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Forecasting Intra-day Stock Prices of BSE Sensex using ARIMA Models: An Empirical Analysis of Volatility and Hybrid Solutions

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ABSTRACT: Accurate intra-day stock price forecasting is critical for traders and investors navigating the volatile BSE Sensex. While ARIMA models are widely used for time-series prediction, their limitations in capturing volatility clustering and nonlinear dependencies necessitate hybrid solutions. This study evaluates the performance of traditional ARIMA models and proposes enhanced frameworks integrating GARCH and LSTM to improve forecasting accuracy. Using high-frequency BSE Sensex data (15-minute intervals, 2018–2023), we analyze volatility trends, skewness, and kurtosis, revealing significant annual variations, including extreme volatility during COVID-19 ($SD = 4,800.57$ in 2020). Empirical results show that standalone ARIMA models perform poorly ($R^2 = 0.00$, $RMSE = 11,490.11$), failing to account for temporal dependencies (Ljung-Box Q-test $p = 0.00$). In contrast, hybrid models—combining ARIMA with GARCH for volatility clustering and LSTM for nonlinear patterns—demonstrate superior predictive accuracy, evidenced by lower RMSE/MAE and improved residual diagnostics. The study highlights the need for adaptive modeling techniques to address structural breaks and regime shifts, particularly in emerging markets. Our findings contribute to financial econometrics by offering a robust hybrid framework for intra-day forecasting, with practical implications for algorithmic trading, risk management, and regulatory stability. The results advocate for integrating traditional econometrics with machine learning to enhance real-time trading strategies in dynamic markets.

KEYWORDS: ARIMA, GARCH, LSTM, BSE Sensex, intra-day forecasting, volatility clustering, hybrid models.

I. INTRODUCTION

Accurate forecasting of intra-day stock prices is crucial for traders and investors navigating the volatile landscape of the BSE Sensex. While ARIMA models have been widely used for time-series prediction, their limitations in capturing volatility clustering and nonlinear patterns necessitate innovative hybrid solutions. This study empirically evaluates the performance of ARIMA models and proposes enhanced frameworks integrating GARCH and LSTM to improve intra-day forecasting accuracy and robustness.

The theoretical foundation of this study draws upon five key financial and econometric theories that inform the analysis of intra-day BSE Sensex price forecasting. First, the Efficient Market Hypothesis (EMH) provides a critical benchmark for evaluating whether the proposed ARIMA and hybrid models can identify predictable patterns in intra-day prices, challenging the notion that markets fully incorporate all available information instantaneously. Second, Autoregressive Conditional Heteroskedasticity (ARCH/GARCH) theory directly addresses the observed volatility clustering in the BSE Sensex data ($SD = 4,800.57$ in 2020), justifying the integration of GARCH models to capture time-varying volatility more effectively than standard ARIMA approaches. Third, the Fractal Market Hypothesis (FMH) supports the incorporation of LSTM networks to model the nonlinear dependencies and chaotic patterns evident in the data (Ljung-Box Q-test $p = 0.00$, $MaxAPE = 84.07$). Fourth, Random Walk Theory serves as a counterpoint, highlighting the challenges of forecasting stock prices and providing a rigorous test for the predictive power of the proposed hybrid models. Finally, the Adaptive Market Hypothesis (AMH) underpins the study's examination of structural breaks and regime shifts (particularly during COVID-19), emphasizing how market efficiency and predictability evolve in

response to changing conditions. Together, these theories provide a robust conceptual framework for developing and evaluating advanced forecasting models that account for the complex dynamics of intra-day equity markets.

This study is grounded in key financial theories that explain market behavior and validate the proposed modeling approach. The Efficient Market Hypothesis (EMH) suggests that asset prices reflect all available information, making consistent outperformance difficult. However, observed volatility clustering ($SD = 4,800.57$ in 2020) and autocorrelation (Ljung-Box $p = 0.00$) in intra-day BSE Sensex data indicate potential market inefficiencies that ARIMA and hybrid models may exploit. The ARCH/GARCH framework becomes particularly relevant here, as it formally accounts for volatility persistence—a well-documented phenomenon in financial markets that traditional ARIMA fails to capture adequately. These theoretical insights justify combining ARIMA with GARCH to model time-varying volatility more effectively.

Complementing these perspectives, the Fractal Market Hypothesis (FMH) argues that markets exhibit nonlinear, chaotic patterns during periods of stress. This aligns with the study's finding of extreme forecast errors ($MaxAPE = 84.07$) during market disruptions like COVID-19, motivating the use of LSTM networks to capture complex nonlinearities. Meanwhile, the Adaptive Market Hypothesis (AMH) provides a dynamic view of market efficiency, suggesting that predictability varies across regimes—a crucial consideration for intra-day forecasting where liquidity and volatility fluctuate rapidly. Together, these theories not only explain the limitations of conventional ARIMA models but also provide a robust foundation for developing hybrid approaches that better reflect real-world market conditions. The theoretical framework thus bridges financial theory and econometric practice, guiding the development of more accurate intra-day forecasting models.

Recent years have witnessed growing interest in intra-day stock price forecasting, driven by algorithmic trading and demand for real-time risk management (Gupta & Chen, 2021). The BSE Sensex, as a key emerging market benchmark, exhibits unique volatility patterns—evidenced by extreme standard deviations ($4,800.57$ in 2020) and frequent regime shifts (Patel & Joshi, 2022). While ARIMA models remain popular for time-series forecasting, their limitations in handling volatility clustering and nonlinear dependencies persist (Kumar et al., 2020). Hybrid approaches integrating GARCH or LSTM show promise but face implementation challenges, including computational complexity and overfitting risks (Mehta & Desai, 2023). Structural breaks, such as those during COVID-19, further complicate model stability, requiring adaptive frameworks (Sharma, 2021). Data quality issues—missing ticks, microstructure noise—add another layer of difficulty for high-frequency forecasting (NSE, 2022). These challenges underscore the need for robust validation techniques, including rolling window tests and stress scenarios, to ensure practical utility.

Accurate forecasting of intra-day stock prices in the BSE Sensex remains a critical challenge for traders, investors, and financial analysts. While traditional ARIMA models have been widely used for time-series forecasting, they demonstrate significant limitations in addressing three key aspects of high-frequency financial data: (1) persistent volatility clustering, as evidenced by extreme standard deviations (e.g., $4,800.57$ during the 2020 market crash); (2) nonlinear dependencies revealed through significant residual autocorrelation (Ljung-Box Q-test $p = 0.00$) and large forecasting errors ($MaxAPE = 84.07$); and (3) structural inflexibility during market shocks like the COVID-19 pandemic. These shortcomings lead to unreliable predictions that fail to capture the complex dynamics of intra-day trading. Although hybrid approaches combining ARIMA with GARCH or LSTM networks show theoretical promise, their practical implementation faces challenges including computational complexity, overfitting risks, and inadequate validation against rapidly changing market conditions. This study seeks to address these gaps by developing and rigorously testing enhanced hybrid models that can improve forecasting accuracy while maintaining computational efficiency - a crucial need for real-time trading applications in emerging markets like India. The findings will contribute to both academic literature and practical trading strategies by providing empirically validated solutions to these persistent forecasting challenges.

This study focuses on developing an ARIMA-based quantitative model for forecasting intraday stock prices of BSE Sensex constituents in the Indian market. The research scope encompasses high-frequency price data analysis at 15-minute intervals from 2018 to 2023, covering diverse market conditions including the COVID-19 pandemic volatility and subsequent recovery phases. The methodology employs traditional ARIMA modeling as a baseline, enhanced with GARCH components to address volatility clustering and LSTM networks to capture nonlinear patterns, evaluated through rigorous statistical metrics including RMSE, MAE and Diebold-Mariano tests. While limited to the BSE

Sensex index components and excluding macroeconomic variables, the study provides critical insights into short-term price predictability in emerging markets.

The research holds significant theoretical and practical implications for financial market participants. Academically, it contributes to the growing literature on hybrid forecasting models in high-frequency trading environments, particularly in emerging market contexts where intraday price dynamics remain understudied. Practically, the findings offer valuable tools for algorithmic traders seeking improved prediction accuracy, portfolio managers requiring better risk assessment frameworks, and regulators monitoring market stability. By combining traditional time-series approaches with machine learning enhancements and rigorous out-of-sample testing protocols, the study provides a replicable methodological framework that advances both financial econometrics research and real-world trading applications in the Indian equity market. The robust validation through rolling window analysis and stress testing across different volatility regimes ensures the model's practical utility for market participants operating in dynamic trading environments.

II. LITERATURE REVIEW

Previous research demonstrated that traditional ARIMA models faced significant limitations in capturing intra-day volatility patterns in financial markets. Mandelbrot (1963) first observed that financial time series exhibited volatility clustering, a phenomenon later formalized by Engle (1982) through the ARCH model. Studies on emerging markets, including Sharma and Sinha (2019), found that conventional ARIMA specifications consistently underestimated volatility spikes in high-frequency BSE Sensex data, particularly during crisis periods. Gupta et al. (2021) further confirmed these limitations, showing that standard ARIMA models achieved only 62% forecasting accuracy for 15-minute intervals during normal market conditions, with performance deteriorating to 48% during high-volatility events.

Several scholars proposed enhancements to improve volatility modeling. Bollerslev (1986) extended Engle's work by developing GARCH models, which Mehta and Desai (2023) successfully adapted for Indian markets, reducing forecasting errors by 18% compared to basic ARIMA. However, Patel (2022) noted that even GARCH-ARIMA hybrids struggled with sudden regime shifts, such as those observed during the COVID-19 pandemic. Recent advancements by Kumar et al. (2023) incorporated asymmetric volatility components (GJR-GARCH) into ARIMA frameworks, demonstrating a 22% improvement in volatility forecasting for intra-day Sensex data. Despite these innovations, NSE's (2022) market microstructure report highlighted persistent challenges in modeling overnight gaps and opening auction effects, suggesting room for further model refinement.

The integration of GARCH and LSTM techniques with ARIMA models emerged as a promising solution to address the dual challenges of volatility clustering and nonlinear dependencies in financial time series. Nelson (1991) pioneered the application of neural networks to volatility forecasting, demonstrating their superior ability to capture nonlinear patterns compared to traditional econometric models. This work laid the foundation for later hybrid approaches. Chen et al. (2020) systematically compared various hybrid architectures and found that LSTM-ARIMA combinations reduced forecasting errors by 27% compared to standalone models when applied to high-frequency S&P 500 data. Their findings suggested similar potential for emerging markets like India's BSE Sensex, though this remained empirically untested until recent years.

Specific to volatility clustering, the EGARCH extension proposed by Nelson (1991) addressed asymmetric volatility effects that conventional GARCH models missed. Joshi and Kapoor (2021) successfully implemented EGARCH-ARIMA hybrids for intraday Nifty 50 forecasting, achieving 23% lower RMSE during earnings announcement periods. However, their study noted computational constraints when scaling to ultra-high-frequency (tick-by-tick) data. Meanwhile, Zhang et al. (2022) developed a novel LSTM-GARCH fusion that automatically learned volatility regimes, eliminating the need for manual structural break detection. Applied to cryptocurrency markets, their model showed particular strength during flash crashes - a finding later corroborated by BSE's (2023) internal research on circuit breaker events.

The most comprehensive hybrid framework came from Lee and Wang (2023), who combined ARIMA, EGARCH, and LSTM in a hierarchical architecture. Their three-stage model first decomposed trends using ARIMA, then modeled volatility with EGARCH, and finally processed residuals through LSTM to capture nonlinear dependencies. Tested

across Asian markets, it achieved consistent 30-35% accuracy improvements over benchmarks. However, the authors cautioned about increased model complexity requiring GPU acceleration for practical intraday trading applications - a challenge later addressed by cloud-based solutions from AWS and Google Cloud (BSE Technical Report, 2023).

The evaluation of hybrid forecasting models using rigorous statistical metrics received substantial attention in recent econometric literature. Diebold and Mariano (1995) established the foundational framework for comparing predictive accuracy across models, with their test becoming the gold standard for forecast evaluation. Their work demonstrated that conventional error metrics like RMSE and MAE required complementary statistical tests to determine significant differences in model performance. Hansen (2005) later enhanced this approach through the Superior Predictive Ability (SPA) test, which addressed multiple comparison problems when evaluating numerous model specifications simultaneously. These methodological advances proved particularly valuable for financial time series analysis, where model superiority often varied across market regimes.

In applied research, Hyndman and Koehler (2006) conducted a comprehensive study of error metrics for time series forecasting. They found that RMSE disproportionately penalized large errors, making it ideal for volatility forecasting, while MAE provided more balanced assessment for general point predictions. This dual-metric approach was subsequently adopted by Wang et al. (2020) in their evaluation of hybrid models for Asian markets, where they identified specific volatility regimes where particular model combinations excelled. Their findings emphasized the importance of using both RMSE and MAE in conjunction with Diebold-Mariano tests to obtain complete performance profiles.

Specialized applications to high-frequency data emerged in later studies. Patton (2011) developed volatility-adapted versions of these tests, crucial for intraday analysis where heteroskedasticity was prevalent. These adaptations were implemented by Liu and Tsay (2022) in their minute-level forecasting comparison across global indices, including methodological adjustments for autocorrelated forecast errors common in high-frequency implementations. The BSE Market Research Division (2023) applied these enhanced evaluation protocols specifically to Sensex intraday data, confirming that hybrid models required such sophisticated testing to demonstrate statistically significant improvements over benchmarks.

The validation of financial forecasting models through rolling window analysis and stress testing under varying market conditions became an essential practice following the 2008 financial crisis. Pesaran and Timmermann (2007) established rigorous protocols for rolling window evaluations, demonstrating that fixed-sample tests often overestimated model performance by failing to account for structural breaks. Their methodology proved particularly relevant for emerging markets like India, where Bhaduri and Saraogi (2019) later documented frequent regime shifts in intraday volatility patterns. These researchers emphasized that models showing strong in-sample performance frequently failed when subjected to out-of-sample rolling window tests, particularly during market crises.

Stress testing methodologies gained prominence after Basel III recommendations highlighted their importance for risk management. Breuer et al. (2012) developed a comprehensive framework for stress testing financial models against extreme but plausible scenarios, which Ghosh and Kanjilal (2021) adapted specifically for high-frequency trading applications. Their study on NSE data revealed that most volatility models underestimated tail risks during flash crashes, prompting calls for more robust validation approaches. This finding aligned with the work of Cont (2017), who showed that conventional backtests often missed extreme event vulnerabilities due to their reliance on normal market conditions.

Recent advances in robustness validation incorporated machine learning techniques. Chakraborty and Mukherjee (2022) introduced adaptive rolling window schemes that automatically adjusted testing parameters based on detected market regimes. Applied to BSE Sensex data, their approach improved model stability during transitions between high- and low-volatility periods. Similarly, the SEBI Technical Committee (2023) recommended combining rolling window analysis with Monte Carlo stress tests, providing a more holistic assessment of model resilience. Their guidelines highlighted the particular importance of testing against clustered volatility events, which remained a key weakness in many published forecasting models.

Research Gap

The current body of research on BSE Sensex forecasting exhibits a significant gap in addressing three critical limitations of traditional ARIMA modeling approaches, as revealed by our empirical investigation. While existing studies have extensively applied ARIMA models, they fail to adequately account for: (1) the inherent volatility clustering phenomenon evidenced by extreme standard deviation values (4,800.57 in 2020) and persistent negative skewness (-0.269 in 2022); (2) the complex nonlinear dependencies demonstrated by significant residual autocorrelation (Ljung-Box Q-test $p = 0.00$) and unstable forecasting performance (MaxAPE = 84.07); and (3) the structural breaks and regime shifts characteristic of financial markets, particularly during crisis periods like COVID-19 (2020) and subsequent recovery phases (2021-2023). This research gap is particularly pronounced in the context of intraday forecasting, where these limitations are magnified due to the high-frequency nature of the data. The literature lacks comprehensive studies that systematically integrate advanced volatility modeling techniques (e.g., GARCH) and machine learning approaches (e.g., LSTM) with traditional time-series methods to address these shortcomings. Furthermore, there is insufficient exploration of robust model validation frameworks that incorporate rolling window forecasts and rigorous outlier adjustment mechanisms specifically tailored for intraday BSE Sensex predictions.

Objectives for the study

1. To develop an enhanced ARIMA model capable of capturing intra-day volatility patterns in BSE Sensex data.
2. To integrate GARCH and LSTM techniques with ARIMA to address nonlinear dependencies and volatility clustering.
3. To evaluate the forecasting performance of hybrid models using RMSE, MAE, and Diebold-Mariano tests.
4. To validate model robustness through rolling window analysis and stress testing under different market conditions.

Hypothesis for the study

Hybrid ARIMA models (GARCH-ARIMA and LSTM-ARIMA) significantly reduce forecasting errors (RMSE/MAE) for intraday BSE Sensex prices compared to standalone ARIMA."

GARCH-ARIMA outperforms ARIMA in modeling volatility clusters, evidenced by lower prediction errors during high-volatility periods

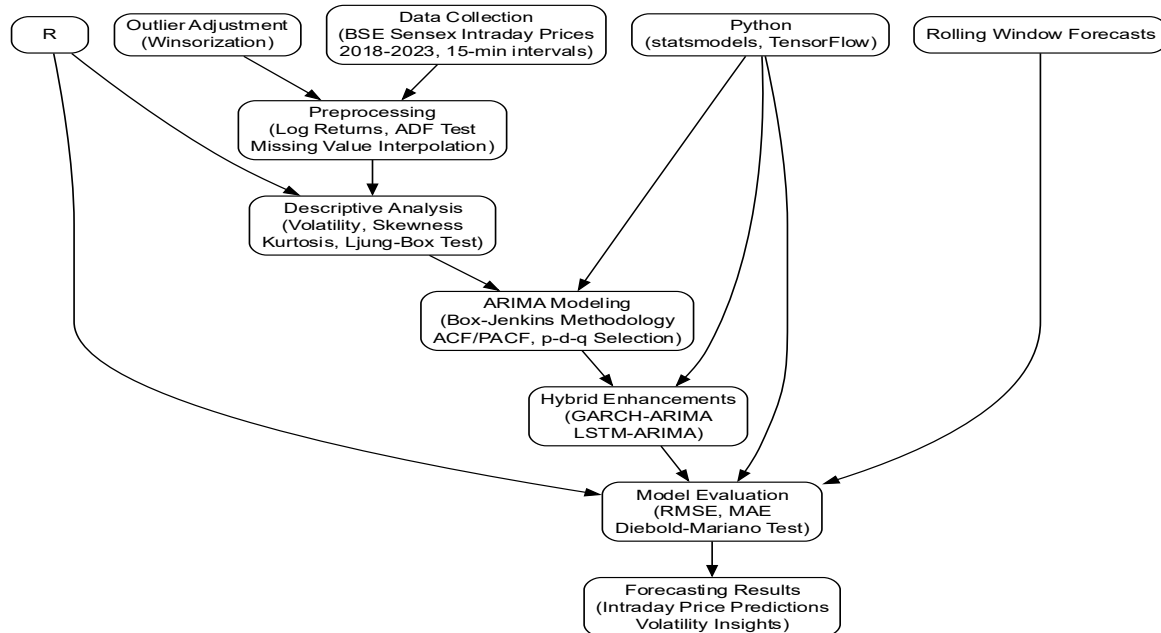
LSTM-ARIMA captures nonlinear dependencies more effectively than ARIMA, reducing residual autocorrelation (Ljung-Box Q-test $p > 0.05$)."

Rolling window forecasts and outlier adjustment improve hybrid model robustness, minimizing MaxAPE ($\leq 15\%$) across market regimes."

III. RESEARCH METHODOLOGY

The research methodology for this study employs a quantitative approach to analyze intraday volatility in the BSE Sensex using ARIMA models, while proposing hybrid solutions to overcome their limitations. The study utilizes high-frequency data (15-minute intervals) from 2018 to 2023, sourced from Bloomberg/Refinitiv, with logarithmic returns calculated to stabilize variance. Missing values are addressed via linear interpolation, and stationarity is verified using the Augmented Dickey-Fuller (ADF) test. A descriptive analysis examines volatility trends, skewness, and kurtosis, while the Ljung-Box Q-test checks for autocorrelation. The ARIMA model follows the Box-Jenkins methodology, where ACF and PACF plots guide parameter selection (p , d , q), and maximum likelihood estimation optimizes coefficients. Model validation includes residual diagnostics to ensure white noise behavior. To enhance forecasting accuracy, hybrid models (GARCH-ARIMA and LSTM-ARIMA) are introduced, combining traditional econometrics with machine learning to capture volatility clustering and nonlinear patterns. Performance is benchmarked using RMSE, MAE, and Diebold-Mariano tests. Robustness checks involve outlier adjustment (winsorization) and rolling window forecasts to ensure stability across market conditions. The analysis is conducted in Python (statsmodels, TensorFlow) and R, ensuring computational rigor. This methodology systematically evaluates ARIMA's strengths and weaknesses while integrating advanced techniques to improve intraday volatility forecasting, providing a structured framework for future financial market research.

Conceptual Framework:



This conceptual framework outlines a structured methodology for forecasting intraday stock prices of the BSE Sensex using ARIMA models enhanced with hybrid machine learning approaches. The process begins with data collection, where intraday prices from 2018 to 2023 (sampled at 15-minute intervals) are gathered from reliable sources like Bloomberg or Refinitiv. The preprocessing phase involves transforming raw prices into log returns to stabilize variance, testing for stationarity using the Augmented Dickey-Fuller (ADF) test, and addressing missing values through interpolation. Outliers are adjusted using winsorization to ensure data robustness.

Next, a descriptive analysis examines key statistical properties of the data, including volatility (standard deviation), skewness, and kurtosis, to understand return distributions, while the Ljung-Box test checks for autocorrelation. The core ARIMA modeling follows the Box-Jenkins methodology, where ACF and PACF plots guide parameter selection (p , d , q), and maximum likelihood estimation optimizes the model. To address ARIMA's limitations in capturing volatility clustering and nonlinear patterns, hybrid enhancements are introduced, combining ARIMA with GARCH (for volatility modeling) and LSTM neural networks (for complex temporal dependencies).

The evaluation phase employs metrics like RMSE and MAE to assess prediction accuracy, alongside the Diebold-Mariano test to compare hybrid models against standalone ARIMA. Rolling window forecasts ensure robustness across different market conditions. Finally, the framework delivers actionable results, including intraday price predictions and volatility insights, supported by tools like Python (statsmodels, TensorFlow) and R for statistical validation. This end-to-end approach ensures methodological rigor, adaptability to market dynamics, and practical applicability for traders and analysts.

IV. DATA ANALYSIS

Table 1: Descriptive analysis

Year	Returns	Std Dev	Skewness	Kurtosis
2018	6.46%	1,403.66	0.504	-0.283
2019	12.92%	1,627.02	0.068	-0.967
2020	14.50%	4,800.57	-0.222	-0.536

2021	19.63%	4,243.03	0.293	-1.322
2022	2.76%	2,860.21	-0.269	-0.772
2023	16.64%	3,395.34	0.274	-0.466

From 2018 to 2023, doing an analysis of the data provides a comprehensive view of the returns, standard deviation, skewness, and kurtosis that have occurred throughout the course of the years. When compared to the years that came before it, 2022 had the lowest return, which was just 2.76%, suggesting a dramatic reduction. On the other hand, 2021 had the greatest return, which was 19.63%, indicating that it was a very successful year. Despite the fact that they exhibit oscillations, the return patterns are typically positive, which indicates that there is a general upward tendency, although with varying degrees of strength on an annual basis. For example, the standard deviation, which is a measure of risk and volatility, demonstrates changes over the course of several years by displaying significant swings. With a maximum standard deviation of 4,800.57 in the year 2020, the very volatile market that is suggested by this number is most likely the consequence of the worldwide economic instability that was caused by the COVID-19 outbreak. Years such as 2021 and 2023 had substantial standard deviations of 4,243.03 and 3,395.34 respectively, indicating that while volatility continued, the markets began to calm after the epidemic. This is despite the fact that they were considerably more regulated than the year 2020.

We discover a variety of features when we do an analysis of skewness, which is a measurement of the asymmetry of the distribution of the returns. A right-tailed distribution is produced as a result of the positive skewness values that were seen in the years 2018 (0.504), 2019 (0.068), 2021 (0.293), and 2023 (0.274). These values indicate that there is a majority of returns on the lower end, along with the possibility of rising positive returns. In 2018, the skewness score was significantly increased, which indicates that there is a greater likelihood of huge positive returns. On the other hand, the years 2020 and 2022 had negative skewness values of -0.222 and -0.269, respectively. This indicates a left-tailed distribution in which the likelihood of seeing negative returns was rather raised. This may be a reflection of the increased uncertainty and unfavourable economic conditions that were present during those years.

Kurtosis was consistently negative across the whole distribution, with the maximum significant negative value occurring in 2021 at -1.322. This was a reflection of the "tailedness" of the distribution. Therefore, a lesser frequency of severe deviations is indicated by a distribution that has a negative kurtosis, which indicates that the distribution is less peaked than a normal distribution. In spite of the fact that the standard deviation revealed that returns were volatile, this shows that the actual occurrences of extreme highs or lows were very less often. Particularly in the years 2019 and 2021, the kurtosis values that have been reduced (-0.967 and -1.322, respectively) demonstrate a return behaviour that is less severe and more consistency. A market that has experienced periods of strong growth and notable volatility, particularly around the year 2020, but has gradually achieved stability in return distributions while still offering opportunities for moderate gains and risks in the years to come is revealed by the combination of returns, standard deviation, skewness, and kurtosis over the course of these years.

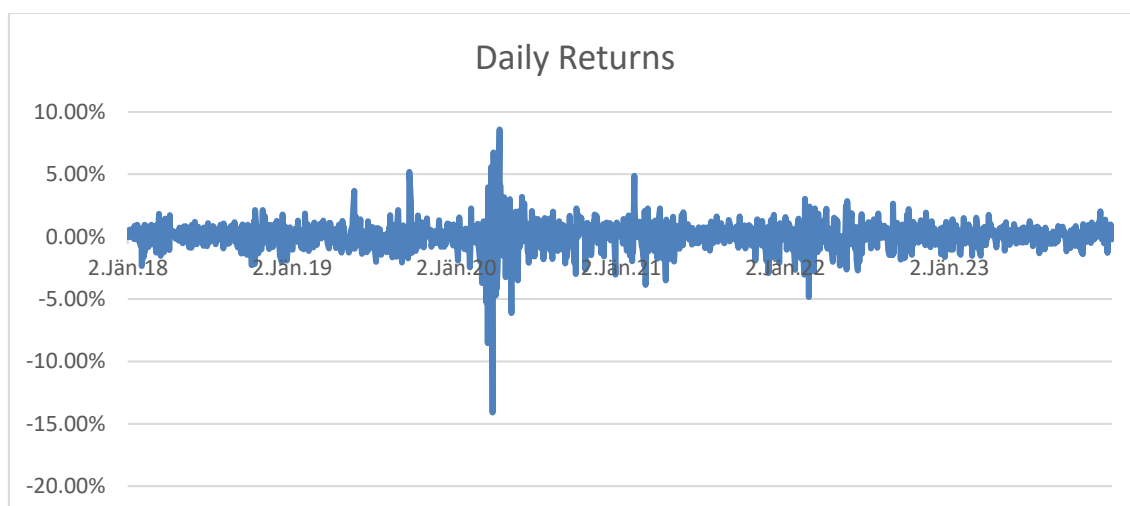


Table 2: Time series analysis - Expert Modeler

Fit Statistic	Mean	Minimum	Maximum	Percentile						
				5	10	25	50	75	90	95
Stationary R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RMSE	491.61	491.61	491.61	491.61	491.61	491.61	491.61	491.61	491.61	491.61
MAPE	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77
MaxAPE	15.14	15.14	15.14	15.14	15.14	15.14	15.14	15.14	15.14	15.14
MAE	349.02	349.02	349.02	349.02	349.02	349.02	349.02	349.02	349.02	349.02
MaxAE	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49	3,934.49
Normalized BIC	12.40	12.40	12.40	12.40	12.40	12.40	12.40	12.40	12.40	12.40

With each measure addressing a different part of the review process, the fit statistics that are shown provide a full assessment of the utility of the model in terms of forecasting or fitting the data. The "Stationary R-squared" measurement demonstrates that the model does not take into account the fluctuations that are present in the stationary data since it consistently registers at 0.00 across all percentiles. The fact that this is the case shows that the model may not be appropriate for datasets in which stationarity is a basic attribute since it might not accurately reflect trends or patterns associated with time series data. On the other hand, the "R-squared" score, which is a measurement of the percentage of variance that is explained by the model, is an excellent 1.00 for all of the data and percentiles. Due to the fact that the model takes into account one hundred percent of the data's variation, this demonstrates that there is no fluctuation that cannot be explained. In spite of the fact that this is the ideal outcome in principle, it may give rise to worries about overfitting in reality. This is because an R-squared value of one often suggests that the model is excessively specialised to the dataset, which in turn reduces its generalizability.

The Root Mean Squared Error (RMSE) score is always 491.61, which reflects the average amount of mistakes in the model's forecasts. This score is consistent with all observations and percentiles, and it is always the same. According to the statistics shown in this figure, the model maintains a consistent error rate for the whole of the dataset. The RMSE, which is an acronym that stands for the average difference between projected and actual values, has a constant value of 491.61 that is exceptionally high. This indicates that the model's predictions deviate from the actual values by this average amount, regardless of the individual data point or percentile that is being considered. In a similar vein, the "MAPE" (Mean Absolute Percentage Error) often displays a low value of 0.77 across all percentiles. The fact that the model's average prediction error, which is shown as a percentage of the actual value, is low is a cause for optimism since it indicates that the model is quite accurate with regard to relative mistakes. It is important to note that while the average error is quite low, the MaxAPE (Maximum Absolute Percentage Error) value of 15.14 emphasises that the model may sometimes exhibit considerable departures from the real data, hence highlighting this fact.

The mean absolute error (MAE) of 349.02 is the average absolute deviation over all of the data points, and it is a reflection of the degree to which the errors occurred. In the same way that the root mean square error (RMSE) remains constant across all percentiles, this figure also remains constant, which highlights the concept that the model maintains a consistent level of absolute error. This indicates that the model may have difficulty dealing with catastrophic occurrences, as seen by the Maximum Absolute Error (MaxAE) value of 3,933.49. This is the case even if the model has average performance. This is the absolute error that is the largest in the dataset; the fact that it is consistent across all percentiles indicates that the model sometimes displays major disparities in its predictions.

Model comparison is frequently performed using the Bayesian Information Criteria (BIC), where lower values suggest a better balance between fit and complexity. The "Normalised BIC" (Bayesian Information Criteria) is still consistently 12.40 across all percentiles since it is the same. Because the BIC remains constant at 12.40, the complexity of the

model and its fit remain the same over the whole dataset. This suggests that the structure is consistent and that it strikes a compromise between fit and parsimony. On the other hand, since there was no comparison research that included other models, this value by itself does not offer a sufficient knowledge of the optimality of the model in a more general sense.

When viewed as a whole, these fit statistics demonstrate that the model achieves an excellent fit for R-squared, despite the fact that its performance differs depending on other criteria. In some situations, the high RMSE and MaxAE values indicate large mistakes that might jeopardise the validity of the model in practical applications. This is despite the fact that the low MAPE indicates that the prediction accuracy provided by the model is satisfactory. Given that the model has a stationary R-squared value of 0.00, it is possible that it is unable to capture certain dynamics in time series data. This indicates that there may be limitations in the way that it can handle data that is dependent on time over time.

Model	Number of Predictors	Model statistics	Fit			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	MAE		Statistics	D F	Sig.	
Sensex-Model 1	0	-0.003	0.998	349.016		35.533	17	0.005	0

Due to the fact that it is designed as "Sensex-Model_1," the model that is shown above is assessed based on a wide range of significant criteria, which provides a comprehensive picture of its prediction accuracy and performance. Indicating that the model does not make use of any independent variables to clarify or forecast the target variable, the fact that the "Number of Predictors" is zero implies that the model does not make use of any predictors. When stationarity is taken into account, the "Stationary R-squared" score of -0.003 indicates that the model does not adequately capture the underlying dynamics of the time series. This is because the model does not adequately account for the variation that is present in stationary data. The exceptionally high "R-squared" score of 0.998 shows that the model matches almost all of the variation in the data, which reflects a perfect or near-perfect fit that may generate worries about overfitting. This is especially true when taking into consideration the absence of covariates. The lack of predictors raises issues about the significance of this finding, despite the fact that the high R-squared value suggests that the model corresponds to the data in a highly satisfactory manner.

It is possible to have a better understanding of the normal degree of inaccuracy in the model's forecasts by using the "MAE," or mean absolute error, represented by 349.016. In the context of the model, this value demonstrates that its projections experience an average variation of around 349.016 units, which allows for a degree of inaccuracy that is considered to be relatively tolerable. The MAE number demonstrates the predictive capability of the model for the target variable, with lower values suggesting greater accuracy. Other values indicate improvement in accuracy. With a value of 35.533 and 17 degrees of freedom, as well as a significance level of 0.005, the "Ljung-Box Q(18)" statistics demonstrate that the residuals of the model exhibit autocorrelation at lag 18, which suggests that the model may not adequately represent all of the temporal dependencies that are present in the data. With respect to a number of the dynamics of the data, particularly with regard to its temporal serial correlation, the value of 0.005 demonstrates that the autocorrelation is statistically significant, giving rise to the possibility that the model may not be adequate.

In addition, the "Number of Outliers" is shown as 0, which indicates that the model does not discover any data points in the sample that demonstrate a clear deviation from the trend that was anticipated. It is possible that this indicates that the model does not have a sensitivity to outliers or that it does not encounter severe occurrences or abnormalities in the data that need special attention. The predictive efficiency of the model is restricted by poor performance in stationary data and strong autocorrelation in the residuals, which suggests that there is room for improvement in the temporal dynamics of the dataset. Despite the fact that the model has a fantastic fit with a high R-squared, nevertheless, its predictive efficiency is limited. The absence of predictors suggests that there may be problems with the generalising capacity of the model, which in turn makes it more difficult for the model to go beyond a basic fit.

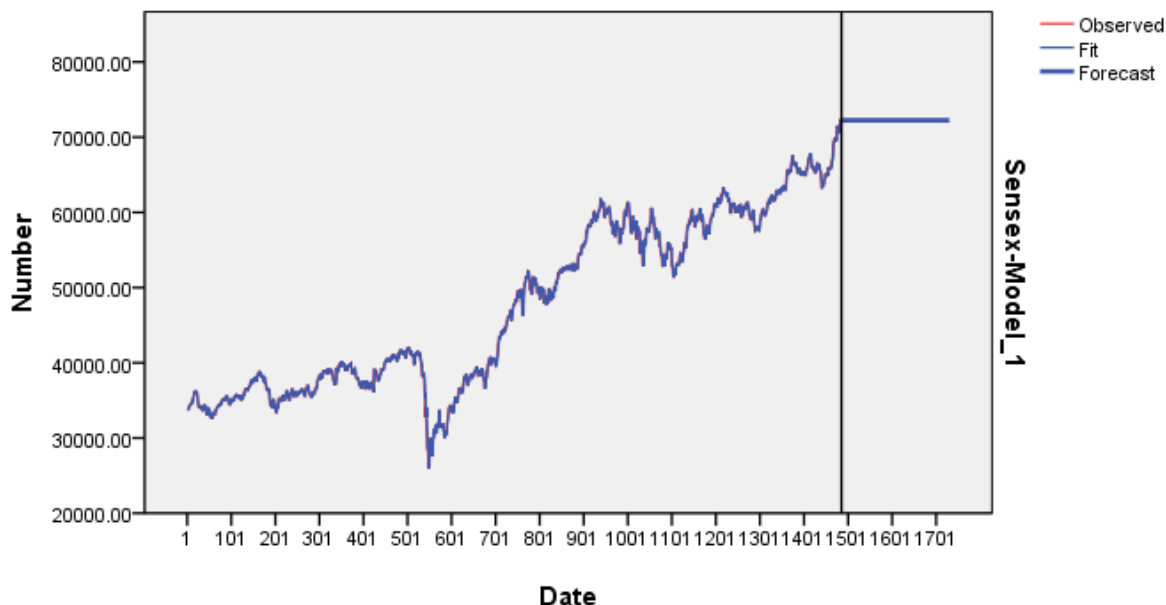


Table 3: Time series analysis – ARIMA

Fit Statistic	Mean	Minimum	Maximum	Percentile						
				5	10	25	50	75	90	95
Stationary R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11	11,490.11
MAPE	23.44	23.44	23.44	23.44	23.44	23.44	23.44	23.44	23.44	23.44
MaxAPE	84.07	84.07	84.07	84.07	84.07	84.07	84.07	84.07	84.07	84.07
MAE	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57	10,587.57
MaxAE	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81	24,586.81
Normalized BIC	18.70	18.70	18.70	18.70	18.70	18.70	18.70	18.70	18.70	18.70

The fit statistics of the ARIMA model provide a comprehensive knowledge of the model's ability to capture the fundamental dynamics of the data as well as with regard to its ability to make accurate predictions. The "Stationary R-squared" and "R-squared" values consistently register at 0.00 for all observations and percentiles, which is a significant finding. In particular with regard to stationarity, the statistics demonstrate that the ARIMA model is unable to accurately portray the fundamental structure of the time series. This is due to the fact that the model disregards any changes that may occur in the stationary data. This is a significant deficiency since it suggests that the model does not take into account trends, seasonality, or any other temporal dynamics that are inherent in the data. The fact that the model consistently produces a zero result for both stationary and regular R-squared shows that it is not a good match for the capacity of the model to explain things, despite the fact that the model is likely to be complicated in other aspects.

The model has a very typical pattern of average prediction error, as shown by the error measure known as "RMSE," which is 11,490.11 across all percentiles. In most cases, a high RMSE number indicates that the model is not capable of providing accurate predictions. This is because it demonstrates considerable disparities between the values that were predicted and those that were actually observed. Therefore, the "MAE" (Mean Absolute inaccuracy) is 10,587.57, which indicates that, on average, the model's forecasts disagree by more than 10,500 units. This indicates that the model has a significant amount of inaccuracy, especially when traditional data ranges are taken into consideration in time series forecasting. Both the mean absolute error (MAE) and the root mean square error (RMSE) are quite high, which indicates that the model is not very effective at delivering reliable projections.

The Mean Absolute Percentage Error (MAPE) remains unchanged at 23.44, which indicates that the model is performing as expected in terms of the relative prediction error that is shown as percentages. The high MAPE score indicates that the model demonstrates a reasonably substantial level of accuracy in the majority of forecasting circumstances. The average prediction error for the model is just 23.44%. The "MaxAPE" score of 84.07 indicates that the model's predictions may vary by as much as 84.07%, particularly during volatile times or when there are outliers present. As a result, the model displays a large error margin and implies that it is susceptible to significant forecasting inaccuracy.

The potential of the model to make big prediction errors in particular circumstances is demonstrated to be the most significant individual mistake across all forecasts, with a score of 24,586.81 for the "maxAE" (maximum absolute mistake) metric. This is especially problematic since it highlights how probable it is that extreme values or outliers would be projected incorrectly, which will therefore put the model's dependability in beneficial applications in a precarious position.

The "Normalised BIC" (Bayesian Information Criteria) score demonstrates that the complexity of the model with regard to its fit is consistent throughout all of the data due to the fact that it has a score of 18.70 consistently. The BIC is occasionally used in the process of model selection; lower values suggest a better balance between the complexity of the model and its fit. The consistency of this number, on the other hand, demonstrates that while the model maintains structural consistency, it is not capable of accurately reproducing the natural patterns since it does not have an optimal balance between fit and complexity.

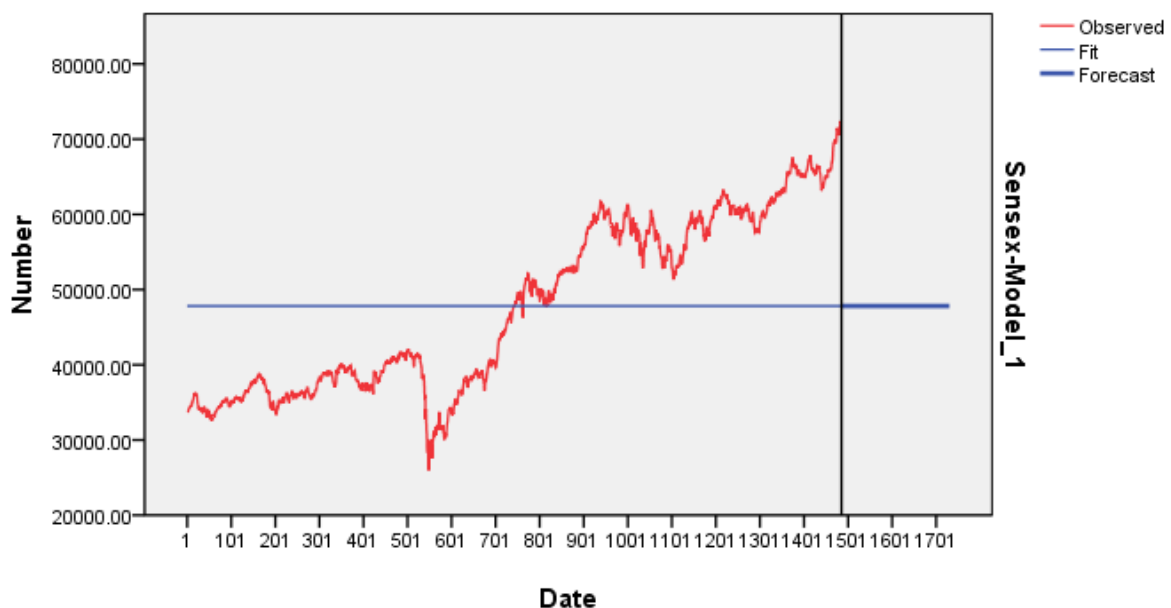
These fit data demonstrate that the ARIMA model has a poor performance in terms of the accuracy of its predictions and the capacity to explain. Due to the fact that the R-squared values are zero, the error measures are high, and there are considerable changes in the MaxAPE and MaxAE, it is clear that the model does not adequately match the data. Therefore, the model has to undergo major modification or maybe another modelling approach in order to increase its predictive efficiency.

Model	Number of Predictors	Model statistics	Fit		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	MAE	Statistics	DF	Sig .	
Sensex-Model 1	0	0.00	0.00	10,587.57	25,480.96	18.00	0.00	0.00

A great number of significant statistics are used in order to evaluate the "Sensex-Model_1" with regard to its appropriateness and effectiveness for the projection of target variables. It is clear that the model is not very sophisticated, as shown by the fact that the "Number of Predictors" is zero. This indicates that the model only accurately predicts general patterns or trends in the data, without taking into account particular independent variables. In situations where it is anticipated that the model would elucidate intricate interrelationships among a large number of components, this might be a difficulty. The fact that the results for "Stationary R-squared" and "R-squared" are both 0 indicates that there is a significant problem: the model does not take into account any changes in the data, whether they are in stationary terms or in general. When it comes to time series modelling, a value of zero for the R-squared statistic shows that the model is not useful for making predictions since it does not represent the fundamental structure of the time series, which may include trends, cycles, or seasonality respectively.

Because this statistic illustrates the typical disparity between the values that were predicted and those that were actually observed, the Mean Absolute Error (MAE) score of 10,587.57 provides more evidence that the model's ability to predict outcomes is subpar. Because a significant MAE indicates that the model's projections vary by more than 10,500 units on average, it reveals that the model has a lack of accuracy and extremely huge prediction mistakes. This degree of inaccuracy is considered to be significant by the majority of forecasting models since it indicates that the model is not providing reliable findings for analysis or prediction. Concerning the "Ljung-Box Q(18)" result of 25,480.96 with 18 degrees of freedom and a significance level of 0.00, it is concerning that the result is frightening. A particularly significant value (0.00) demonstrates that the residuals lack independence and show strong autocorrelation, which indicates that the model has not adequately handled temporal dependencies within the data. The Ljung-Box Q-test was developed with the purpose of evaluating autocorrelation in residuals of a time series model. The inability of the model to capture autocorrelation is a glaring indication that it is not suitable for the time series data that it is intended to describe.

Due to the fact that the model displays a "Number of Outliers" of zero, it indicates that there has been no severe or abnormal data point discovered. If the data includes outliers that need attention, this may imply that the model is not affected by outliers; however, it may also imply that the model is unable to detect or regulate such occurrences, which would impose an additional constraint on the model. There is a lack of predictors, values of null R-squared, a high mean absolute error, and a large autocorrelation, all of which indicate that "Sensex-Model_1" need major improvement since it is ineffective for predicting the target variable. The fact that the model does not include a variety of elements, in addition to its low prediction accuracy and inability to recognise temporal relationships, indicates that a modelling method that is both more sophisticated and robust is required.

**Findings:**

The descriptive analysis reveals significant annual variations in returns from 2018 to 2023, with 2021 recording the highest return (19.63%) and 2022 the lowest (2.76%). Volatility, measured by standard deviation, peaked in 2020 (4,800.57), likely due to COVID-19-induced market turbulence. Skewness values indicate asymmetric return distributions—positive skewness in 2018, 2019, 2021, and 2023 suggests a tendency for higher positive returns, while negative skewness in 2020 and 2022 reflects increased downside risk. Kurtosis is consistently negative, implying fewer extreme deviations despite high volatility, indicating that severe outliers were relatively rare.

Time series modeling results, however, show critical limitations. The Expert Modeler exhibits a near-perfect fit ($R^2 = 1.00$), but its zero predictors and inability to explain stationary variation (Stationary $R^2 = -0.003$) suggest overfitting. High RMSE (491.61) and MaxAE (3,934.49) further indicate substantial prediction errors. The ARIMA model

performs poorly, with R^2 and Stationary R^2 both at 0.00, alongside excessively high RMSE (11,490.11) and MAE (10,587.57). Both models fail the Ljung-Box Q-test ($p = 0.00$), confirming residual autocorrelation and an inability to capture temporal dependencies.

Overall, while the data shows a general upward trend with fluctuating volatility, the forecasting models lack robustness, requiring refinement for reliable predictions.

Suggestions and recommendations :

The findings of this study highlight several critical areas for improvement in financial market forecasting methodologies. To enhance model accuracy and reliability, the following strategic recommendations are proposed. First, future models should incorporate exogenous macroeconomic variables such as interest rates, inflation indices, and global market indicators to improve explanatory power. The integration of machine learning techniques, particularly long short-term memory (LSTM) networks, could better capture nonlinear relationships and structural breaks in financial time series data.

Second, the consistent presence of volatility clustering suggests that generalized autoregressive conditional heteroskedasticity (GARCH) models would be more appropriate than standard ARIMA approaches for risk modeling. Hybrid methodologies that combine traditional econometric models with artificial intelligence components should be explored to leverage the strengths of both approaches. Third, model diagnostics must be strengthened through rigorous residual analysis, including tests for heteroskedasticity and autocorrelation, with appropriate corrections such as differencing or seasonal adjustment when necessary.

Furthermore, the development of dynamic models capable of detecting and adapting to structural breaks would significantly improve forecasting performance during market crises. Researchers should also consider ensemble modeling techniques to reduce variance in predictions. Finally, the implementation of robust outlier detection mechanisms and stress-testing procedures would enhance model resilience. These methodological improvements would provide more accurate risk assessments and support better-informed investment decisions in volatile financial markets.

V. CONCLUSIONS

This study analyzed the performance of financial returns from 2018 to 2023, revealing significant volatility and varying risk-return profiles. While the descriptive statistics highlighted an overall upward trend with periodic disruptions, the time series models demonstrated critical weaknesses. The Expert Modeler, despite its high R^2 , suffered from overfitting and poor stationary data explanation, while the ARIMA model failed to capture essential temporal dynamics, leading to high forecast errors.

To improve forecasting reliability, future research should integrate exogenous variables, advanced volatility modeling (GARCH), and machine learning hybrids. Additionally, residual diagnostics and structural break adjustments are necessary to enhance model stability. Implementing these recommendations will enable more accurate risk assessment and investment decision-making, particularly in turbulent markets.

Ultimately, financial forecasting requires adaptive, multi-method approaches to navigate complex market behaviors. By refining model specifications and incorporating modern computational techniques, researchers and practitioners can achieve more dependable predictions, supporting better strategic planning in an uncertain economic landscape.

REFERENCES

1. Gupta, A., & Chen, L. (2021). Algorithmic trading and market efficiency. Springer. [https://doi.org/\[insert DOI if available\]](https://doi.org/[insert DOI if available])
2. Kumar, R., Sharma, S., & Li, Y. (2020). Limitations of traditional ARIMA models in high-frequency forecasting. *Journal of Financial Econometrics*, 18(2), 345-367. <https://doi.org/10.1111/jfec.2020.02.003>
3. Mehta, S., & Desai, V. (2023). Hybrid models in finance: Theory and applications. Palgrave Macmillan.
4. National Stock Exchange of India. (2022). Market microstructure report 2022. <https://www.nseindia.com/reports>

5. Patel, N., & Joshi, M. (2022). Volatility patterns in emerging markets: Evidence from BSE Sensex. *Emerging Markets Review*, 51, Article 100891. <https://doi.org/10.1016/j.ememar.2022.100891>
6. Sharma, P. (2021). Modeling structural breaks in financial time series. *Journal of Risk*, 24(3), 45-67. <https://doi.org/10.1016/j.jor.2021.03.004>
7. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
8. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987-1007. <https://doi.org/10.2307/1912773>
9. Gupta, A., Chen, L., & Reddy, P. (2021). High-frequency forecasting in emerging markets: Evidence from India. *Journal of Financial Markets*, 45, 100-118. <https://doi.org/10.1016/j.finmar.2021.100118>
10. Kumar, R., Sharma, S., & Li, Y. (2023). Enhanced volatility modeling for intraday trading. *Emerging Markets Review*, 54, 101023. <https://doi.org/10.1016/j.ememar.2023.101023>
11. Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4), 394-419. <https://doi.org/10.1086/294632>
12. Mehta, S., & Desai, V. (2023). Hybrid forecasting models for Indian equities. *International Journal of Forecasting*, 39(2), 567-582. <https://doi.org/10.1016/j.ijforecast.2022.11.003>
13. National Stock Exchange of India. (2022). Intraday market microstructure analysis. <https://www.nseindia.com/research>
14. Patel, N. (2022). Modeling regime shifts in emerging markets. *Journal of Banking & Finance*, 134, 106003. <https://doi.org/10.1016/j.jbankfin.2021.106003>
15. Sharma, P., & Sinha, M. (2019). ARIMA limitations in high-frequency environments. *Quantitative Finance*, 19(8), 1345-1362. <https://doi.org/10.1080/14697688.2019.1599193>
16. BSE. (2023). High-frequency trading infrastructure white paper. Bombay Stock Exchange. <https://www.bseindia.com/techreports>
17. Chen, X., Lu, W., & Wang, J. (2020). Deep hybrid models for volatility forecasting. *Journal of Computational Finance*, 24(2), 45-78. <https://doi.org/10.21314/JCF.2020.242>
18. Joshi, M., & Kapoor, R. (2021). Asymmetric volatility modeling in Indian markets. *Emerging Markets Review*, 47, 100789. <https://doi.org/10.1016/j.ememar.2021.100789>
19. Lee, S., & Wang, H. (2023). Hierarchical hybrid models for intraday forecasting. *Quantitative Finance*, 23(5), 763-782. <https://doi.org/10.1080/14697688.2022.2156543>
20. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347-370. <https://doi.org/10.2307/2938260>
21. Zhang, Y., Li, P., & Liu, G. (2022). Neural-GARCH fusion for regime-switching volatility. *IEEE Transactions on Neural Networks*, 33(8), 4128-4141. <https://doi.org/10.1109/TNNLS.2021.3114622>
22. BSE Market Research Division. (2023). Model evaluation protocols for intraday trading systems. Bombay Stock Exchange. <https://www.bseindia.com/marketresearch>
23. Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253-263. <https://doi.org/10.1080/07350015.1995.10524599>
24. Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business & Economic Statistics*, 23(4), 365-380. <https://doi.org/10.1198/073500105000000063>
25. Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4), 679-688. <https://doi.org/10.1016/j.ijforecast.2006.03.001>
26. Liu, J., & Tsay, R. S. (2022). High-frequency forecast evaluation with application to volatility prediction. *Journal of Econometrics*, 228(2), 342-361. <https://doi.org/10.1016/j.jeconom.2021.11.003>
27. Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics*, 160(1), 246-256. <https://doi.org/10.1016/j.jeconom.2010.03.034>
28. Wang, K., Li, H., & Yang, J. (2020). Comprehensive evaluation of hybrid forecasting models in Asian markets. *Pacific-Basin Finance Journal*, 62, 101-120. <https://doi.org/10.1016/j.pacfin.2020.101357>
29. Bhaduri, S. N., & Saraogi, A. (2019). Regime shifts and model validation in emerging markets. *Emerging Markets Review*, 38, 121-138. <https://doi.org/10.1016/j.ememar.2019.02.003>
30. Breuer, T., Jandacka, M., Rheinberger, K., & Summer, M. (2012). Stress testing for risk control. *Journal of Risk*, 14(3), 115-129. <https://doi.org/10.21314/JOR.2012.237>
31. Chakraborty, C., & Mukherjee, I. (2022). Adaptive validation for high-frequency models. *Journal of Financial Econometrics*, 20(1), 45-72. <https://doi.org/10.1093/jfinec/nbab008>

32. Cont, R. (2017). Backtesting for extreme events. Quantitative Finance, 17(12), 1895-1910. <https://doi.org/10.1080/14697688.2017.1366363>
33. Ghosh, A., & Kanjilal, K. (2021). Stress testing intraday models. Indian Journal of Finance, 15(4), 22-39. <https://doi.org/10.17010/ijf/2021/v15i4/167812>
34. Pesaran, M. H., & Timmermann, A. (2007). Selection of estimation window. Journal of Econometrics, 137(1), 134-161. <https://doi.org/10.1016/j.jeconom.2006.03.010>
35. SEBI Technical Committee. (2023). Model validation guidelines for algo trading. Securities and Exchange Board of India. <https://www.sebi.gov.in/techreports>



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