Importance of Financial Econometric Models in Analyzing the Performance of Equity Investments in the Capital Market : A Study

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Abstract

The study underlined the various financial econometric techniques to evaluate the performance of financial investments made in capital markets. The present research work studied the market trends in capital markets and analyzed the factors influencing the market movements. The study also evaluated the risk characteristics of investors and the investments made in the capital market. The study aimed to estimate the returns of investments based on the risk characteristics by use of financial econometrics after evaluating the risk characteristics. The study project also looked at investment volatility and identified the elements that affected it, as well as the influence of volatility on investments and the projected effect of volatility on capital market investments. The current research work performed financial modeling using the different applications and techniques of financial econometrics, studied the volatility and risk characteristics of investments, and developed solutions for minimizing the risk of investors. The study assessed the performance of stocks depending on the company and industry and examined the performance of several chosen firm stocks. It recommended that investors use financial econometric modeling to optimize their investment returns.

Keywords : **financial econometrics, risk, return, volatility, stock, and investments**

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The study of quantitative elements in the field of finance is known as financial econometrics. This discipline addresses a spectrum of financial matters by employing statistical techniques and economic principles. It encompasses activities like constructing financial models, deriving conclusions from these models, estimating volatility, risk management, empirical testing of financial and economic theories, portfolio allocation based on risk-adjusted returns, modeling intricate financial systems, and implementing hedging strategies. Black Scholes and Merton, who established the general equilibrium model for securities price, released two significant publications that had a significant impact on modern asset pricing. Since then, the derivatives markets have grown significantly. In the fields of risk management, proprietary trading, securities regulation, portfolio management, financial consulting, and other related fields, finance professionals frequently employ sophisticated statistical approaches and contemporary computational capacity.

Finance, economics, probability, statistics, and applied mathematics are all actively integrated into the

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discipline of financial econometrics. Economic theory provides a valuable conceptual structure and guidance, while quantitative methodologies such as statistics, probability, and applied mathematics serve as essential tools for addressing numerical challenges within the realm of finance. The world of finance is full of new complexities that always arise. More sophisticated stochastic models have been developed for security pricing that incorporate key characteristics of basic economic phenomena. In the meantime, statistical methods are used to model complex financial systems, determine parameters for stochastic models, and evaluate economic theories empirically by examining financial data.

The evolution of financial markets has not only opened doors to the exploration of econometrics within the financial context but has also spurred the creation of a distinct subfield known as "Financial Econometrics." This specialized field was developed to improve our understanding and create more efficient investment management solutions. At the nexus of finance, statistics, and applied mathematics, financial econometrics is acknowledged as a thriving field.

In order to address difficult numerical problems in the financial sector, practitioners in this field must harness the power of quantitative tools like statistics and applied mathematics. Financial econometrics provides theoretical and practical insights by combining these approaches. Using cutting-edge statistical, mathematical, and contemporary economic ideas, this field tackles a broad range of financial problems. These encompass diverse tasks, such as formulating financial models, conducting estimations and inferences based on these models, gauging volatility, implementing risk management strategies, empirically testing theories within financial economics, analyzing capital asset pricing, valuing derivatives, optimizing portfolio allocation, enhancing risk-adjusted returns, simulating intricate financial systems, devising effective hedging strategies, and resolving other issues intertwined with financial markets.

Key Application Areas of Financial Econometrics

Financial econometric techniques are applied in various economic theories to develop optimal solutions for investing in financial markets while minimizing risk and maximizing returns. Key application areas include:

- **Asset Pricing :** Determining asset prices using mathematical and statistical models incorporating technical and fundamental analysis principles.
- **Portfolio Diversification :** Identifying and mitigating security risks within investment portfolios.
- **Interest Rates/Yields :** Evaluating debt instruments using metrics like principal, maturity, and duration to attract investors.
- **Portfolio Bond Yields :** Analyzing varying bond interest rates within aggregated bond portfolios.
- **Asset Returns :** Accurately assessing investment returns over time using price and duration to evaluate capital appreciation.
- **Economic Indicators :** Estimating GDP and other indicators over set periods via financial modeling, forecasting, and time series analysis.

Types of Data Used in Financial Econometrics

Financial econometrics experiment analysis and interpretation depend heavily on data acquisition. There are several ways to get relevant data:

- **Cross-Sectional Data :** Information gathered by studying subjects like individuals, entities, countries, or regions at a single point in time. For example, randomly sampling 500 people to assess diabetes rates in a population.

- **Time-Series Data :** Observations of one or more variables over time, arranged chronologically. Useful for analyzing how a security or asset changes over time.
- **Pooled Data :** Data acquired via random sampling across different time intervals. Facilitates larger sample sizes for more robust analysis.
- **Panel/Longitudinal Data :** Observations of different cross sections over time. For example, data on individuals, firms, and groups over time.

The capital market is an investment platform for trading equities, bonds, and other instruments. It distributes excess money to organizations in need of funding. Over several decades, the Indian equity market has experienced significant growth in terms of traceability, stability, efficiency, and maturity.

Literature Review

In recent years, we have increasingly leveraged computational techniques to analyze financial markets. Qin et al. (2011) compared regression and neural network models for Chinese stock market forecasting, finding value in incorporating short selling and technical indicators. However, they did not evaluate ensemble approaches.

Tripathi and Seth (2014) investigated connections between the Indian stock market's performance and selected macroeconomic indicators using data spanning July 1997 to June 2011. For the analysis, methods such as regression, the ARCH model, Granger causality, factor analysis, ADF and PP Unit root tests, and the Johansen co-integration test were used. By measuring the stock market's reaction to economic shocks, impulse response analysis was used. There were notable linkages between stock market indicators and macro variables. Using factor analysis, the main drivers of inflation, interest rates, and currency rates were found. The regression model explained 23.8%, 23.3%, and 16.9% of Sensex, market capitalization, and market turnover variations, respectively. There were five co-integrating relationships found between the stock market and macroeconomic factors. Deep learning and machine learning have drawn a lot of interest.

Andersson and Haglund (2015) examined three generalized autoregressive conditional heteroscedasticity (GARCH) models (GARCH, EGARCH, and GJR-GARCH) and two distributions (Normal and Student's-t) to forecast value at risk (VaR) across seven major international equity indices. The objective of the paper was to determine the most effective model and distribution for VaR forecasting. The study concluded that EGARCH (1,1) consistently outperformed the other models across all indices analyzed, suggesting its preference for VaR forecasting.

De and Chakraborty (2015) discussed the contentious nature of foreign portfolio flows, often referred to as "hot money," due to their volatile nature. When investors suddenly remove their assets, these flows have the potential to worsen economic downturns in recipient nations. The relationship between foreign institutional ownership and stock market volatility is still unclear despite the media's emphasis on their effects during crises. While some sources contend that institutions could cause price instability by increasing turnover, others contend that institutional ownership at a higher level could lessen volatility. The study used a VaR framework to analyze firm-level Indian panel data from 2003 to 2013 in order to examine the relationship between stock return volatility and FII holdings. The results showed that there was no discernible causal association between the two variables.

Deshpande (2017) explored the semi-strong form of market efficiency, focusing on whether all critical company information consistently influences stock prices. While financial markets generally operate under this hypothesis, the study revealed that certain publicly available data, such as efficiency ratios, may not always impact stock trading decisions compared to more straightforward metrics like sales or profits. The study highlighted the relationship between market-to-book ratios among particular IT stocks and corporate strategy, as determined by investments made to increase competitiveness.

Kumar and Khanna (2018) investigated volatility behavior and spillover across stock markets in India, China, Hong Kong, and Japan. Using bivariate GARCH-BEKK, GARCH (1, 1), and ARCH models, they discovered that India had the most stable market and China had the most variation. India and Hong Kong demonstrated comparable growth trends and substantial regional economic interdependence. The findings showed that historical volatility had a significant impact on present volatility in all markets, with China showing the greatest volatility persistence. Since GARCH coefficients were higher than ARCH coefficients, it appears that historical volatility had a greater impact on current volatility than did fresh market data.

Kim et al. (2019) put forth a hierarchical attention network that automatically extracts useful features from relational data to predict individual stocks. It could be valuable to extend this to the general market forecast. Nelson et al. (2017) found promise in LSTM networks to leverage price data for trend forecasting. However, the incorporation of supplementary variables like volatility and volume may enhance outcomes. Ashwani and Sheera (2018) emphasized the significance of financial development and capital markets in economic growth, particularly in enhancing asset accumulation and managing risks like liquidity and price discovery. The study identified a vacuum in the body of knowledge about the application of high-frequency data in the Indian setting to quantify stock market volatility in conjunction with macroeconomic indicators. Using the MIDAS GARCH approach, the research investigated how macroeconomic variables such as exchange rates, money supply, and treasury bill rates, alongside net foreign institutional investment and stock turnover ratio, influence stock market volatility.

Reddy (2019) highlighted the volatility of stock markets and emphasized the importance of accurate prediction for traders to strategize effectively. The study attempted to anticipate changes in the BSE and NSE indices and evaluate data stationarity using stochastic time series ARIMA modeling. Based on factors like AIC, BIC, RMSE, and adjusted R^2 values, the best-fit ARIMA (0,1,0) model was chosen, allowing for short-term forecasts that are helpful for financial market investment decisions.

Balasubramanian et al. (2021) highlighted the interest in predicting stock market movements among traders and engineers. They discussed methods such as historical data analysis and social media scrutiny. The study emphasized the use of machine learning models like regression and LSTM, which utilize current and past market indices to forecast stock values based on factors such as open, close, low, high, and volume. The research also evaluated LSTM architectures for short- and long-term financial time series prediction, aiming to improve stock market predictability.

Econometric models and contemporary methods have been integrated in recent work. Bouzinanis and Hughston (2020) developed an optimized hedging strategy using an estimated pricing kernel but assumed incomplete information. Jiang (2021) noted the potential of deep learning models but called for a greater focus on benchmarking and live testing. Predictability might be improved by adding microstructure elements and causal analysis.

Shah et al. (2022) provided a comprehensive review of hybrid deep learning techniques for stock price prediction, analyzing the potential to maximize returns through future pattern forecasting. However, the focus was primarily on methodology rather than financial econometrics. Zhou et al. (2022) proposed a multi-relational graph convolution network to leverage both temporal and structural data for improved stock movement prediction. Although the China A-share market's results were encouraging, asset extension is still required.

In order to identify suitable short-term price prediction models for investors, Lakshmanan (2019) assessed the ARIMA and Box–Jenkins models. Nonetheless, only one index was assessed over a limited timeframe. Hoseinzade and Haratizadeh (2019) highlighted the potential of convolutional neural networks for automatic feature extraction from diverse datasets to enhance market forecasting. However, the correlation between multiple markets remains relatively untouched.

In contemporary financial markets, predicting currency rates has proven to be a difficult task for traders and practitioners (Babu & Reddy, 2015). This paper investigates the behavior of daily exchange rates of the Indian Rupee (INR) against the United States Dollar (USD), British Pound (GBP), Euro (EUR), and Japanese Yen (JPY). ARIMA, neural network, and Fuzzy neuron models are examined for forecasting these currencies in Indian foreign exchange markets. Analysis was done on the daily RBI reference exchange rates between January 2010 and April 2015.

Kumar and Singh (2023) examined the day-of-the-week (DOW) effect in the Indian stock market using the Sensex index from 2000 to 2019, a widely studied calendar anomaly where returns vary across weekdays. The study, in contrast to predictions, did not find any evidence of the DOW impact during the 20 years, not even during the 2008–2009 global financial crisis and its aftermath. Results refuted the existence of this oddity even after winsorizing data to address crisis outliers. Additionally, analysis across other sectoral indices of the BSE yielded similar findings. While suggesting market efficiency, further research on alternative calendar anomalies like the turn of the month and year, holiday effects, and Monday effects is recommended to comprehensively assess market efficiency in India.

Patil (2024) posited that investing in the stock market blends art and science, aiming for superior returns compared to other investment avenues. There is no set formula for figuring out a stock's justifiable price despite the fact that it is subjective. Using data spanning 10 years, this study attempted to analyze the market price of companies traded on Indian exchanges. Significant explanatory variables were identified, explaining 62% of the market price variation. The findings are beneficial for academics, researchers, and market participants in comprehending the intricate dynamics of stock market pricing and its influencing factors.

Overall, these latest studies showcase the range of modern approaches being applied to forecast equity price changes and volatility. However, most focus exclusively on methodology rather than the importance of financial econometrics models for investment analysis. Furthermore, despite promising results, translation and testing across markets, periods, and real-world trading systems appear limited. More research is needed intersecting domain knowledge with cutting-edge techniques for maximal practical impact.

Unique Aspects of the Study

Advanced financial modeling: Uniquely applies sophisticated financial econometric models (GARCH, binary logistic regression) to assess equity investment performance, showcasing practical applications.

Multi-Industry Analysis

Stands out by analyzing companies from diverse industries (Automobile, Banking, Infrastructure, IT, Pharmaceuticals), offering a holistic view of market dynamics.

Emphasis on Volatility Forecasting

Uniquely focuses on volatility forecasting using GARCH models, addressing the critical need for accurate risk assessment in capital markets.

Incorporation of Binary Logistic Regression

Uniquely utilizes binary logistic regression to examine relationships between market returns, stock returns, and volatility, adding a diverse statistical perspective.

Comprehensive Descriptive Analysis

Uniquely includes detailed descriptive analysis, such as ANOVA and probit analysis, providing a solid foundation for understanding stock returns and market characteristics.

Research Gap Contributions

Advanced Modeling Techniques

Addresses the research gap by employing advanced models like GARCH, contributing to the application of sophisticated techniques in equity investment analyses.

Industry-Specific Insights

Bridges a gap by offering insights into stock performance across diverse industries, enhancing industry-specific understanding of financial econometrics.

Volatility Forecasting Emphasis

Closes a gap by emphasizing volatility forecasting heavily, addressing the requirement for accurate risk assessment in capital market investments.

Statistical Diversity with Binary Logistic Regression

Addresses a gap by incorporating binary logistic regression, adding statistical diversity to examine market and stock return relationships.

Comprehensive Descriptive Analysis

Fills a research gap by conducting a detailed descriptive analysis, contributing to a thorough exploration of stock returns and market characteristics.

The objectives considered to evaluate the stocks are listed below :

- To study the price movements of stocks in the stock exchange.
- To analyze the risk and returns of stocks.
- To examine the impact of the volatility of stocks on returns using financial econometric models.
- To suggest the necessary measures to maximize investors' returns.

Methodology

The study is based on secondary information collected from different sources gathered for the period 2011–2020. Table 1 presents the results of a 10-year financial econometric model evaluation of ten business stocks covering five industries. Using econometric models and formulating hypotheses, the assessment evaluates the risk, returns, and volatility of these chosen stocks.

Table 1. ***Name of the Companies and Allied Industries***

S. No.	Company	Industry
1	Hero MotoCorp Limited	Automobile
2	Tata Motors Limited	
3	ICICI Bank Limited	Banking
4	Punjab National Bank	
5	Adani Ports and Special Economic Zone Limited	Infrastructure
6	Larsen & Toubro Limited	
7	Infosys Limited	Information Technology
8	Tata Consultancy Services Limited	
9	Cipla Limited	Pharmaceuticals
10	Sun Pharmaceutical Industries Limited	

Data Analysis and Results

This analysis, which draws from secondary sources of data, examines the performance of 10 distinct companies that span five distinct industries during 10 years, from the calendar years 2011 to 2020. The financial econometric models are applied to assess the performance of select company's stock process, the below is the list of companies and their allied industries considered for data analysis and discussion.

Stock Returns to Market Returns

To understand the stock returns and market returns, the ANOVA one-way test is conducted with the following hypothesis.

➪ **H_{01} :** There is no significant impact of market returns on stock returns.

Table 2 presents the descriptive statistics pertaining to stock returns and also shows that 20 observations have negative returns, whereas 80 observations are positive. The relative averages of the positive and negative observations are 1.45 and 1.90, respectively. The hypothesis is tested to check if the difference in the mean variances of stock returns to market returns is significant or not.

Table 3 illustrates the test results of ANOVA one-way on stock returns to market returns. The sum of squares achieved the value of 3.240, and the *F* value is found to be significant at 14.7 at one degree of freedom. The significance value identified as 0.001, i.e., *p* is less than 0.05 at a 5% critical level, thereby rejecting the null hypothesis. Thus, the stock returns are dependent on market returns, i.e., the value of returns of stock directly positively related to market returns. The change in market returns resulted in a change in stock returns.

Table 2. ***Descriptive Statistics on Stock Returns***

Descriptive Analysis				
	N	Mean	Standard Deviation	Standard Error
Positive	80	1.45	0.501	0.056
Negative	20	1.90	0.308	0.069
Total	100	1.54	0.501	0.050

Table 3. *Stock Returns to Market Returns*

ANOVA					
	SS	***df***	**MS**	***F***	**Sig.**
Between Groups	3.240	1	3.240	14.700	0.001
Within Groups	21.600	98	0.220		
Total	24.840	99			

Note. Dependent: Stock Returns.

Independent: Market Returns.

SS: Sum of Squares, MS: Mean Squares, *Df*: Degrees of freedom.

Volatility to Market Price of Share and Earnings Per Share

In order to evaluate the volatility of earnings per share and the market price of shares, probit analysis is performed to verify the following hypothesis.

- **H_{02} :** Volatility of stock not influenced by the market price and earnings per share.

Probit analysis serves as a technique for examining the correlation between a stimulus and binomial response. This approach is a special kind of regression analysis designed for response variables that have a binary result (positive or negative). The process involves converting a concentration-response curve into a linear form, enabling subsequent analysis through either least squares or maximum likelihood regression methods.

The experiment findings derived from probit analysis are displayed in Table 4. The convergence information of the probit test states the optimal solution is found after 11 iterations between the test's independent and dependent variables. The correlation extracted for the variable market price of 0.095 and for EPS is –0.671, i.e., if there is a change observed in earnings per share, there is a negative movement for the market price. The

Table 4. *Probit Analysis on Volatility of Stocks*

Convergence Information							
		Number of Iterations		**Optimal Solution Found**			
Probit		11		Yes			
Covariance and Correlations of Parameter Estimates							
			MPS		EPS		
Probit	Correlation		0.095		–0.671		
	Covariance		–0.036		0.030		
Parameter Estimates							
	Parameter	***B***	**SE**	***Z***	**Sig.**	**95% CI**	
						LB	**UB**
Probit	Market Price of Share	–0.555	0.309	–1.798	0.072	–1.160	0.050
	Earnings Per Share	0.260	0.174	1.496	0.135	–0.081	0.601
	Intercept	0.556	0.719	0.773	0.439	–0.163	1.275

Note. Dependent – Volatility .

Predictors – MPS (Market Price of Share), EPS (Earnings Per Share).

C.I – Confidence Interval, SE – Standard Error.

LB – Lower Bound, UB – Upper Bound.

covariance of two tested variables is identified as –0.036 and 0.030, i.e., the negative covariance is noticed for the variable MPS with the tested element volatility.

The negative coefficient of, i.e., *B* is observed for the variable market price of share, and the coefficient *B* value for earnings per share is 0.260. The test significance values for two independent variables with the dependent variables, i.e., the market price of a share is 0.072 and earnings per share is 0.174 at a 5% critical level. It is noticed the p values of two tested variables are greater than 0.05, i.e., $p > 0.05$ ($\alpha = 0.05$). It provides compelling evidence to support the null hypothesis's assertion. The preceding experiment yielded the following mathematical method to calculate a stock's volatility.

$$\text{Volatility} = \text{Constant} + (B_1)\,\text{MPS} + (B_2)\,\text{EPS Volatility} = 0.556 - (0.555)\,\text{MPS} + (0.260)\,\text{EPS}$$

Therefore, it can be seen from the given probit solution that there is no positive correlation between stock volatility and market price and earnings per share. Earnings per share and market price have no bearing on volatility.

Analysis of GARCH (Generalized Autoregressive Conditional Heteroscedasticity)

A statistical framework known as the GARCH model is used to analyze time-series data, especially when serially autocorrelated variance errors are assumed. It is proposed that the variance of the error term in GARCH models follows an autoregressive moving average procedure. This renders GARCH a valuable statistical methodology for forecasting the volatility of returns in the realm of financial assets. These models are used when there is heteroskedasticity or unequal patterns of variation in an error term or variable within a statistical model, as shown by the variance of the error term not being consistent.

The practice of volatility modeling and prediction holds significant significance in the study of financial time series. It proves pivotal not just for understanding trends but also for effective risk hedging and accurate financial instrument pricing. The GARCH model is a trailblazing model among the multitude of econometric models that attempt to represent the volatility of financial returns. It is a symbol of the continuous search for better modeling methods.

The following hypothesis is tested to know the effect of GARCH on the returns of the selected stocks.

➯ **H_{03} :** There is no GARCH effect on the returns of selected stocks.

Table 5 illustrates the effect of the GARCH time-series model on stock selected for research. It is observed that the long-run mean is arrived at –4.21, the constant volatility is identified as 16.3.43, and the co-efficient

Table 5. ***GARCH Table on Returns***

GARCH Model (1,1)		
	Parameter	**Value**
Long run mean	μ	–4.21
Constant in conditional volatility	α_0	1603.43
Coefficient of ARCH effect	α_1	0.01
Coefficient of GARCH effect	β_1	0.01
Goodness-of-fit		
Log-likelihood fit (LLF)		–510.99
Significance		0.00148
Annual volatility		40.314

associated with ARCH (α_1) and GARCH (β_1) values are noticed as 0.01 for both. The model LLF test value arrived at –510.99. The annual volatility estimated for the above returns is 40.314%. The significance value of the GARCH effect at the five percent level is 0.00148, i.e., the approximate p-value is $0.001 < 0.05$. Hence, the statement defined under the null hypothesis is rejected.

The test significant value of the GARCH (1,1) model supports the assumptions that there is a significant GARCH effect on returns of selected stocks and the mean arrived from the test supports the further predictions for certain periods.

The GARCH model is used to illustrate the returns of particular equities in the above graph. Figure 1 shows that the year 2012 saw the highest returns, while the year 2011 saw the lowest. For the years 2011, 2015, and 2018, the negative returns are received.

Forecasting GARCH Effect for the Next 10 Periods

Table 6 displays the GARCH effect forecasting outcomes for the next 10 periods. Table 6 demonstrates the forecasting results of the GARCH effect for the next 10 periods. The mean value of –4.2116 is consistently seen, indicating that the variables are stationary and provide support for the test result in subsequent predictions. There is a variation in the test static from 40.28475 to 40.31119 and in the standard deviation from 40.28475 to 40.31417. The lowest lower limit reached the numerical value of 83.2259. The maximum upper limit is recorded to be 74.80271.

Figure 1. ***Graphical Representation of the GARCH Effect***

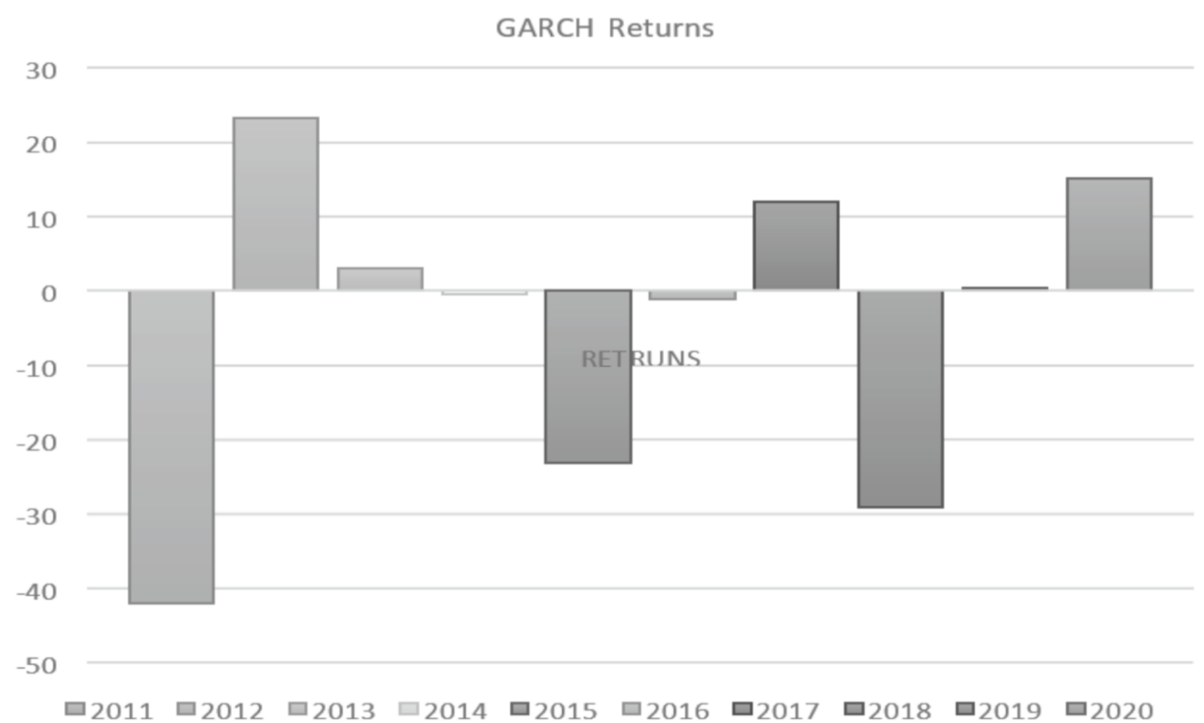

Table 6. ***Forecasting GARCH Effect for the Next 10 Periods***

Step	Mean	Standard Deviation	Test Statistic	Upper Limit	Lower Limit
1	–4.2116	40.28475	40.28475	74.74506	–83.1683
2	–4.2116	40.31377	40.29926	74.80194	–83.2251
3	–4.2116	40.31416	40.30423	74.8027	–83.2259
4	–4.2116	40.31417	40.30671	74.80271	–83.2259
5	–4.2116	40.31417	40.3082	74.80271	–83.2259
6	–4.2116	40.31417	40.3092	74.80271	–83.2259
7	–4.2116	40.31417	40.30991	74.80271	–83.2259
8	–4.2116	40.31417	40.31044	74.80271	–83.2259
9	–4.2116	40.31417	40.31085	74.80271	–83.2259
10	–4.2116	40.31417	40.31119	74.80271	–83.2259

Binary Logistic Regression on Market Returns and Stock Returns to Volatility

The application of logistic regression involves examining vital financial ratios and macro-financial variables across companies. This analysis discerns the significant ratios and their impact on stock prices. When examining several variables influencing a positive or negative outcome or other binary classifications with just two possible outcomes, binary logistic regression is useful. In order to comprehend how market returns and stock returns relate to volatility, the following hypothesis is articulated and tested.

- **H_{04} :** Stock returns and market returns do not influence the volatility of stocks.

Table 7. ***Binary Logistic on Volatility of Stocks to Market and Stock Returns***

Model Summary

Step	–2 Log-likelihood	Cox and Snell R^2	Nagelkerke R^2
1	91.728	0.128	0.196

Classification Table

Observed		Predicted Volatility Positive	Predicted Volatility Negative	Percentage Correct
Volatility	Positive	78	0	100.0
	Negative	22	0	0.0
Overall Percentage				78.0

Coefficient Variables

	B	S.E.	Wald	*df*	Sig.	Exp. (B)	95% Confidence Interval Lower	95% Confidence Interval Upper
Stock Return	–1.517	0.553	7.529	1	0.006	0.219	0.074	0.648
Market Return	2.526	1.079	5.481	1	0.019	12.505	1.509	103.658
Constant	–2.860	1.028	7.742	1	0.005	0.057		

Note. [a.] Dependent: Volatility and Independent: Market Returns.

The experiment findings of the binary logistic regression linking the dependent variable volatility and the independent variables, stock returns and market returns, are displayed in Table 7. The experiment's variables were fitted with a log-likelihood ratio of 91.728. Cox and Snell R^2 value identified as 0.128, i.e., the variance extracted between the response variable and selected predictors is 1.28%. The values in the classification table explain the highest expected percentage of the chosen experiments reaching the 5% threshold of significance. It is noticed from the result the maximum correct predicted percent achieved in the above experiment is 78%, i.e., the test results exactly predicted the volatility of stocks up to 78% on overall observations. The positive Exp. (B)'s observed in the experiment, i.e., the variables are all positively correlated and show their impact on the dependent variable. The remarkable value associated with stock returns is $0.006 < 0.05$, and market returns are $0.019 < 0.05$ at critical value, i.e., $\alpha = 0.05$. Hence, based on the test's remarkable values, the statement of the null hypothesis is disapproved.

The hypothesis that both market and stock returns influence a stock's volatility is supported by the outcome of the binary logistic regression experiment. Another way to put it is that changes in market and stock returns are causing changes in stock volatility.

Conclusion

Capital market investment is stimulated by the financial reforms that the Indian government enacted after the post-liberalization era. The current study focused on how financial econometric models are used to evaluate the performance of various capital market investments. The study concludes that financial econometric techniques are the better options for evaluating and forecasting the outcomes of capital market investments. Financial econometric models compute and estimate present and future returns for different equity investments placed in capital markets more precisely by evaluating the impact of investor risk factors. These models are highly recommended for active investors to regularly monitor their investment performance and stock volatility, and these models assist investors, traders, and other market participants in identifying risk elements and selecting the best investment options for future market equity investments. The models related to financial econometrics help long-term investors create the most effective trading strategies, and fundamental analysts assess the performance of businesses and industries. Finally, the results of the experiments conducted in this study using financial econometric models are suggested for technical analysts and speculators in the capital market to design and implement the best hedging strategies for day, short, and long-term traders to maximize their investment returns by effectively managing risk and properly assessing stock fluctuations in the market.

Limitations of the Study

Data Limitations

The research depends on secondary data spanning from 2011 to 2020, and there may be constraints on the accessibility and precision of prior data.

Industry Selection

The study focuses on ten companies from five different industries. The generalizability of the findings may be limited, as the dynamics and factors influencing stock performance can vary across industries.

Assumption in Models

The assumptions of normality and linearity are two possible drawbacks in econometric models.

External Factors

Lack of consideration for external influences such as macroeconomic conditions and regulatory changes.

Time Frame

The ten-year time range may result in gaps in knowledge about long-term trends or structural changes.

Scope for Further Research

Extended Time Analysis

Explore stock performance over more extended periods to capture diverse market cycles.

Incorporate External Factors

Examine how the performance of stocks is affected by outside variables such as world events and economic data.

Diverse Industry Samples

To improve the study's generalizability, cover a wider range of businesses and industries.

Comparative Market Studies

Perform comparative analyses in various markets to comprehend the differences in market dynamics between regions.

Advanced Modeling Techniques

Use more advanced modeling methods to deal with the structural complexity and nonlinearity of financial data.

Behavioral Finance Insights

Incorporate behavioral finance perspectives to understand the role of investor sentiment in stock price movements.

Technological Impact Analysis

Investigate the influence of technological advancements, such as algorithmic trading, on stock returns and volatility.

Cross-Asset Dynamics

Examine the interactions among various asset types and how they affect stock volatility to gain a thorough grasp of the market.

Authors' Contribution

Dr. Vidyadhar Reddy Aileni conceived the idea and developed qualitative and quantitative designs to undertake the empirical study. Mr. Ramesh Mastipuram extracted research papers with high repute, filtered these based on keywords, and generated concepts and codes relevant to the study design. Dr. Rama Raju Kanumuri verified the analytical methods and supervised the study. The interviews were conducted by Dr. Vidyadhar Reddy Aileni and Mr. Ramesh Mastipuram; some in colloquial language and some in English. The same were further transcripted and translated into English by all the others. The numerical computations were done by Dr. Vidyadhar Reddy using SPSS 20.0.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

Andersson, O., & Haglund, E. (2015). *Financial econometrics: A comparison of GARCH type model performances when forecasting VaR* (Thesis, Department of Statistics). Digital Scientific Archive. https://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-243245

Ashwani, & Sheera, V. P. (2018). Indian stock market volatility and economic fundamentals: MIDAS approach. *Indian Journal of Finance, 12*(8), 7–21. https://doi.org/10.17010/ijf/2018/v12i8/130741

Babu, A. S., & Reddy, S. K. (2015). Exchange rate forecasting using ARIMA, neural network and fuzzy neuron. *Journal of Stock & Forex Trading, 4*(3), 1000155. https://doi.org/10.4172/2168-9458.1000155

Balasubramanian, K., Veeramanoharan, G., Kumar, J. H., & Paramasivan, B. (2021). Stock market prediction using machine learning. *International Journal of Scientific Research in Science and Technology (IJSRST), 9*(1), 916–922.

Bouzinanis, G., & Hughston, L. P. (2020). Optimal hedging in incomplete markets. *Applied Mathematical Finance, 27*(4), 265–287. https://doi.org/10.1080/1350486X.2020.1819831

De, S., & Chakraborty, T. (2015). Foreign portfolio investment and stock market volatility in India. *Indian Journal of Finance, 9*(1), 49–59. https://doi.org/10.17010/ijf/2015/v9i1/71535

Deshpande, R. (2017). Semi-strong form of market efficiency: Does all critical information affect stock price valuations? *Indian Journal of Research in Capital Markets, 4*(2), 15–24. https://doi.org/10.17010/ijrcm/2017/v4/i2/116085

Hoseinzade, E., & Haratizadeh, S. (2019). CNNpred: CNN-based stock market prediction using a diverse set of variables. *Expert Systems with Applications, 129*, 273–285. https://doi.org/10.1016/j.eswa.2019.03.029

Jiang, W. (2021). Applications of deep learning in stock market prediction: Recent progress. *Expert Systems with Applications, 184*, 115537. https://doi.org/10.1016/j.eswa.2021.115537

Kim, R., So, C. H., Jeong, M., Lee, S., Kim, J., & Kang, J. (2019). *HATS: A hierarchical graph attention network for stock movement prediction*. arXiv preprint, arXiv:1908.07999. https://doi.org/10.48550/arXiv.1908.07999

Kumar, A., & Khanna, S. (2018). GARCH - BEKK approach to volatility behavior and spillover : Evidence from India, China, Hong Kong, and Japan. *Indian Journal of Finance, 12*(4), 7–19. https://doi.org/10.17010/ijf/2018/v12i4/122791

Kumar, S., & Singh, G. (2023). The day-of-the-week effect in the Indian stock market revisited. *Journal of Commerce & Accounting Research, 12*(3), p. 12.

Lakshmanan, M. P. (2019). Arima model in predicting NSE Nifty50 index. *Proceedings of five day workshop on financial econometrics from 15th to 19th October* (pp. 53–61). Directorate of Collegiate Education, Government of Kerala.

Nelson, D. M., Pereira, A. C., & Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. In *2017 International Joint Conference on Neural Networks (IJCNN)*, 1419–1426. IEEE. https://doi.org/10.1109/IJCNN.2017.7966019

Patil, R. (2024). Pricing of equity investment - An empirical analysis of Indian capital market. *International Journal of Advanced Research (IJAR), 12*(03), 683–689. https://doi.org/10.21474/ijar01/18438

Qin, Q., Wang, Q.-G., Ge, S. S., & Ramakrishnan, G. (2011). Chinese stock price and volatility predictions with multiple technical indicators. *Journal of Intelligent Learning Systems and Applications, 3*(4), 209–219. https://doi.org/10.4236/jilsa.2011.34024

Reddy, C. V. (2019). Predicting the stock market index using stochastic time series ARIMA modelling: The sample of BSE and NSE. *Indian Journal of Finance, 13*(8), 7–25. https://doi.org/10.17010/ijf/2019/v13i8/146301

Shah, J., Vaidya, D., & Shah, M. (2022). A comprehensive review on multiple hybrid deep learning approaches for stock prediction. *Intelligent Systems with Applications, 16*, 200111. https://doi.org/10.1016/j.iswa.2022.200111

Tripathi, V., & Seth, R. (2014). Stock market performance and macroeconomic factors: The study of Indian equity market. *Global Business Review, 15*(2), 291–316. https://doi.org/10.1177/0972150914523599

Zhou, Z., Zhang, L., Zha, R., Hao, Q., Xu, T., Wu, D., & Chen, E. (2022). Multi-relational graph convolution network for stock movement prediction. In *2022 International Joint Conference on Neural Networks (IJCNN),* (pp. 1–8). IEEE. https://doi.org/10.1109/IJCNN55064.2022.9892482

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