\sigma = \sqrt{[1/(N-1) \times \Sigma(R_t - \bar{R})^2]}$$

where σ represents the estimated volatility, R_t is the daily return, \bar{R} is the average return, and N is the total number of observations. Despite its simplicity, the close-to-close method serves as a fundamental benchmark for volatility analysis.

2. Parkinson

Introduced by Parkinson in 1980, this is the first alternative to the basic close-to-close volatility estimator. Instead of relying on closing prices, this method uses high and low prices on the trading day. However, it has limitations: it tends to underestimate volatility because it ignores intraday price jumps and assumes consistent trading hours, which may vary across markets. However, one of its strengths is that it produces consistent volatility estimates regardless of the geographical location of the exchange where the security or index (such as the CNX Nifty in this study) is traded. The formula used is:

$$\sigma_P = \sqrt{[1/(4\ln(2)N) * \Sigma(\ln(H_t/L_t))^2]}$$

3. Garman-Klass

Later in 1980, Garman and Klass improved Parkinson's model by incorporating opening and closing prices along with the high and low prices of the day. Their method offers greater accuracy by leveraging the concept of Brownian motion, which assumes zero drift and no jumps. Using this method, the volatility is calculated as follows:

$$\sigma_{\text{GK}} = \sqrt{[1/N * \Sigma(0.5(\ln(H_t/L_t))^2 - (2\ln(2) - 1)(\ln(C_t/O_t))^2)]}$$

4. Roger-Satchell

Developed in 1991 by Rogers and Satchell, this volatility estimator uses four price points: open, high, low, and close. While it still assumes no price jumps at market opening, which can lead to slight underestimations, it improves on earlier models by allowing for non-zero drift. This means that it accounts for the average directional movement in prices, offering a more realistic reflection of market behaviour. The formula is:

$$\sigma_{\text{RS}} = \sqrt{[1/N * \Sigma(\ln(H_t/C_t)\ln(H_t/O_t) + \ln(L_t/C_t)\ln(L_t/O_t))]}$$

5. Yang-Zhang

In 2000, Yang and Zhang introduced a more robust volatility model that explicitly accounts for overnight price jumps—something earlier estimators ignored. This method combines three components: overnight volatility (close-to-open), the open-to-close volatility, and the Rogers-Satchell component. It is also drift-independent, which enhances accuracy. Research suggests that this method is approximately 14 times more efficient than the close-to-close method. The volatility is estimated using

$$\sigma^2_{\text{YZ}} = \sigma^2_{\text{o}} + k\sigma^2_{\text{c}} + (1 - k)\sigma^2_{\text{RS}}$$

$$k = 0.34 / (1.34 + (N + 1)/(N - 1))$$

5.2.4. Forecasting Models

To forecast the future volatility of financial time series, various advanced time-series and machine learning models were employed in this study. Each model has unique strengths in

capturing the different characteristics of financial data, especially the dynamic and often volatile behaviour of stock market indices.

1. ARIMA (AutoRegressive Integrated Moving Average)

The ARIMA model is one of the most widely used linear time-series forecasting techniques. It is particularly effective for modelling and predicting future values in univariate time series data, where trends and patterns are present.

- ARIMA (p, d, q) consists of three components.
- p : the number of autoregressive (AR) terms,
- d : the number of differencing required to make the series stationary,
- q : number of lagged forecast errors in the moving average (MA) model.

Model Selection: The appropriate values of p , d , and q are determined by analysing the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and using statistical criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Strengths: ARIMA captures the linear relationship in time series data and is effective in modelling short-term dynamics.

2. GARCH (Generalized Autoregressive Conditional Heteroskedasticity)

GARCH models are specifically designed to handle volatility clustering, a common feature of financial time series in which periods of high volatility tend to be followed by high volatility and low by low.

The GARCH (p, q) model extends the basic ARCH model by allowing the conditional variance to depend not only on past squared residuals but also on past variances.

- p : the order of the GARCH terms (past variances),
- q : order of the ARCH terms (past squared residuals).

Parameter Estimation: Parameters are estimated using Maximum Likelihood Estimation (MLE).

Strengths: GARCH is effective in capturing time-varying volatility and volatility persistence in the financial markets.

3. EGARCH (Exponential GARCH)

The EGARCH model, developed by Nelson (1991), is an extension of the GARCH model that allows for asymmetric effects on volatility. In real financial markets, negative news tends to have a greater impact on volatility than positive news, a phenomenon known as the leverage effect.

Key Features:

- Models the logarithm of the variance, ensuring that the variance is always positive.
- Can capture asymmetry without requiring non-negativity constraints on the parameters.

Strengths: The EGARCH model is suitable for financial time series with asymmetric volatility patterns, which are often observed in equity markets.

4. Feedforward Neural Network (FNN)

A Feedforward Neural Network is a type of artificial neural network in which the connections between nodes do not form a cycle. It is a supervised machine learning model that can learn complex nonlinear relationships from data.

Architecture:

- It consists of an input layer, one or more hidden layers, and an output layer.
- Each neuron applies an activation function, such as Rectified Linear Unit (ReLU) or hyperbolic tangent (tanh), to introduce non-linearity.

Training:

- The network is trained using optimisation algorithms, such as Adam or Stochastic Gradient Descent (SGD).
- The loss function used is typically the Mean Squared Error (MSE), which quantifies the difference between the predicted and actual values.

Strengths: Neural networks can capture nonlinear relationships, interactions, and hidden patterns in time-series data that traditional statistical models may miss.

Each of these models offers unique insights into the volatility dynamics. While ARIMA captures the linear and trend-based structure, GARCH and EGARCH are tailored to model volatility changes and asymmetries. Conversely, neural networks provide a flexible approach

to learn nonlinear patterns, making them valuable when market behaviour deviates from linear assumptions.

5.2.5. Evaluation Metrics

The forecasting accuracy was assessed using the following error metrics:

1. Mean Error (ME)

$$ME = (1/n) * \Sigma(\hat{y}_t - y_t)$$

2. Mean Absolute Error (MAE)

$$MAE = (1/n) * \Sigma|\hat{y}_t - y_t|$$

3. Mean Absolute Percentage Error (MAPE)

$$MAPE = (100/n) * \Sigma|\hat{y}_t - y_t| / y_t$$

4. Mean Percentage Error (MPE)

$$MPE = (100/n) * \Sigma(\hat{y}_t - y_t) / y_t$$

5. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{[(1/n) * \Sigma(\hat{y}_t - y_t)^2]}$$

6. Mean Absolute Scaled Error (MASE)

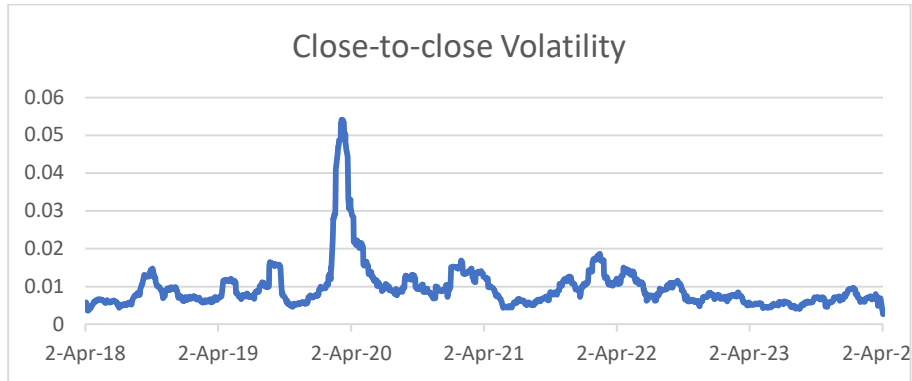
$$MASE = MAE / MAE \text{ of naive forecast}$$

7. Autocorrelation of Forecast Error at Lag 1 (ACF1)

5.3. Data Analysis and Interpretations

Historical or realised volatility estimation is performed by measuring the degree of variation in asset price returns over time. Among the different volatility estimators, the close-to-close, Parkinson, Garman-Klass, Rogers-Satchell, and Yang-Zhang volatility estimators have been used for estimating volatility. Close-to-close is calculated using the standard deviation of the logarithmic difference of the inter-day close price of the Nifty 50 Index. The plot for volatility estimated by the close-to-close method for the Nifty 50 Index is shown in Fig.5.1.

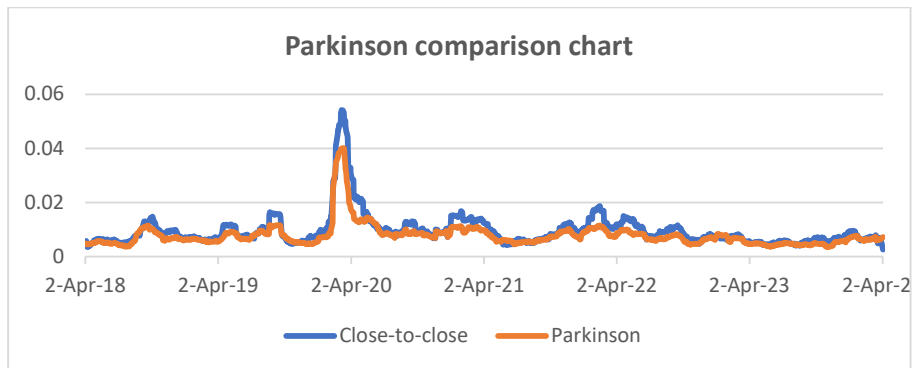
Figure 5.1 Volatility Estimated by Close-To-Close.



Note: Author's Work

Figure 5.1 illustrates the time-series pattern of volatility calculated using the close-to-close method over the sample period from April 2018 to March 2024. This method estimates volatility based solely on closing prices, making it straightforward but limited in its scope. The graph shows several periods of heightened volatility, with the most notable spikes occurring during the midpoint of the dataset and again toward the later years. In contrast, lower-volatility phases were observed primarily during the initial and central portions of the time range. These fluctuations reflect changes in market dynamics, such as price dispersion and investor behaviour. Overall, while the Close-to-Close estimator effectively captures broad volatility trends, it underrepresents intraday variability due to its reliance on a single data point per day.

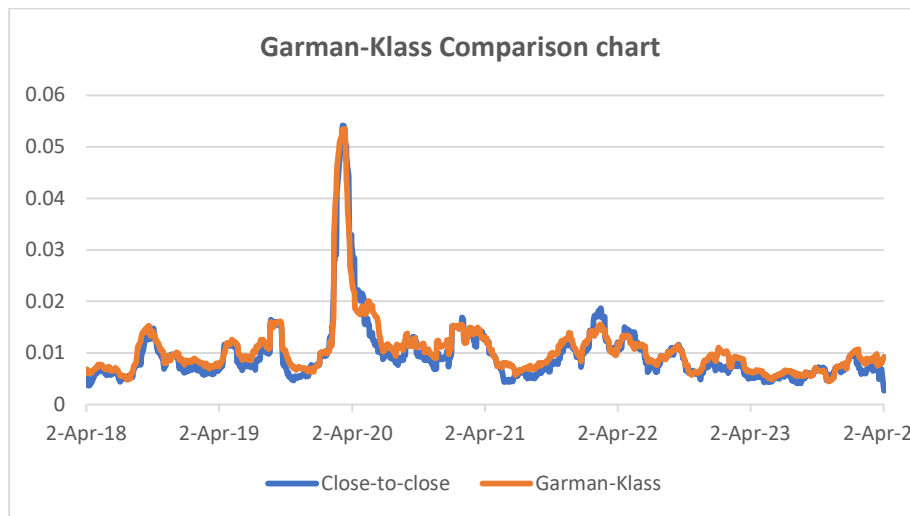
Figure 5.2 Comparison Chart for Volatility Estimated by Parkinson Estimator and Close-To-Close



Note: Author's Work

Figure 5.2 provides a comparative analysis of the Parkinson and Close-to-Close estimators. The Parkinson estimator, which incorporates daily high and low prices, consistently produces higher volatility estimates than the close-to-close method. This is especially evident during periods with wide price ranges, where the difference between the two estimators is more pronounced. The inclusion of intraday highs and lows allows the Parkinson model to capture more price variation, resulting in a more sensitive and informative measure of volatility. Notably, the two estimators move in parallel directionally, but the magnitude of the estimates varies, with the Parkinson estimator reacting more sharply during volatile stretches. This reinforces its utility in environments with substantial intraday price movements.

Figure 5.3 Comparison Chart for Volatility Estimated by Garman-Klass Estimator and Close-to-Close.



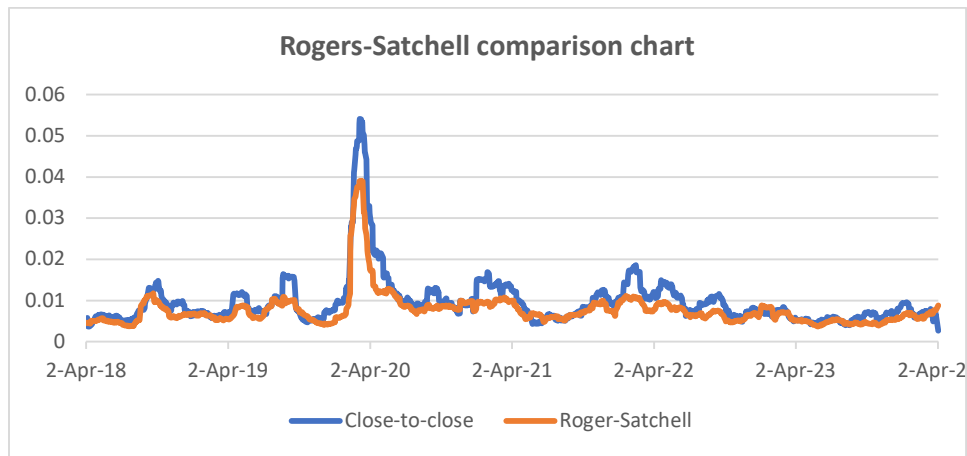
Note: Author’s Work

In Figure 5.3, the Garman-Klass estimator is compared with the close-to-close approach. The Garman-Klass model includes open, high, low, and close prices, enabling it to capture more comprehensive daily price activity. The graph reveals that the Garman-Klass estimator generates a smoother and moderately higher volatility curve than the close-to-close method. Peaks in the Garman-Klass line tend to align with those in the close-to-close graph, but the former offers a more continuous representation of volatility without abrupt jumps. This smoothness is a result of the model's ability to integrate multiple price points into a single volatility estimate, thereby reducing noise and enhancing the stability of the trend.

Figure 5.4 compares the volatility values produced by the Rogers-Satchell estimator with those from the close-to-close model. The Rogers-Satchell approach adjusts for non-zero drift in asset

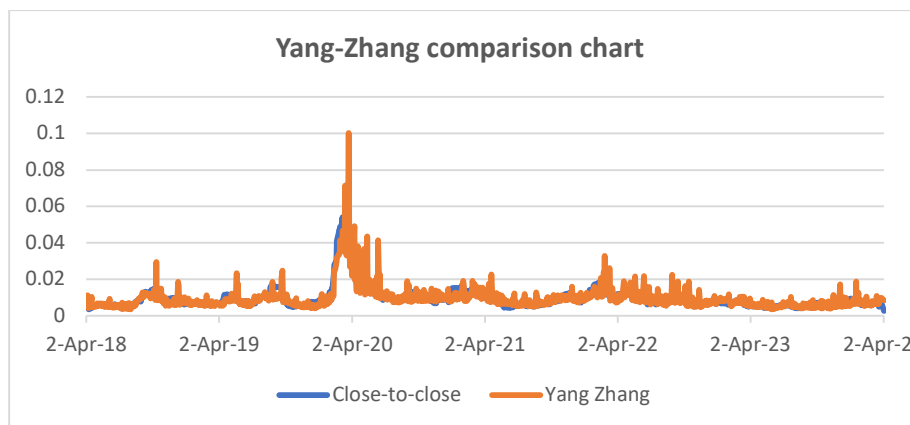
prices and includes open, high, low, and close data points. The graph shows that the Rogers-Satchell estimator often yields higher volatility levels, particularly during trending phases, where the price direction is more pronounced. The estimator captures variability more effectively during such phases compared to the close-to-close model, which tends to understate true volatility. The Rogers-Satchell line also displays smoother and more persistent patterns, reflecting its robustness in capturing both trend- and range-based price behaviours.

Figure 5.4 Comparison Chart for Volatility Estimated by Rogers-Satchell Estimator and Close-to-Close.



Note: Author's Work

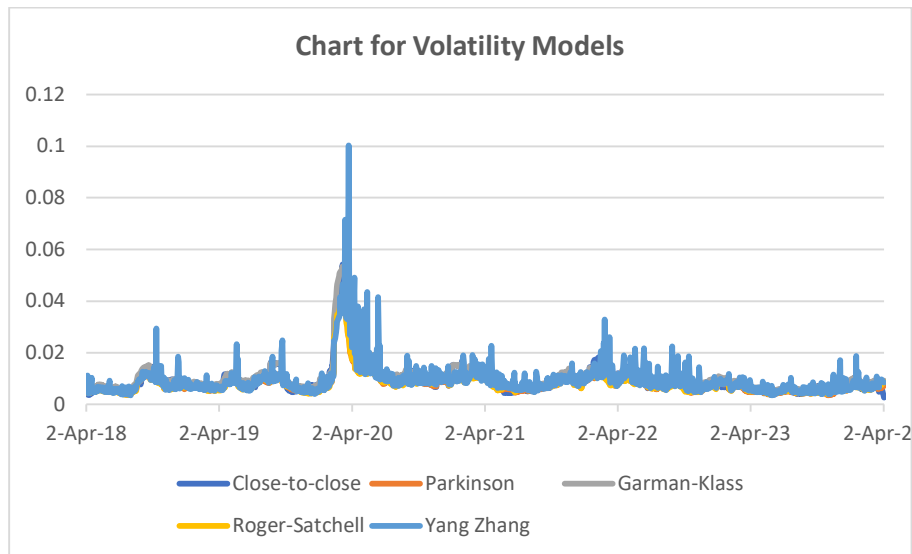
Figure 5.5 Comparison chart for volatility estimated by Yang-Zhang estimator and close-to-close.



Note: Author's Work

Figure 5.5 presents a comparison between the Yang and Zhang and Close-to-Close estimators. The Yang-Zhang model incorporates open-to-close and close-to-open returns and adjusts for drift, providing a comprehensive volatility estimate. The Yang-Zhang line consistently remains above the Close-to-Close line across the entire period, with sharper responses to sudden changes in price behavior. This is particularly evident during time segments where Close-to-Close shows smaller spikes, while Yang-Zhang records significantly higher volatility, indicating its effectiveness in capturing both intraday and overnight price movements. The model's ability to correct for bias and incorporate opening gaps enhances its reliability and accuracy across various market conditions.

Figure 5.6 Comparison Chart for Volatility Models



Note: Author’s Work

Figure 5.6 brings together all five volatility estimation models—close-to-close, Parkinson, Garman-Klass, Rogers-Satchell, and Yang-Zhang—for a direct comparison. The Close-to-Close estimator remains the lowest across most of the period, confirming its limited sensitivity to intraday variation. In contrast, the Yang-Zhang and Rogers-Satchell estimators consistently register the highest volatility values, particularly during periods of increased price movement. The Garman-Klass and Parkinson models fall in between, offering moderate but consistent estimates. The overall trend across the models remains aligned, although the magnitude and responsiveness differ. This comparative analysis highlights the importance of selecting appropriate volatility measures based on the data characteristics and modelling objectives.

Table 5.2 Performance of Volatility Estimators

Volatility Estimator	Bias	Relative Bias	Mean Squared Error (MSE)	Mean Absolute Difference (MAD)
Yang-Zhang	0.000024	0.021641	0.000024	0.002522
Roger-Satchell	-0.001953	-0.201364	0.000004	0.001983
Garman-Klass	0.000684	0.085277	0.000001	0.000684
Parkinson	-0.001819	-0.188306	0.000004	0.001839

Note: Author's Work

The comparison of volatility estimators based on four performance metrics—Bias, Relative Bias, Mean Squared Error (MSE), and Mean Absolute Difference (MAD)—provides a comprehensive assessment of their accuracy and efficiency relative to the Close-to-Close method. The Garman-Klass estimator demonstrated superior performance overall, achieving the lowest values in three out of four criteria: Relative Bias (0.085277), MSE (0.000001), and MAD (0.000684). This indicates that it not only maintains a low average deviation from the close-to-close estimator but also minimises both the squared and absolute deviations, highlighting its efficiency in capturing price volatility. The Yang-Zhang estimator, while not the best in every category, shows the lowest Bias (0.000024) and maintains a relatively small Relative Bias. This suggests that Yang-Zhang closely approximates the close-to-close estimator on average, although it exhibits a slightly higher variation than Garman-Klass, as reflected in its MSE and MAD. In contrast, the Roger-Satchell and Parkinson estimators exhibit negative bias values (-0.001953 and -0.001819, respectively), indicating a consistent tendency to underestimate volatility compared to the close-to-close method. Although Roger-Satchell performs better than Parkinson in terms of MAD, both estimators show relatively higher relative bias and less favourable overall efficiency than the other estimators.

In summary, the Garman-Klass emerges as the most efficient and accurate volatility estimator in this analysis. Yang-Zhang closely follows this, demonstrating a strong bias reduction performance. These findings suggest that the Garman-Klass is particularly well-suited for scenarios in which precision in volatility estimation is critical, especially when using intraday price components.

In this study, historical or realised volatility was forecasted using models designed to capture the key characteristics of financial time series, such as volatility clustering, inertia, and mean reversion. The models employed include ARIMA, GARCH, EGARCH, and a Neural Network with a feedforward architecture. The primary objective was to evaluate the performance of various volatility estimation techniques and assess the accuracy of the forecasts produced by these models.

After calculating the volatility using multiple estimation methods, a training dataset was created. This dataset served as the foundation for forecasting future volatility using the selected model. The performance of each model was then evaluated based on its ability to predict volatility, with a particular focus on minimising forecast errors.

Tables 5.3, 5.4, 5.5, and 5.6 present a summary of the forecasting accuracy for each volatility estimator, evaluated using a range of error measures. These accuracy metrics were calculated based on the difference between the forecasted and actual volatility values. For each volatility estimator, different forecasting models, such as ARIMA, GARCH, EGARCH, and Neural Networks, were applied and evaluated using RStudio. The table consolidates the results and provides a comparative overview of the model performance across various error criteria.

Table 5.3 Volatility Forecasting Accuracy using ARIMA Model

ARIMA	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Close-to-close	0.00149080	0.00182458	0.00150063	0.21050295	0.21417942	17.4291504	0.93932388
Parkinson	0.00066501	0.00101288	0.00073734	0.1039297	0.11763934	18.3741117	0.97871842
Garman-Klass	0.00099367	0.00145195	0.00106079	0.1162169	0.12574273	18.6019777	0.98063700
Roger-Satchell	0.00045710	0.00086444	0.00059868	0.0702898	0.09741723	14.8519524	0.95356302
Yang-Zhang	0.00027073	0.00167091	0.00106649	-0.0014888	0.14718947	0.78865746	0.19143847

Note: Author's Work

In Table 5.3, the ARIMA model's forecasting performance is evaluated using five volatility estimators. The Roger-Satchell estimator stands out with the lowest RMSE (0.00086) and MAPE (9.74%), suggesting that it is the most compatible with the ARIMA framework for capturing volatility patterns. The Close-to-close estimator also performs decently but with slightly higher error metrics. On the other hand, Yang-Zhang demonstrated weak performance with a MAPE of 14.7% and low ACF1 (0.19), implying less persistence in residuals but also instability in prediction. Thus, Roger-Satchell is the preferred volatility estimator for ARIMA.

Table 5.4 Volatility Forecasting Accuracy using GARCH Model

GARCH	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Close-to-close	0.00089147	0.00116407	0.00091588	0.12305266	0.13099411	10.6376000	0.87210754
Parkinson	0.00061534	0.00096814	0.00070707	0.09554743	0.11292548	17.6198513	0.97836879
Garman-Klass	0.00090566	0.001367285	0.00100022	0.10520993	0.11862389	17.5396484	0.98004178
Roger-Satchell	0.00040851	0.00082178	0.00057062	0.06195325	0.09299772	14.1555899	0.95203459
Yang-Zhang	-0.00401450	0.00440548	0.00414187	-0.6799543	0.68829752	3.0628538	0.33058570

Note: Author's Work

Table 5.4 reveals that the GARCH model improves forecasting accuracy compared to ARIMA for most of the volatility estimators. Again, Roger-Satchell showed excellent results, achieving the lowest RMSE (0.00082) and MAPE (9.29%) with reasonably low autocorrelation in the residuals (ACF1 = 0.95). In contrast, the Yang-Zhang estimator produces the worst results, with an alarmingly high RMSE (0.0044) and MAPE (68.8%), indicating large errors and a poor model fit. This table reinforces that GARCH handles volatility clustering well, particularly with the Roger-Satchell and Parkinson estimators.

As shown in Table 5.5, the EGARCH model, which is designed to handle asymmetry in volatility, is unexpectedly ineffective here. All estimators, including typically reliable ones such as Roger-Satchell and Parkinson, showed extremely high error metrics. For example,

Parkinson has a MAPE of 144% and an MASE of 144, indicating severe forecasting inaccuracy. Even the best performer, Yang-Zhang, yielded a MAPE close to 98%. Persistently high ACF1 values also suggest significant residual autocorrelation. In short, EGARCH fails to deliver reliable forecasts in the dataset context and underperforms across the board.

Table 5.5 Volatility Forecasting Accuracy using EGARCH Model

No	EGARCH	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
1	Close-to-close	0.00673038	0.00676533	0.00673038	0.99451838	0.99451838	78.1701044	0.6126141
2	Parkinson	0.00577894	0.00581554	0.00577894	0.99468078	0.99468102	144.008225	0.7886393
3	Garman-Klass	0.00775619	0.00780877	0.00775619	0.99440022	0.99440022	136.011080	0.8078342
4	Roger-Satchell	0.00564161	0.00567915	0.00564164	0.99387259	0.99387851	139.955524	0.7783602
5	Yang-Zhang	0.00645580	0.00669820	0.00646352	0.98114131	0.98252787	4.77967884	0.2766502

Note: Author's Work

Table 5.6 Volatility Forecasting Accuracy using Feedforward Neural Network

No.	FNN	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
1	Close-to-close	-5.59E-05	0.00061333	0.00050898	-0.0171294	0.07842924	5.91158583	0.79865537
2	Parkinson	-4.68E-05	0.00057448	0.00050815	-0.0168059	0.08678923	12.6628223	0.97022312
3	Garman-Klass	-4.21E-05	0.00079312	0.00069263	-0.0147549	0.08788397	12.1458899	0.97226221
4	Roger-Satchell	-0.0001215	0.00058032	0.00049894	-0.03007448	0.08722271	12.3775015	0.93501862
5	Yang-Zhang	-0.003355	0.00373849	0.00351697	-0.5776460	0.588297291	2.600748045	0.191476499

Note: Author's Work

Table 5.6 highlights the superior performance of the Feedforward Neural Network (FNN). The Close-to-close and Parkinson estimators particularly shine here, with MAPE values of 7.84% and 8.67%, respectively. The Close-to-close estimator also exhibited the lowest RMSE (0.00061) and minimal bias (ME nearly zero), making it the most effective combination overall. Across the board, the FNN delivers consistent and low-error results, except for the Yang-Zhang estimator, which again performs poorly (MAPE ~58.8%). Low ACF1 values across all estimators indicate that the FNN model successfully captures volatility's underlying structure.

5.4. Conclusion

This chapter undertakes a detailed exploration of historical or realised volatility estimation using five prominent estimators: Close-to-Close, Parkinson, Garman-Klass, Rogers-Satchell, and Yang-Zhang. Through graphical and quantitative comparisons, this analysis highlights the strengths and limitations of each estimator. While the Close-to-Close method provided a simple yet limited measure of volatility based solely on daily closing prices, the other models, particularly Garman-Klass and Yang-Zhang, captured more nuanced price behaviour by incorporating additional intraday data points and adjusting for bias and drift.

Among all estimators, Garman-Klass demonstrated the best overall statistical accuracy in terms of bias, relative bias, mean squared error (MSE), and mean absolute difference (MAD), making it the most reliable estimator in terms of consistency and precision. The Yang-Zhang estimator, though exhibiting a minimal average bias, showed greater variance in forecast accuracy, especially when used in volatility forecasting models.

In the second phase, volatility forecasts were generated using four different models: ARIMA, GARCH, EGARCH, and a Feedforward Neural Network (FNN). These models were evaluated across the five volatility estimators using various error metrics, including ME, RMSE, MAE, MPE, MAPE, MASE, and ACF1.

The ARIMA and GARCH models yielded reasonable performance, particularly when paired with the Rogers-Satchell and Parkinson estimators, which consistently showed lower forecasting errors than the others. In particular, the GARCH-Rogers-Satchell combination delivered the best performance under traditional time-series assumptions, reaffirming GARCH's strength of GARCH in modelling volatility clustering and persistence.

However, the Feedforward Neural Network clearly outperformed all traditional models in terms of forecast accuracy. It achieved the lowest RMSE, MAE, and MAPE values, particularly

with the Close-to-Close and Parkinson estimators. The neural network model's ability to learn complex nonlinear relationships is advantageous in capturing the underlying structure of volatility. This indicates that machine learning models can offer significant improvements over conventional time-series models in forecasting financial volatility, particularly in large datasets with complex patterns.

In contrast, the EGARCH model, despite its theoretical advantage in capturing asymmetries, failed to perform adequately across all estimators. It exhibited high forecast errors and residual autocorrelation, suggesting model misspecification or poor compatibility with dataset characteristics.

CHAPTER – 6

IMPLIED VOLATILITY STRUCTURE BY INDIAN NIFTY 50 INDEX OPTIONS

6.1. Introduction

A financial option is a contract that gives the holder flexibility, but not the requirement, to either buy or sell an underlying asset at a fixed price on or before a specified date. There are two main options for this. call options, which allow the holder to buy the asset, and put options, which allow the holder to sell the asset. European-style options can only be exercised on the exact date of expiration, whereas American-style options offer more flexibility by allowing the holder to exercise the option at any time until the expiration date.

For both types, implied volatility represents the level of future volatility that the market implicitly assigns to the option, such that the theoretical value derived from a pricing model aligns with the option's current market price. In other words, implied volatility is the volatility input that yields a theoretical option price equal to the observed market price when it is used in a particular pricing model.

Therefore, the option pricing process essentially involves assuming a volatility level in advance, which may or may not align with the actual realised volatility level. The most widely recognised model for option pricing, the Black-Scholes model (1973), provides a structured approach for estimating option values by incorporating implied volatility, which reflects market expectations of the future volatility of the underlying asset.

According to the Black–Scholes model, when implied volatility is plotted against strike prices for options with the same expiration date, the result should ideally be a flat horizontal line. This implies that all options—regardless of whether they are calls or puts and regardless of their strike prices—should exhibit the same implied volatility, provided that they are written on the same underlying asset and share the same maturity.

However, empirical research has shown that this is rarely the case. Instead, implied volatility typically follows a U-shaped pattern, rising as the strike price moves away from the at-the-money level. For call options, implied volatility increases as they move from deep in-the-money to at-the-money and again as they become deep out-of-the-money. A similar pattern was

observed for put options, although the directionality was reversed. This phenomenon, more pronounced in short-term options, results in what is commonly referred to as the "volatility smile", so named because the graph of implied volatility against strike price resembles the curved grin of the Cheshire Cat.

Analysts often translate option prices into implied volatilities when studying options with different strike prices, to better understand market expectations. Ideally, based on the Black-Scholes and Black models, implied volatility should remain constant across strike prices, forming a flat line (Black and Scholes, 1973; Black, 1976). However, real-world data frequently shows otherwise. A noticeable pattern often emerges where implied volatilities are higher for both low and high strike prices than for money. This pattern, known as the "volatility smile", reflects a U-shaped curve and signals deviations from the predictions of traditional models.

In contrast, stock index options typically exhibit a different trend, where implied volatility tends to decline as the strike price rises, forming what's known as a "volatility skew" (Rubinstein, 1994). Even so, many practitioners and researchers continue to use the term "volatility smile" broadly to refer to strike-dependent behaviour in implied volatility.

The so-called Smile Effect highlights the U-shaped relationship between strike price and implied volatility for options with the same maturity. This suggests that both in-the-money and out-of-the-money options are priced with higher implied volatilities than money options, pointing to market imperfections or differing risk perceptions (Dumas et al., 1998).

The Black-Scholes model, introduced in 1973, remains a foundational tool in option pricing. It assumes a single constant implied volatility for all options on the same underlying asset (Black & Scholes, 1973). However, consistent and systematic discrepancies between model and actual market prices have been widely documented. In practice, implied volatility varies not only across strike prices but also with time to maturity.

This leads to two important phenomena: the volatility smile, which describes changes in implied volatility across strike prices; and the term structure of implied volatility, which refers to changes over different expiration dates (Christensen and Prabhala, 1998). Together, these patterns underscore the limitations of the Black-Scholes model in fully capturing the dynamics of market-based option pricing.

Several empirical studies have analysed these patterns. For example, MacBeth and Merville (1979) found that in-the-money options with a shorter time to maturity often show higher implied volatilities than those with longer durations, supporting the idea that market behaviour deviates from standard theoretical models.

Shu and Zhang (2004) reported systematic deviations from the Black-Scholes model and noted that the structure of implied volatility varies depending on the option's time to maturity.

Shastri and Wethyavivorn (1987) identify a smile-shaped volatility structure in foreign currency options traded on the Philadelphia Stock Exchange (PHLX). Similarly, Sheikh (1991) found a U-shaped pattern in implied volatility for S&P 100 options on the CBOE during 1983–1985.

Heynen (1993) proposed that the smile function could explain the implied volatility structure in stock index options traded on the European Options Exchange (EOE). Rubinstein (1994) linked the smile effect to price jumps in the underlying security, as well as market frictions such as illiquidity, transaction costs, and trading restrictions, which prevent the existence of a single arbitrage-free option price.

Taylor and Xu (1994) also documented U-shaped implied volatility functions for foreign currency options on the PHLX from 1984 to 1992, noting that the intensity of the smile diminishes with longer times to maturity.

Duque and Paxson (1994) provide evidence of the smile pattern in equity call options on LIFFE, highlighting the relatively higher implied volatility for in-the-money options. Longstaff and Andreas (1996) and Canina and Figlewski (1993) explored the impact of transaction costs on option pricing and concluded that these costs significantly contribute to the divergence of implied volatility across strike prices.

Peña et al. (1998) confirmed the presence of a smile pattern in the Spanish IBEX-35 index options, while Hafner and Wallmeier (2001) found that market participants' perception of crash risk significantly shapes volatility smile.

Dumas, Fleming, and Whaley (1998) demonstrated that the implied volatility structure of index options can vary, ranging from a symmetric smile to a more skewed "sneer" shape. Building on this, Brown (1999) observed that in-the-money call options typically trade at higher implied volatilities than out-of-the-money call options.

Engström (2002) identified a U-shaped implied volatility pattern in the Stockholm Stock Exchange (StSE) during the 1995–1996 period. Similarly, Bollen and Whaley (2004) find a sneer-shaped volatility structure in S&P 500 index options based on an analysis of 20 stock options traded on the CBOE.

In the Indian context, Varma (2002) noted the presence of a volatility smile in the options market, accompanied by the mispricing.

Misra et al. (2006) found that both deeply in-the-money and deeply out-of-the-money options exhibit higher implied volatilities compared to at-the-money options.

Deo et al. (2008) explored the implied volatility surface for individual stock call options traded on the NSE and provided evidence supporting a U-shaped volatility structure. Their findings also indicate that in-the-money options tend to display greater implied volatility than out-of-the-money options.

Although Indian studies provide evidence of a volatility smile in the domestic options market, they are limited by the use of relatively short data periods, primarily because of the recent emergence of the derivatives market in India. Consequently, to obtain more conclusive results and a clearer understanding of the smile structure, it is necessary to examine implied volatility using a broader and more comprehensive dataset. This study undertakes this task, aiming to address the existing research gap in the literature on the Indian options market.

6.2. Research Methodology

6.2.1. Data Description

The analysis in this study is based on secondary data collected from Nifty 50 options traded on the NSE India, covering the period from 1 April 2018 to 31 March 2024. To examine the structure of both call and put options, a large dataset comprising 4,54, 645 call option observations and 4,58, 862 put option observations was utilised. A filtration criterion was applied to ensure the inclusion of only the liquid and relevant data. After applying the filtering process, the dataset retained 159,505 call options and 191,595 put option observations to analyse the implied volatility structure.

Filtration was based on specific criteria to enhance data quality and minimise biases. The primary criterion involved excluding all options with fewer than seven or more than 90 trading days remaining until expiration. This range was chosen to reduce potential liquidity distortions,

which often have minimal time premiums, making them highly sensitive to even small measurement errors, whereas long-term options typically experience low trading activity or are not traded at all on the exchange. This filtering approach aligns with prior studies, such as Bakshi et al. (1997) and Dumas et al. (1998), who implemented similar time-to-expiration thresholds in their analyses.

The second criterion involved removing option records with zero transaction volume at the close, as these do not reflect actual market activity and thus do not contribute meaningful data for analysis.

The third filtration criterion aimed to eliminate option prices that violated the basic arbitrage conditions, specifically, any call or put option priced below the corresponding Black-Scholes value at zero volatility. This was intended to minimise the influence of pricing anomalies arising from non-synchronous trading between options and their underlying assets.

6.2.2. The Black-Scholes option pricing model

The Black-Scholes Option Pricing model was employed to estimate the implied volatility of the options in this study. Various methodologies exist to determine the level of moneyness; however, the present analysis adopts the approach outlined by Engström (2001). Based on this framework, options were categorised into five distinct moneyness groups: deep in-the-money, in-the-money, at-the-money, out-of-the-money, and deep out-of-the-money. Prior to estimating the implied volatility, it was necessary to calculate both the time to maturity and the continuously compounded risk-free interest rate, as these are fundamental inputs in the generation of the implied volatility series.

The Black-Scholes model calculates the theoretical price of a European option using the following formula:

$$C = SN(d_1) - Xe^{-rT} N(d_2) \quad \text{Eq-6.1}$$

$$P = Xe^{-rT} N(-d_2) - SN(-d_1) \quad \text{Eq-6.2}$$

$$d_1 = \frac{\log(s/x) + (r + \sigma^2/2)t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

Where:

- C = Price of the call option (the cost to buy the right to purchase the asset)
- P = Price of the put option (the cost to buy the right to sell the asset)

- S = Current market price of the underlying stock or asset
- X = Strike (exercise) price of the option—the predetermined price at which the asset can be bought or sold
- T = Time to expiration, expressed in years (e.g., 3 months = 0.25 years)
- r = Continuously compounded annual risk-free interest rate applicable over period T
- σ (sigma) = Annualized volatility of the asset's return (a measure of how much the price fluctuates)
- $N(\bullet)$ = Cumulative distribution function of the standard normal distribution (i.e., the probability that a value from a standard normal distribution is less than or equal to a given number)

The risk-free interest rate is an important variable for estimating the implied volatility. In the present analysis, we used the yield from 91-day Treasury bills for the relevant timeframe. 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.

6.2.3 Time to maturity

Time to maturity refers to the remaining period until a financial instrument, typically a bond or derivative, reaches its predetermined expiration or maturity date, when the issuer repays the principal or settles the contract. It is a critical factor in financial valuation that directly influences the pricing, yield, and risk profile of securities. Longer maturities usually imply greater exposure to interest rate fluctuations, increasing duration, and interest rate risk, whereas shorter maturities are more sensitive to reinvestment risk. In derivatives such as options, time to maturity affects the time value component of pricing models like Black-Scholes, with value generally eroding as maturity approaches—a phenomenon known as time decay. Investors and portfolio managers strategically use time-to-maturity to align investments with liquidity needs, risk tolerance, and market outlook, often employing techniques such as bond-laddering or barbell strategies to optimise returns and manage risk.

6.2.4. Moneyness

Moneyness is a fundamental concept in options theory that reflects the intrinsic value of an option relative to the current market price of an underlying asset. This indicates the degree to which an option is profitable or unprofitable if exercised immediately. Moneyness is typically expressed as the ratio between the spot price (S) and the strike price (K). It significantly

influences both the option premium and the likelihood of exercising. The following are the commonly used moneyness categories:

Table: 6.1. Models for the Estimation of Moneyness

S. No.	Moneyness Formula	Author(s)	Description
1	$M_n = X / F$	Jackwerth & Rubinstein (1996)	Ratio of strike to forward price
2	$M_n = 1 - (X / F)$	Dumas, Fleming & Whaley (1996)	Relative deviation from forward price
3	$M_n = 1 - (F / K)$	Brown (1999)	Relative measure using strike as denominator
4	$M_n = \ln (X / S)$	Malin Engström (2001)	Log-moneyness using strike and spot price
5	$M_n = (S - PVD) \cdot e^{(-rt)}$	Bollen & Whaley (2002)	Present value difference adjusted for interest rate and dividends

6.2.5. Moneyness Categories and Interpretation for Calls and Puts

1. Deep In the Money (DITM)

- Call Option: $\frac{S}{K} > 1.10$
- Put Option: $\frac{K}{S} > 1.10$
- A deep in-the-money option has a substantial intrinsic value. For a call option, this means that the spot price is significantly higher than the strike price, making it highly profitable to exercise. Conversely, for a put option, the strike price is significantly higher than the spot price. These options are more expensive because of their high intrinsic value and delta approaching 1 (for calls) or -1 (for puts).

2. In the Money (ITM)

- Call Option: $1.05 < \frac{S}{K} \leq 1.10$

- Put Option: $1.05 < \frac{K}{S} \leq 1.10$
- In The Money options have a positive intrinsic value but to a lesser extent than DITM. For calls, the spot is moderately above the strike price, and for puts, the strike is moderately above the spot price. These options are often exercised if held until expiration and are more sensitive to changes in volatility (Vega) and interest rates (Rho).

3. At the Money (ATM)

- Both Call and Put Options: $0.95 \leq \frac{S}{K} \leq 1.05$
- ATM options occur when the strike price is nearly equal to the spot price. These options typically have no intrinsic value but possess the highest time values. They are the most sensitive to volatility and changes in the underlying price (gamma is maximised).

4. Out of the Money (OTM)

- Call Option: $0.90 \leq \frac{S}{K} < 0.95$
- Put Option: $0.90 \leq \frac{K}{S} < 0.95$
- An OTM option has no intrinsic value and would not be profitable if exercised immediately. For calls, the strike is above the spot, and for puts, the strike is below the spot. These options are cheaper and are generally used for speculative purposes or high-risk hedges.

5. Deep Out of the Money (DOTM)

- Call Option: $\frac{S}{K} < 0.90$
- Put Option: $\frac{K}{S} < 0.90$
- DOTM options are far from being profitable and have very low premium rates. The probability of them expiring in the money is extremely low. However, they offer high leverage with limited capital, which attracts speculative traders.

6.2.6. Moneyness Definitions (with Ratios)

S= Spot Price ; K = Strike Price

Table 6.2 Moneyness Category (Call Options)

Moneyness Category	Condition (S/K)	Interpretation
Deep In the Money (DITM)	$\frac{S}{K} > 1.10$	Spot price is much higher than strike, high intrinsic value
In The Money (ITM)	$1.05 < \frac{S}{K} \leq 1.10$	Spot price moderately above strike — some intrinsic value
At The Money (ATM)	$0.95 \leq \frac{S}{K} \leq 1.05$	Spot and strike are close — no/little intrinsic value
Out of The Money (OTM)	$0.90 \leq \frac{S}{K} < 0.95$	Spot price slightly below strike — no intrinsic value
Deep Out of The Money (DOTM)	$\frac{S}{K} < 0.90$	Spot much below strike — worthless to exercise

Note: Author's work**Table 6.3 Moneyness Category (Put Options)**

Moneyness Category	Condition (S/K)	Interpretation for Put Option
Deep In the Money (DITM)	$S/K < 0.90$	Spot price is much lower than strike price → Put is highly valuable (deeply profitable).
In The Money (ITM)	$0.90 \leq S/K < 0.95$	Spot is still below strike price → Put is profitable, but not deeply so.
At The Money (ATM)	$0.95 \leq S/K \leq 1.05$	Spot is close to strike → Little to no intrinsic value; mostly time value.
Out of The Money (OTM)	$1.05 < S/K \leq 1.10$	Spot is above strike → Put is unprofitable to exercise now.
Deep out of the money (DOTM)	$S/K > 1.10$	Spot is much higher than strike → Put is far from being profitable.

Note: Author's work

6.3. Descriptive Statistic and Result

Table 6.4. Implied volatility in terms of time to maturity of Call options

Statistic	7-10	11-20	21-30	31-40	41-50	51-60	61-70-	71-80	81-90
Mean	0.2902	0.2182	0.1876	0.1832	0.1659	0.1559	0.155	0.1475	0.1424
Minimum	0.0508	0.0446	0.0367	0.0436	0.0363	0.0318	0.043	0.0345	0.0437
Maximum	3.4649	2.2902	1.7289	1.9051	1.6911	1.3623	1.318	1.0356	1.2207
Std. Dev.	0.2289	0.1428	0.0983	0.1040	0.0811	0.0599	0.066	0.0598	0.0613
Total	17451	24356	31835	20951	22206	16113	12093	10085	4415

Note: Author's work

Table 6.5. Implied volatility in terms of Moneyness of the Call option

Statistic	DITM	ITM	ATM	OTM	DOTM
Mean	0.4608	0.2008	0.1489	0.1552	0.2722
Minimum	0.0849	0.0318	0.0345	0.0742	0.0862
Maximum	3.46494	1.4892	0.9677	0.8945	1.4672
Std. Dev.	0.2907	0.0879	0.0567	0.0551	0.1469
Total	8013	24737	54679	51674	20402

Note: Author's work

Tables 6.4 and 6.5 present the descriptive statistics of implied volatility based on different maturities and moneyness levels. Table 6.4 shows that implied volatility varies with time to maturity; it is higher for options with shorter maturities and lower for those with longer maturities. Table 6.5 indicates that implied volatility also changes with moneyness.

Specifically, implied volatility is higher for deep in-the-money and deep out-of-the-money options than for at-the-money options.

These patterns suggest that implied volatility is not constant across different maturities and moneyness levels, potentially resulting in a volatility "smile" rather than a flat implied volatility curve. This observation contradicts the key assumption of the Black-Scholes option pricing model, which assumes constant volatility, regardless of the strike price or time to maturity. Descriptive statistics offer initial evidence of this deviation, and the presence of a volatility smile becomes more apparent when the implied volatility is visualised graphically.

Table 6.6. A bivariate representation of grouped average call implied volatilities concerning moneyness and time to maturity is presented.

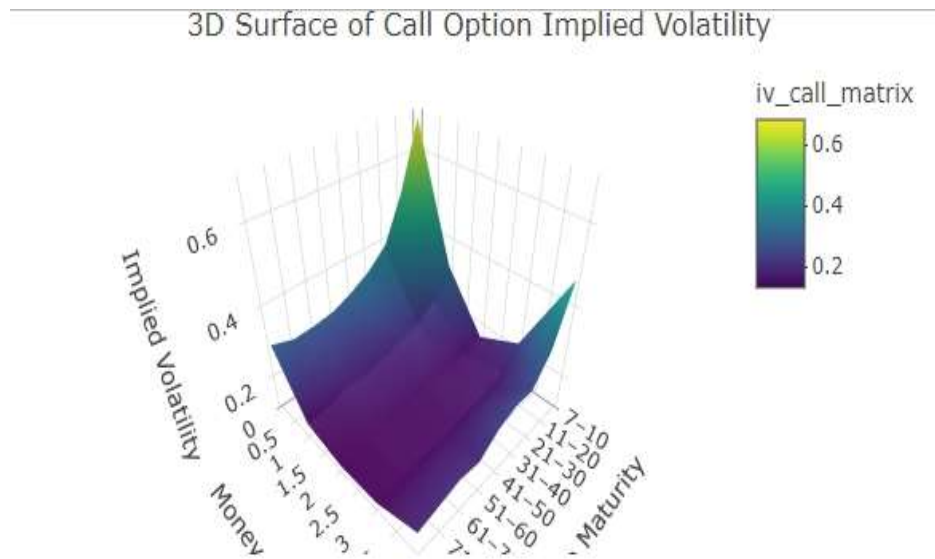
Moneyness Group	Time to Maturity								
	7-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90
DITM	0.6822	0.5130	0.3915	0.3438	0.3125	0.2894	0.2819	0.2797	0.3013
ITM	0.3293	0.2519	0.2123	0.2023	0.1843	0.1731	0.1749	0.1592	0.1545
ATM	0.1719	0.1545	0.1526	0.1551	0.1472	0.1452	0.1429	0.1361	0.1312
OTM	0.2281	0.1803	0.1608	0.1575	0.1492	0.1449	0.1429	0.1386	0.1372
DOTM	0.4737	0.3238	0.2560	0.2585	0.2394	0.1996	0.2078	0.1950	0.1818

Note: Author's work

Table 6.6 shows that the implied volatility for call options generally decreases as the time to maturity increases across all moneyness categories. Deep in the Money (DITM) and Deep Out of the Money (DOTM) options have the highest implied volatilities, reflecting greater risk or uncertainty, whereas At the Money (ATM) options consistently have the lowest volatility, indicating more stable pricing. The pattern reveals a typical volatility smile, where options far from the current price (either DITM or DOTM options) are more volatile. Overall, the market

anticipates less risk over longer time horizons, resulting in lower implied volatilities as maturity extends further.

Figure 6.1 Three-Dimensional graph for volatility implied by Call Index Option Nifty50, NSE



Note: Author's work

Table 6.7. Implied volatility in terms of time to maturity of Put options

Statistic	7-10	11-20	21-30	31-40	41-50	51-60	61-70-	71-80	81-90
Mean	0.4521	0.3396	0.2625	0.1852	0.1693	0.1744	0.1943	0.1832	0.1842
Minimum	0.0365	0.0472	0.0087	0.012	0.0485	0.0434	0.0371	0.0254	0.075
Maximum	2.6370	3.5767	1.7069	1.6177	1.2503	1.0144	0.9647	1.0289	0.869
Std. Dev.	0.2774	0.1917	0.1497	0.1172	0.0884	0.0736	0.0912	0.0801	0.0765
Total	20425	29326	38890	24272	26457	19439	14510	12636	5640

Note: Author's work

Table 6.8. Implied volatility in terms of Moneyness of the Put options

Statistic	DITM	ITM	ATM	OTM	DOTM
Mean	0.345337172	0.17770563	0.15779433	0.242770663	0.442643704
Minimum	0.073727066	0.025424084	0.008791983	0.038652888	0.124207665
Maximum	3.576752507	1.308816396	1.156506098	1.259829535	2.637092212
Std. Dev.	0.20770404	0.073324013	0.081066247	0.11082491	0.238982914
Total	10048	34060	58961	50371	58961

Note: Author's work

The structure of implied volatility (IV) in put options, as shown in Tables 6.7 and 6.8, reveals distinct patterns based on time to maturity and moneyness. Table 6.7 illustrates a downward-sloping term structure, where IV decreases as the time to maturity increases. Short-term options (7–10 days) exhibit the highest average IV, which gradually declines for options with longer maturities (up to 30 days), indicating higher uncertainty and risk premiums in the short term. In contrast, Table 6.8 displays a volatility smile across moneyness levels, where deep in-the-money (DITM) and deep out-of-the-money (DOTM) options have higher implied volatilities than at-the-money (ATM) options, which have the lowest implied volatilities. This smile pattern reflects the market's pricing of extreme-strike options with additional risk premiums due to lower liquidity and greater demand for protective or speculative strategies. Together, these tables confirm that implied volatility is not constant but varies systematically with both the time to maturity and moneyness.

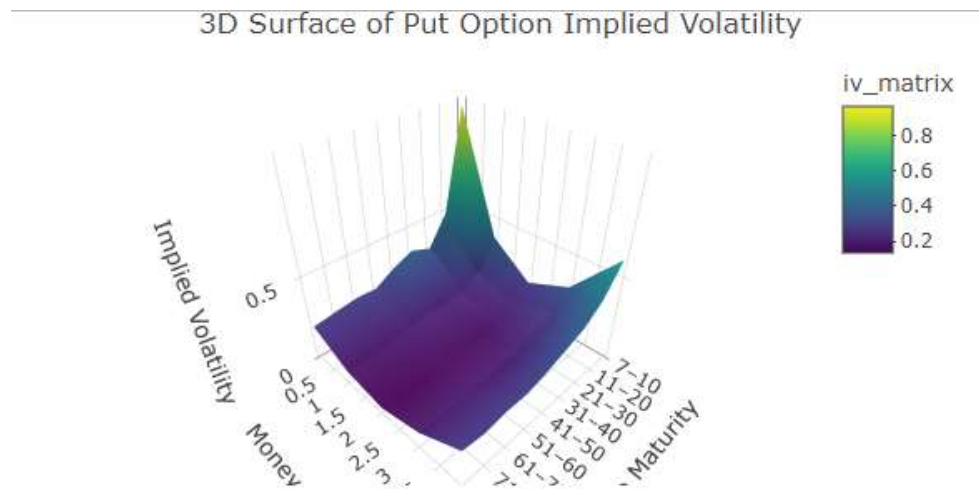
Table 6.9 A bivariate representation of grouped average put implied volatilities concerning moneyness and time to maturity is presented.

Moneyness Group	Time to Maturity								
	7–10	11–20	21–30	31–40	41–50	51–60	61–70	71–80	81–90
DITM	0.9661	0.4979	0.3554	0.3912	0.3512	0.2941	0.2978	0.2852	0.2704
ITM	0.4142	0.2689	0.2180	0.2116	0.2074	0.1896	0.1791	0.1732	0.1721
ATM	0.2702	0.2234	0.185	0.1556	0.1515	0.1502	0.1388	0.1345	0.1371
OTM	0.3557	0.2793	0.2437	0.2091	0.1910	0.1881	0.1916	0.1849	0.1867
DOTM	0.5912	0.4618	0.3897	0.3548	0.3203	0.2948	0.2948	0.2788	0.2905

Note: Author’s work

Table 6.9 illustrates that the put implied volatility declines as the time to maturity increases across most moneyness groups, indicating reduced uncertainty over the long term. Deep in the Money (DITM) and Deep Out of The Money (DOTM) puts show the highest volatilities, especially at shorter maturities, highlighting the higher risk perception. The at-the-money (ATM) and in-the-money (ITM) puts display lower and more stable volatility, suggesting greater pricing confidence. Similar to calls, this also reflects a volatility smile, with extremes in moneyness having elevated volatility. Overall, the trend supports the notion that option premiums shrink with time and risk is perceived to diminish as expiry approaches.

Figure 6.2 Three-Dimensional graph for volatility implied by Put Index Option Nifty50, NSE



Note: Author's work

6.4. Conclusion

A detailed analysis of implied volatility (IV) across Nifty 50 index options provides several important insights into how market participants perceive and price risk. Two dominant patterns emerged from the descriptive statistics and bivariate tables.

First, implied volatility consistently decreases as the time to maturity increases. This trend is evident for both call and put options across all moneyness levels. Short-term options (7–10 days) show significantly higher average implied volatilities than longer-dated contracts (81–90 days). This reflects the market's expectation of greater uncertainty in the short run, as more immediate events (such as earnings, news, or economic announcements) can cause price fluctuations. Conversely, longer-term options are viewed as relatively more stable and thus carry lower implied volatility, suggesting a reduced perceived risk as the expiry horizon extends.

Second, and perhaps more strikingly, the data reveal a volatility smile pattern across moneyness. Whether looking at call or put options, both deep in-the-money (DITM) and deep out-of-the-money (DOTM) options exhibit higher implied volatilities than ATM (at-the-

money) options. This U-shaped curve is a common phenomenon in real-world markets and reflects several practical considerations. For instance, DOTM options are often used for speculative strategies or tail-risk protection, leading to higher demand and, hence, higher premiums. Similarly, DITM options may have liquidity issues or reflect strong directional bets, contributing to the increased volatility. Meanwhile, ATM options are the most actively traded and typically reflect a consensus view of market pricing; hence, they exhibit relatively lower volatility.

These patterns contrast with the constant volatility assumption of the Black-Scholes model, which assumes that implied volatility is uniform across all strikes and maturities. The observed data clearly challenge this assumption and highlight the need for more flexible models that incorporate the actual behaviour of implied volatility in the market, such as stochastic volatility models or those with volatility skew and smile adjustments.

In conclusion, the structure of implied volatility is far from being flat or constant. It is shaped by the time to maturity and the option's moneyness, reflecting the complex nature of investor expectations, risk perceptions, and market dynamics. These findings not only improve our understanding of option pricing behaviour but also reinforce the importance of choosing the right volatility model for accurate forecasting and valuations.

CHAPTER 7

FINDINGS, SUGGESTIONS AND CONCLUSION OF THE STUDY

7.1. Introduction

Over the past few decades, derivatives have emerged as essential financial instruments in several emerging economies, primarily for risk management. Their introduction has attracted significant attention from policymakers, academics, market participants, and regulators because of their multifaceted utilities. While derivatives offer speculators exposure under the guise of hedging for investors, they simultaneously raise concerns about potentially destabilising spot markets. India, with its long and storied history in the Asian financial landscape dating back to the late 18th century during the era of the East India Company, has witnessed significant evolution in its capital markets, particularly since the liberalisation of its economy in the 1990s. Key institutional developments, including the formation of the Securities and Exchange Board of India (SEBI), the National Stock Exchange (NSE), and technological advancements, have contributed to increased transparency, lower transaction costs, and enhanced investor confidence.

One of the most transformative developments was the introduction of derivative trading, which SEBI formally permitted in 2000. Trading began with index futures and quickly expanded to include options on indices and individual securities, followed by interest rate futures. Today, India stands as the second-largest emerging derivatives market after China, with significant participation from both domestic and global investors. Among the various derivative instruments, options trading has gained particular popularity because of its effectiveness in risk hedging and flexibility for hedgers, speculators, and arbitrageurs alike.

The popularity of options surged following the introduction of the Black-Scholes Option Pricing Model (BSOPM) in 1973, which laid the foundation for pricing efficiency and innovation in financial markets. Although alternative models such as the Binomial Model, Jump Diffusion, Cox-Ross-Rubinstein, Monte Carlo Simulation, and others have been proposed to address the limitations of the BSOPM, it remains a cornerstone of financial theory and practice. A critical application of the BSOPM lies in the estimation of implied volatility, a

forward-looking metric that reflects market participants' expectations of future price fluctuations. While implied volatility is theoretically expected to remain constant, empirical evidence often reveals patterns such as the "volatility smile", reflecting deviations based on the moneyness of options, as discussed in the seminal works of Macbeth and Merville (1979), Rubinstein (1985), and Derman and Kani (1994).

This chapter consolidates the empirical research conducted to analyse the efficiency, volatility dynamics, and implied volatility structures of the Nifty 50 index options traded on the NSE from April 2018 to March 2024. It achieves this by applying a rigorous methodology rooted in both classical financial theory and modern econometric and machine learning approaches. The chapter is organised into several key sections: a restatement of the research hypotheses; a detailed description of the data sources and methodology; an empirical examination of the research objectives; an interpretation of the key findings; practical implications for various stakeholders; and a conclusive summary accompanied by recommendations for future research. Through this integrated framework, this study provides a robust assessment of pricing behaviour, the predictive accuracy of volatility models, and the structural patterns of implied volatility in the Indian options market.

7.2. Research Hypotheses

To evaluate the market efficiency and implied volatility patterns in the Indian options market, the following null hypotheses were formulated and tested.

Ho1: After factoring in transaction costs, there is no significant frequency or magnitude of violations for both call and put Nifty index options when using the Black-Scholes model.

Ho2: There is no significant difference in the forecasting performance of different volatility models in pricing Nifty Index Options.

Ho3: The Indian options market makes a volatility smile.

These hypotheses directly align with the study's overarching goals of testing the theoretical and empirical consistency of the Indian options market with the efficient market hypothesis (EMH) and examining the structural implications of implied volatility across strike prices and maturities.

7.3. Data and Methodology

The data utilised in this study comprise daily observations of Nifty 50 index options, index futures, and the Nifty 50 spot index from 1 April 2018 to 31 March 2024. The dataset includes 454,645 call option contracts and 458,862 put option contracts. After applying the filtering criteria for zero-volume trades, range-bound maturities (7–90 days), and contracts satisfying lower boundary pricing constraints, the effective sample was reduced to 159,505 call options and 191,595 put options.

The additional datasets included the following:

- The risk-free rate data were obtained from 91-day Treasury bills published by the RBI.
- Transaction cost data, including brokerage fees, Securities Transaction Tax (STT), and other trading charges, were collected through interviews with active brokers.
- The methodology is as follows.
- Calculating theoretical option prices using the Black-Scholes model with Weighted Implied Standard Deviation (WISD).
- Five volatility estimation techniques were used.
- Applying econometric and machine learning models to forecast volatility.
- Testing the statistical significance of mispricing via the Mann-Whitney U-test and the Kolmogorov-Smirnov test.
- Mapping implied volatility across moneyness and time to maturity.

7.4. Empirical Methodology

7.4.1. Model Calibration

The Black-Scholes Option Pricing Model (BSOPM) was used to derive the theoretical values for each option in the dataset. Because volatility is unobservable and critical for pricing, this study adopted the WISD as a proxy, allowing for the extraction of implied volatility across varied strike prices and maturities.

7.4.2. Volatility Estimation Models

The following realised volatility estimators were implemented:

- **Close-to-Close Estimator:** Traditional method using daily returns.
- **Parkinson Estimator:** Utilises the high-low price range.
- **Garman-Klass Estimator:** Incorporates open-high-low-close data.
- **Rogers-Satchell Estimator:** Accounts for directional bias.
- **Yang-Zhang Estimator:** Hybrid approach improving forecast accuracy.

7.4.3. Forecasting Models

To evaluate the volatility forecasting accuracy, the following models were tested.

- **ARIMA** (Auto-Regressive Integrated Moving Average)
- **GARCH** (Generalized AutoRegressive Conditional Heteroskedasticity)
- **EGARCH** (Exponential GARCH)
- **Feedforward Neural Network (FNN)**

The performance of each model was assessed using the following:

- **RMSE** (Root Mean Square Error)
- **MAE** (Mean Absolute Error)
- **MAPE** (Mean Absolute Percentage Error)
- **MASE** (Mean Absolute Scaled Error)
- **ACF1** (First-order Autocorrelation)

7.5. Major Findings by Research Objective

7.5.1 Market Efficiency of Nifty Index Options

The efficiency test results revealed that a significant number of pricing violations existed when comparing market prices with theoretical prices.

- **Call Options:** Approximately 28% exhibited mispricing before transaction costs.
- **Put Options:** Over 80% of contracts showed violations before costs.

However, after incorporating transaction costs:

- The exploitability of mispricing falls to **1.87% for call options** (retail investors).

- For **put options**, post-cost arbitrage opportunities were limited to **27% of the retail sample**.

This demonstrates that transaction costs play a crucial role in eliminating arbitrage opportunities and maintaining the market equilibrium.

The Mann-Whitney U-test further confirms that the distribution of profit magnitudes for retail and institutional traders differs significantly, particularly for put options. Institutional investors have a lower negative average profit magnitude than retail traders, reflecting their relatively better access to information, infrastructure, and execution.

7.5.2 Comparing Volatility Forecasting Models

Among the volatility forecasting models evaluated:

- **The FNN (Neural Network)** emerged as the best model across all error metrics, effectively capturing non-linear patterns in market behaviour.
- **EGARCH** followed closely, performing better than ARIMA and GARCH in terms of robustness and adaptability to asymmetric volatility clustering.
- **Close-to-Close estimator** showed the highest forecasting error, reaffirming its limitations in complex derivative pricing environments.

These findings underscore the increasing relevance of machine learning in financial modelling, particularly in volatile and high-frequency trading environments.

7.5.3 Structure of Implied Volatility across Time and Moneyness

The implied volatility surface analysis confirmed the presence of a "volatility smile" in the Indian options market. Key observations:

- **U-shaped curve** was evident across moneyness, with in-the-money and out-of-the-money options priced with higher implied volatilities.
- **Short maturities** exhibit higher IV levels, indicating heightened investor sensitivity to short-term market uncertainty.
- **At-the-money options** presented the lowest IV, which is consistent with the standard theoretical predictions.

These findings reject H_0 , confirming that the Indian options market exhibits a volatility smile and that risk is asymmetrically priced based on strike distance and maturity.

Jointly Contribute to Market Efficiency of Indian Index Options

- **Linking pricing efficiency and volatility forecasting:** If the market is efficient, price changes should already incorporate information about volatility. Showing whether forecasted volatility improves (or fails to improve) efficiency metrics could connect the two strands.
- **Linking pricing efficiency and the implied volatility smile:** The smile captures option market participants' perception of risk and potential mispricing. Discussing whether deviations in the smile align with inefficiencies in the underlying asset market could strengthen the argument.
- **Linking volatility forecasting and the smile:** Since implied volatility embeds forward-looking information, comparing its predictive power with statistical forecasts (e.g., GARCH, ML models) would show whether option-implied measures reinforce or contradict model-based volatility predictions.
- **Overall synthesis:** Position these three analyses as complementary lenses: efficiency tests show how quickly information is priced in; volatility forecasting evaluates the market's predictability; and the volatility smile reflects option traders' pricing of risk. Together, they can provide a multidimensional picture of market efficiency.

Why FNNs can be better than LSTM/GRU:

1. Simplicity and Efficiency

- FNNs have a simpler architecture, making them faster to train and requiring fewer computational resources.
- LSTMs/GRUs are more complex, with gates and recurrent connections, which can be overkill for problems without long-term dependencies.

2. When Data Has Limited Sequential Dependencies

- If the time-series task doesn't strongly rely on long temporal patterns (e.g., if short windows or engineered features already capture the dependencies), FNNs may perform just as well or better.

3. Lower Risk of Overfitting

- LSTMs/GRUs, with their larger number of parameters, are more prone to overfitting, especially with small or noisy datasets.

- FNNs, being less complex, often generalize better in these situations.

4. Easier Hyperparameter Tuning

- Training and optimizing FNNs is usually more straightforward.
- LSTMs/GRUs require careful tuning (learning rate, hidden size, number of layers, sequence length), which can complicate experimentation.

5. Interpretability

- FNNs are easier to interpret and explain in many applications compared to recurrent architectures, which are more “black-box.”

7.6. Implications

The implications of this study are significant in multiple dimensions.

7.6.1. Theoretical Implication of the study

This study contributes to the growing body of literature on market efficiency by examining evidence from an emerging market context. While much of the existing research on derivatives pricing and efficiency has focused on developed markets, this work provides fresh insights into the dynamics of an emerging economy. By doing so, it highlights the extent to which traditional theoretical models remain applicable or require modification when applied outside mature market settings. The findings therefore enrich the discourse on informational efficiency and arbitrage opportunities in less-developed financial systems.

In addition, the study extends the application of option pricing theories, such as the Black–Scholes model and the Put–Call Parity (PCP) framework, to real-world datasets where deviations from theoretical benchmarks are frequently observed. These deviations not only underscore the limitations of classical models but also reflect the presence of practical frictions, behavioral factors, and institutional constraints inherent in actual trading environments. The empirical evidence provided helps bridge the gap between theoretical constructs and observable market outcomes.

A further contribution of the research lies in its demonstration of the role of volatility modeling techniques including GARCH, EGARCH, and neural network approaches in enhancing option pricing accuracy. By comparing alternative volatility forecasting frameworks, the study underscores how improvements in volatility estimation directly translate into reductions in

pricing errors. This reinforces the critical importance of volatility dynamics in derivatives valuation and provides practitioners with more effective tools for managing risk and identifying mispriced securities.

The analysis also sheds light on the effects of moneyness and maturity in explaining observed patterns of option mispricing. The results suggest that deviations from theoretical pricing models are not uniform across the option surface; rather, they systematically vary depending on whether options are in-, at-, or out-of-the-money, as well as across different maturity horizons. These findings provide a more granular understanding of how structural market characteristics and trader behavior interact to shape pricing inefficiencies.

Finally, the study offers a foundation for further theoretical and empirical research on the role of behavioral biases, liquidity constraints, and market microstructure in shaping derivative markets. By documenting systematic departures from classical pricing models, it opens the door to richer theoretical frameworks that integrate elements of investor psychology, trading frictions, and institutional features. This not only deepens the academic understanding of option markets but also has practical implications for regulators, policymakers, and practitioners seeking to foster more efficient and resilient financial systems.

7.7.2 Practical Implication for Investors

The findings of this study carry significant implications for investors operating in emerging derivatives markets. The presence of systematic mispricing opportunities particularly concentrated around at-the-money contracts and those with short maturities suggests that arbitrage gains may be attainable. For sophisticated traders, such inefficiencies provide avenues for profit generation, provided that appropriate risk management and cost considerations are taken into account.

However, the study also demonstrates that reliance on the traditional Black–Scholes framework is insufficient for accurate valuation in these contexts. Investors are therefore encouraged to adopt advanced volatility modeling techniques such as GARCH, EGARCH, or neural network approaches, which have been shown to yield more accurate pricing outcomes. Incorporating such models into trading strategies enhances the reliability of valuations and reduces the likelihood of persistent pricing errors.

At the same time, the potential for arbitrage is tempered by the realities of transaction costs and liquidity risks. These frictions can substantially erode or even eliminate theoretical profit

margins, particularly in emerging markets where market depth may be limited. As such, investors must carefully account for these factors before committing capital to arbitrage-based strategies.

For retail investors, the implications are somewhat different. While they may lack the resources to exploit arbitrage opportunities at scale, understanding systematic mispricing patterns can still enhance decision-making. By being aware of the tendencies of options pricing to deviate from theoretical values, retail investors can manage their risk exposure more effectively and avoid overpaying for contracts.

Finally, the study underscores the value of using derivatives not merely for speculative purposes but also as part of portfolio diversification and hedging strategies. Employing options within a broader investment framework can help investors manage downside risks while retaining opportunities for upside gains, thereby contributing to more resilient portfolio performance.

7.6.3. Practical Implications for Regulators

The evidence of persistent mispricing in the options market raises important considerations for regulatory authorities tasked with maintaining market efficiency and stability. Such pricing inefficiencies suggest that there may be structural weaknesses in the way information is disseminated or absorbed by market participants. Regulators therefore have a critical role to play in enhancing transparency and ensuring timely access to market data, thereby reducing informational asymmetries that may distort price formation.

A central priority should be the reduction of transaction costs and the improvement of market liquidity. High trading frictions and limited depth create barriers to effective arbitrage, allowing mispricing to persist for longer than would be the case in more efficient markets. By fostering a trading environment characterized by low costs and greater participation, regulators can help minimize inefficiencies and promote fairer pricing outcomes.

In addition, the findings highlight the importance of equitable access to market information. Ensuring that both institutional and retail investors have the ability to observe and react to relevant information in a timely manner is vital to maintaining a level playing field. Policies that strengthen disclosure practices and expand the reach of official data dissemination systems would contribute to this goal.

The study also underlines the necessity of robust market surveillance mechanisms. By monitoring unusual price movements and deviations from theoretical pricing models, regulators can detect anomalies that may indicate manipulation or systemic weaknesses. Proactive oversight in this regard not only supports pricing efficiency but also enhances overall market integrity.

Finally, the results emphasize the need for investor education initiatives aimed at improving financial literacy and the responsible use of derivatives. By equipping investors with a stronger understanding of option pricing, volatility, and risk management, regulators can help ensure that derivatives markets are used not only for speculation but also for legitimate purposes such as hedging and portfolio diversification.

7.7. Policy and Practical Approaches

For Regulators

1. Improve Transparency in Option Trading Data

- It provides real-time access to order book data, implied volatility surfaces, and Greeks.
- This reduces information asymmetry and enhances the efficiency of the market.

2. Encourage Use of Advanced Risk Models

- Mandate brokers and clearing members to adopt more robust volatility forecasting models (e.g. GARCH and stochastic volatility).
- It helps in systemic risk management during high-volatility events.

3. Surveillance on Mispricing & Arbitrage

- Monitors deviations between theoretical and market prices.
- Persistent inefficiencies may signal manipulation, illiquidity or systemic risks.

4. Liquidity Enhancement Measures

- Encourage more active market makers to reduce bid-ask spreads in far-out-of-the-money and long-maturity options.
- It improves the efficiency and reliability of the implied volatility surfaces.

5. Standardized IV Surface Reporting

- We introduce a regulatory requirement for exchanges to publish standardised implied volatility (IV) term structures and smiles/skews.
- It promotes better benchmarking and reduces pricing distortions.

For Traders & Market Participants

1. Model Diversification

- Do not rely on a single volatility model (e.g. Black–Scholes).
- Hybrid approaches (for example, GARCH for short-term and stochastic volatility for long-term forecasting).
- It helps mitigate model risk.

2. Exploit Predictable IV Patterns

- Implied volatility term structure and moneyness skews were monitored.
- Traders can design spread strategies (e.g. calendar and vertical spreads) to exploit temporary mispricings.

3. Risk Management via Realized vs. Implied Volatility

- Regularly compare implied volatility (from options) with the realised volatility (from historical data).
- Helps identify overpriced/underpriced options and manage hedging costs.

4. Liquidity-Aware Strategy Design

- Avoid overexposure to illiquid strikes, where bid–ask spreads are wide.
- Liquidity-adjusted option pricing is used to prevent slippage losses.

5. Adapt to Regime Shifts

- Nifty options often exhibit volatility clustering (high-volatility versus low-volatility regimes).
- Use regime-switching models and dynamic hedging instead of static assumptions.

6. Arbitrage & Hedging Opportunities

- Deviations from the put–call parity or misaligned implied volatilities across maturities are identified.
- Structured arbitrage or delta–gamma hedging can yield consistent gains if executed carefully.

Detailed Relevance of Findings for Market participants

1. Market Efficiency of Nifty Index Options

Key Finding Recap:

- Mispricing exists (28% calls, 80% puts before costs).
- After transaction costs, exploitable mispricing drops sharply (1.87% calls, 27% puts for retail).
- Institutional traders have an advantage due to lower costs, better access to infrastructure, and superior execution.

Hedgers:

- **Implication:**
Hedgers (e.g., mutual funds, FIIs, corporates) use options primarily for risk protection (buying puts for downside insurance or calls for upside exposure). The finding shows that after costs, mispricing opportunities are minimal — meaning **hedgers face relatively fair pricing**. They cannot rely on inefficiencies to reduce hedging costs.
- **Practical Application:**
 - When hedging, they should focus on execution quality (timing orders, using liquid strikes) rather than searching for underpriced contracts.
 - They might structure hedges using spreads or collars to reduce the cost of expensive puts (since puts are more mispriced).
- **Constraints:**
High liquidity is available mainly for near-the-money, short-maturity options. Hedging in illiquid strikes (far OTM) is costly and risky.

Speculators:

- **Implication:**
Speculators try to profit from directional or volatility bets. Since arbitrage profits are minimal after costs, they **shouldn't rely on systematic mispricing**.
- **Practical Application:**
 - Use predictive signals (like volatility models) rather than arbitrage.
 - For example, if they believe Nifty will rally, they buy calls rather than chase "cheap" options (which rarely exist after costs).

- **Constraints:**
Transaction costs (bid-ask spreads, brokerage) can erode profits, especially for small trades or illiquid contracts. Retail speculators face higher hurdles than institutions.

Arbitrageurs:

- **Implication:**
Arbitrageurs look for risk-free (or near risk-free) opportunities. While raw mispricing looks large, post-cost opportunities are rare and thin. Institutional players still find some profits, especially in puts, thanks to lower trading costs and faster execution.
- **Practical Application:**
 - Engage in **put-call parity arbitrage** or index arbitrage, but only if transaction costs and margin requirements are low enough.
 - Use algorithmic execution to capture fleeting mispricings.
- **Constraints:**
For retail, arbitrage is almost impossible. For institutions, scalability is limited — profits shrink quickly as opportunities are competed away.

2. Volatility Forecasting Models

Key Finding Recap:

- FNN (Neural Network) outperformed others in forecasting volatility.
- EGARCH was next best, more robust than ARIMA/GARCH.
- Close-to-Close was weakest (highest error).
- Machine learning captures non-linear market behavior better.

Hedgers:

- **Implication:**
Hedgers can reduce costs by **hedging strategically based on volatility forecasts**. For example:
 - If volatility is expected to rise, hedge earlier before option premiums increase.
 - If volatility is predicted to fall, they might delay hedging or use cheaper instruments.
- **Practical Application:**
Large hedgers (like FIIs) can incorporate neural network forecasts into risk management systems.

- **Constraints:**
Smaller hedgers may lack the infrastructure for advanced forecasting models. Their practical edge lies in adopting simplified signals (e.g., VIX trend, EGARCH estimates).

Speculators:

- **Implication:**
Volatility traders benefit the most. Superior forecasts mean better chances of profit in strategies like straddles, strangles, and volatility spreads.
- **Practical Application:**
 - Buy straddles if models predict a volatility surge.
 - Write options if models forecast declining volatility.
- **Constraints:**
 - Forecasting models require large datasets and computing power.
 - Execution risk: correct forecast but poor trade management → losses.

Arbitrageurs:

- **Implication:**
Volatility arbitrage (buying underpriced volatility, selling overpriced volatility, and delta-hedging) hinges on accurate forecasts. Institutions with advanced ML tools (like FNNs) can better identify when implied volatility deviates from expected realized volatility.
- **Practical Application:**
 - Implement **statistical arbitrage** strategies (long-short volatility portfolios).
 - Trade variance swaps or structured volatility products (where available).
- **Constraints:**
Requires **low transaction costs, deep liquidity, and hedging infrastructure**. Out of reach for retail investors.

3. Implied Volatility (IV) Smile: Structure Across Time & Moneyness

Key Finding Recap:

- Volatility smile is present: IV is U-shaped across strikes.
- Short maturities = higher IV.
- ATM options = lowest IV.
- Confirms risk is asymmetrically priced.

Hedgers:

- **Implication:**
Hedgers pay more for protection in OTM puts (commonly used for downside hedging).
- **Practical Application:**
 - Instead of buying expensive OTM puts, hedgers might:
 - Use collars (sell calls to fund put purchases).
 - Use ATM puts (cheaper IV) and dynamically adjust.
- **Constraints:**
Deep OTM hedges are costly due to the smile; liquidity in these strikes is also lower.

Speculators:

- **Implication:**
Speculators can exploit relative IV differences.
- **Practical Application:**
 - **Buy ATM options** (lowest IV) if they expect a big move.
 - **Sell far OTM options** (high IV) if they believe extreme risks are overpriced.
 - Construct **butterfly spreads** or **ratio spreads** to exploit smile curvature.
- **Constraints:**
Thin liquidity in far OTM contracts makes selling them risky. Margin requirements can be high.

Arbitrageurs:

- **Implication:**
Smile is not arbitrageable but is tradable via **volatility arbitrage and relative-value trades**.
- **Practical Application:**
 - **Calendar spreads:** exploiting term-structure differences in IV (short-term IV higher than long-term).
 - **Dispersion trades:** trading index options vs. constituent options.
- **Constraints:**
Requires fast execution and significant capital. Smile patterns are structural, not mispricings, so only sophisticated strategies are viable.

7.8. Conclusion

This study makes several meaningful contributions to the understanding of the Indian index options market. First, it demonstrates that observed mispricings based on the Black-Scholes model are largely nullified once realistic market frictions such as transaction costs are considered. Thus, the market exhibits micro-efficiency consistent with the weak form of the Efficient Market Hypothesis (EMH).

Second, volatility forecasting is an indispensable component of pricing and risk management. Among the models studied, neural networks demonstrated the highest predictive accuracy, thereby making a strong case for integrating AI-based tools into financial decision-making.

Finally, the structural patterns of implied volatility, such as the volatility smile and term structure effects, are clearly present in the Indian options market. These findings challenge the assumptions of constant volatility in classical models and indicate that traders' expectations are embedded in the option premiums.

In summary, although still evolving, the Indian derivatives market is maturing in terms of its pricing mechanisms. With improved regulatory oversight, technological advancements, and greater institutional participation, it is poised to become a globally relevant tool. Future research can extend this work by incorporating real-time high-frequency data, cross-asset volatility contagion analyses, and sentiment-driven volatility models.

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