JÖNKÖPING UNIVERSITY

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Empirical Research Assignment:

The Impact of Stock Volatility and Time Horizon on Machine Learning Forecasting Accuracy

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Abstract:
This empirical research extends the work of Omar et al. (2022) by evaluating the forecasting performance of machine learning models on stocks with distinct volatility profiles, rather than across different time periods. We analyze an aggressive stock (Apple/AAPL) and a defensive stock (Procter & Gamble/PG) over 5-year and 10-year data windows using four models: Random Forest, XGBoost, LASSO, and Elastic Net. The key finding is that model accuracy is critically dependent on both the stock's volatility and the forecasting horizon. Contrary to the common assumption that complex models are superior, our results demonstrate that simpler, regularized linear models (LASSO and Elastic Net) were the most robust and accurate. They achieved the lowest error rates (MAE, RMSE) and highest R^2 values for both volatile and stable stocks across short and long-term horizons. In contrast, the tree-based models performed well only for the stable stock in the short term and suffered from severe overfitting and performance degradation with high volatility and over the 10-year period. This study concludes that for reliable stock price forecasting, model simplicity with regularization can be more effective than complexity, and the optimal model choice must align with the asset's risk profile and the investment horizon.

1. Introduction

In the field of time series forecasting, stock market prediction has attracted significant research attention over the past few decades, resulting in an extensive body of work published in several leading journals (Henrique et al., 2019). Due to the random-walk nature of stock prices, in which the probability distribution of a price change remains the same each time, it has become challenging to develop a model or framework to predict the size and direction of stock price changes (Fama, 1995; Kumar Meher et al., 2021). Thus, many investors seek a more complex and accurate forecasting method to facilitate well-informed decision-making in their current portfolio and future investment plans.

Based on extensive initial research in finance, the most widely used method of stock forecasting is the autoregressive integrated moving average (ARIMA) model, that are mainly used to predict stock price trends (Ariyo et al., 2014; Challa et al., 2020; Omar et al., 2022). However, in recent years, breakthroughs in machine learning have introduced the idea of a hybrid model that combines a traditional model with more advanced machine learning methods. Therefore, scientists have developed and improved machine learning algorithms to anticipate stock market trends and achieve greater outcomes. One example from Shen et al. (2012), who used a support vector machine (SVM) to forecast the NASDAQ, S&P 500, and DJIA, shows that the SVM model achieves higher accuracy than the traditional statistical benchmark. In addition, findings from Omar et al. (2022), which serve as the basis for this empirical study, show that random forest and deep neural network models perform significantly better than the traditional statistical model (ARIMA).

Omar et al. (2022) explicitly indicate in the basis article for this empirical study that the goal of their research is to forecast the Karachi Stock Exchange (KSE) index data using daily closing price series and analyze it in three different time frames: the whole period (*1 January 2001-20 August 2021*), the pre-COVID-19 period (*1 January 2001-25 February 2020*), and the COVID-19 period (*26 February 2020-20 August 2021*). In their study, they used a mix of traditional statistical models and more complex hybrid machine learning models, which include: ARIMA, Random Forest (AR), and Deep Neural Network (DNN) models. To measure the models' performance, Omar et al. (2022) use mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and R-squared as performance metrics. In their research, Omar et al. (2022) found that both the autoregressive deep neural network model (AR-DNN) and the autoregressive random forest model (AR-RF) performed best across the whole period, the pre-COVID-19 period, and the COVID-19 period, compared to the traditional autoregressive moving average model (ARIMA). Furthermore, they also state that AR-DNNs are better suited to data with a large number of observations, while AR-RF models are recommended for time series with fewer observations.

In this empirical study, we will build on Omar et al.'s (2022) research by analyzing two stocks with different characteristics (Aggressive and Defensive) rather than comparing stock prices across various periods. The notion arises from the understanding that during the COVID-19 pandemic and other crises, the stock market exhibited greater volatility than in regular periods (Omar et al., 2022). Moreover, machine learning methods have demonstrated their effectiveness in comprehending the unpredictable dynamics of the stock market. (Gu et al., 2020) and (Leippold et al., 2022) both argue that machine learning methods excel at predicting returns for large, more liquid stocks and portfolios. In terms of the specific stock selection, the Apple (AAPL) stock will be chosen for its more aggressive price fluctuations, and Procter & Gamble (PG) will be selected as a more defensive stock. The decision to pick specific stocks is based on the unique characteristics of the markets in which each stock operates. Apple (AAPL) stock represents the technology sector of the market, which is notorious for its rapid innovation cycle, high growth expectations, and changing consumer preferences (Asness et al., 2013; Shi & Herniman, 2023). On the other hand, Procter & Gamble (PG) operates in the consumer staples industry, where it primarily produces essential household goods with relatively stable demand (Asness et al., 2013; Zhao et al., 2025). In addition to the market characteristics, this empirical study will also calculate the volatility measure of annualized standard deviation (σ) and beta coefficient (β) to further justify each stock's level of volatility (Ang et al., 2004).

This empirical study will feature two regularization methods (LASSO & Elastic Net) and two tree-based methods (Gradient Boosting & Random Forest) to forecast the future closing price of each stock (Chen & Guestrin, 2016; Coqueret & Guida, 2020; Kozak et al., 2020; Omar et al., 2022). The inclusion of tree-based models is primarily driven by their ability to handle large datasets with thousands of variables (Coqueret & Guida, 2020). Furthermore, tree-based models also have the unique ability to automatically balance a dataset when one class occurs less often than the others (Chen & Guestrin, 2016; Coqueret & Guida, 2020). Furthermore, the regularization techniques of LASSO and Elastic Net uniquely reduce the problem of model overfitting by incorporating a penalty term into the regression, thereby enhancing generalization on new and unseen data, which is crucial for reliable stock market forecasting (Kozak et al., 2020; Rapach et al., 2013). The reasoning behind excluding deep neural networks or any deep learning model, as featured in Omar et al.'s paper, is primarily due to simplicity and the scope of our course. Lastly, to align with the findings of Omar et al. (2022) on machine learning's performance over a given time span, this empirical study will analyze both stocks across two different time frames: 5-year and 10-year data windows. Thus, the goal of this study is to compare the forecasting performance of four machine learning models (Random Forest, XGBoost, LASSO, and ElasticNet) in predicting stock prices of companies with different volatility characteristics. In addition, by evaluating model accuracy over 5-year and 10-year periods, the study aims to determine how market volatility and data horizon influence the effectiveness of linear and nonlinear predictive models.

2. Methods

The following section describes the overall methods used to conduct the data analysis in this empirical study. This section will include: an overview of all of the featured machine learning models, a brief explanation of the feature engineering process, and the metrics used to evaluate the model performance.

2.1 Machine Learning Methods

2.1.1 Random Forest

The random forest model is classified as a tree-based ensemble statistical method that consolidates prediction results from multiple fundamental decision trees after adjusting for randomized subdivision of predictors and training data (Breiman, 2001; Campisi et al., 2024; Coqueret & Guida, 2020; Díaz et al., 2024). According to Breiman (2001), the random forest method works on the same principle as the bootstrap aggregation procedure (also known as bagging), in which the model improves the prediction accuracy of a regression tree by calculating the average results from multiple, single regression trees that are fitted to many bootstrapped subsamples of training observations. This study will primarily focus on stock forecasting, where the Random Forest's distinctive ability to identify and analyze the hidden correlations between stock price volatility indicators and lagged stock prices will be advantageous compared to more linear models (Breiman, 2001; Campisi et al., 2024; Omar et al., 2022). However, the inclusion of long-term data (10-year period) is anticipated to affect model performance, as Random Forests are particularly prone to bias when the relationships among features evolve over time (Breiman, 2001; Campisi et al., 2024; Coqueret & Guida, 2020; Díaz et al., 2024; Omar et al., 2022).

2.1.2 Extreme Gradient Boosting (XGBoost)

The gradient boosting method is a statistical learning method that learns slowly, since it sequentially grows a regression tree by improving on the previously obtained tree growth information (Campisi et al., 2024; Chen & Guestrin, 2016; Díaz et al., 2024; Fischer & Krauss, 2018). The gradient boosting method used in this study (XGBoost) improves on the foundational principle by leveraging residuals to calibrate each iteration based on the previous prediction, thereby optimizing the model's loss function and improving overall model accuracy (Chen & Guestrin, 2016). In this empirical study, the XGBoost model serves as an alternative tree-based ensemble method that leans more towards a bias-reduction approach than the random forest model's variance-reduction approach (Chen & Guestrin, 2016). XGBoost's capacity to provide varying weights to incorrect predictions is particularly suitable and appropriate for predicting a volatile stock like Apple (AAPL), where rapid price fluctuations may substantially affect error terms in a fundamental machine learning model (Campisi et al., 2024; Díaz et al., 2024).

2.1.3 LASSO Regression

The least absolute shrinkage and selection operator (LASSO) method is a type of linear regression that utilizes a penalization process to simplify the model and perform variable selection from the data (Tibshirani, 1996). In the context of this study, the LASSO model can help prevent the model from overfitting and classify the most significant predictor variables, as the inclusion of rolling and lagged features in time-series data creates a significant multicollinearity problem (Díaz et al., 2024; Rapach et al., 2013). The inclusion of the LASSO model in this study supports the finding of Omar et al. (2022) that a simpler machine learning model tends to achieve lower performance scores than a more complex model during periods of high stock price volatility. However, a simpler model can perform better when the features in the data exhibit a more stable, linear relationship. Thus, the LASSO model can be considered a perfect fit for predicting a more stable stock, such as Procter & Gamble, which has a relatively stable stock price trend.

2.1.4 Elastic Net

Similar to LASSO, the Elastic Net method can also be classified as a linear regression that uses a penalization process. However, the main aspect that differentiates the two is the penalization function used in the method. As proposed by Zou & Hastie (2005), the elastic net method combines both the penalization function from LASSO (L1) and the Ridge regression method (L2). Given the highly correlated features standard in autoregressive data, the hybrid method that balances variable selection and coefficient shrinkage offered by Elastic Net provides a strong rationale for its inclusion in this study (Rapach et al., 2013). In the context of this study, Elastic Net may provide a balance measure between model interpretability and flexibility by preserving clusters of closely related predictor variables, such as lagged values and rolling averages, that capture the stock price momentum (Kozak et al., 2020; Rapach et al., 2013).

2.2 Market Benchmark and Volatility Measures

To substantiate the assertion that the Apple (AAPL) stock exhibits greater volatility or aggressiveness than Procter & Gamble (PG), two fundamental risk metrics, annualized standard deviation (σ) and beta coefficient (β), will be employed to assess the volatility of each stock. In addition, historical data for the S&P 500 index will be included as a reference point to assess each stock's volatility, as it reflects the broader market trend.

2.2.1 Annualized standard deviation (σ)

Annualized standard deviation or annualized volatility denotes the extent to which a return value of a stock is dispersed in a yearly context; hence, many stock investors rely on this measure to determine their investment risk (Bollerslev, 1986; Hull, 2018). The annualized volatility is calculated using the following formula:

$$\sigma = s_d \times \sqrt{262}$$

where s_d represent the standard deviation of daily log returns, and 252 represents the approximate number of trading days in a year. The results from this approach show that AAPL stock, with a measure of 0.2838 (28.38%), is 10.15% more volatile than PG, with a measure of 0.1823 (18.23%). These results justify the classification of AAPL stock as volatile (Bollerslev, 1986; Hull, 2018).

2.2.2 Beta Coefficient (β)

Different from the volatility measures, the beta coefficient (β) calculates the volatility level of a stock in relation to the overall market condition (S&P 500). Beta is defined as the covariance between the stock’s returns and the market returns divided by the variance of the market returns (Ang et al., 2004; Sharpe, 1964).

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

A beta greater than 1 indicates a more aggressive market behavior, while a beta less than 1 indicates a more defensive market behavior (Ang et al., 2004). The resulting calculation confirms that AAPL (1.1904 > 1) is an aggressive or volatile stock, while PG (0.5756 < 1) is a more defensive or stable stock.

2.3 Evaluation Metrics

In order to maintain consistency with the research done by Omar et al. (2022) and the broader research in the field of machine learning forecasting, the performance of each model will be evaluated by the following metrics:

2.3.1 Mean Absolute Error (MAE)

Measures the average absolute deviation between predicted and actual values, providing an intuitive sense of prediction error in price units.

$$MAE = \frac{1}{n}\sum |y_t - \hat{y}_t|$$

2.3.2 Root Mean Square Error (RMSE)

Penalizes larger errors more heavily and reflects model sensitivity to volatility.

$$RMSE = \sqrt{\frac{1}{n}\sum (y_t - \hat{y}_t)^2}$$

2.3.3 Mean Absolute Percentage Error (MAPE)

Expresses forecast error as a percentage of the actual value, making it easier to interpret across different price levels.

$$MAPE = \frac{100}{n}\sum \left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

2.3.4 Correlation Coefficient (R^2)

Captures how well model predictions explain the variance in actual prices.

$$R^2 = 1 - \frac{\Sigma(y_t - \hat{y}_t)^2}{\Sigma(y_t - \hat{y}_t)^2}$$

3. Data

3.1 Data Source and Description

The dataset used in this study was collected from Yahoo Finance, where financial data, especially that associated with the stock market, can be openly extracted for analysis via their publicly available API. The data collected primarily comprises historical closing prices for Apple (AAPL) and Procter & Gamble (PG) stock. In addition, the closing prices of the S&P 500 index are included as the benchmark for calculating the measure of stock volatility described in the "Methods" section. The data also include the "Date" variable, which ranges from 2 January 2014 to 22 December 2023, yielding a total of 2,516 observations. For the study's analysis, the data will be divided into two groups based on different time frames: 5 years (2 January 2019 – 22 December 2023) and 10 years (2 January 2014 – 22 December 2023). The 5-year time frame will reflect short- to medium-term market dynamics, while the 10-year time frame will reflect long-term structural market patterns. The 5-year observation window is long enough to reveal typical market phases such as growth periods, market recoveries, and market corrections, while also being short enough to provide insights into current corporate and macroeconomic conditions; hence, it is commonly used in a lot of empirical studies in finance to denote a medium-term investment cycle (Sinha, 2021). On the other hand, the 10-year window will enable evaluation of the market's structural stability over the long term and help capture the business fundamental transformation driven by technological innovation that may be missed in the short 5-year interval (Sinha, 2021). The use of two different time frames (a dual-period design) provides a balanced framework for examining each machine learning model's robustness across different time scales. Much prior research in machine learning highlights the importance of the chosen lookback period in determining model accuracy, as most studies find that a short-term dataset (smaller) tends to place greater emphasis on recent market volatility (Omar et al., 2022; Sinha, 2021). In contrast, a long-term dataset (larger) may run the risk of taking into consideration completely outdated data relationships; in other words, the model will capture more noise in the dataset (Omar et al., 2022; Sinha, 2021).

3.2 Statistical Summary

***Table 1** | Descriptive Statistics of AAPL, PG, and S&P 500*

Time Frame	Variable	Mean	Median	Min	Max	Std. Dev
5-year (2019 - 2023)	AAPL	120.5	131.5	33.8	196.4	46.4
	PG	121.0	123.0	75.9	149.5	18.4
	S&P 500	3755.8	3907.4	2237.4	4796.6	634.1
10-year (2014 - 2023)	AAPL	75.3	45.7	15.5	196.4	56.3
	PG	92.9	77.9	51.2	149.5	31.3
	S&P 500	3005.9	2798.2	1741.9	4796.6	901.3

The table above presents a fundamental statistical summary of Apple (AAPL), Procter & Gamble (PG), and the S&P 500 index over five- and ten-year intervals. The statistical data shown provide insights into the price dispersion, central tendency, and overall price range for each variable, thereby providing a crucial foundation for the upcoming model assessment in this study.

From the statistical results, we can infer that Apple (AAPL) stock exhibits the characteristics of a more volatile stock. In both the 5-year and 10-year horizons, the standard deviation value of Apple (AAPL) compared to Procter & Gamble (PG) reveals a significantly wider dispersion, with 46.4 vs 18.4 in the 5-year horizon and 56.3 vs 31.3 in the 10-year horizon, thus further supporting the classification of both stocks as aggressive and defensive stocks. Furthermore, the gradual increase in the average closing price of the S&P 500 indicates stable market growth in both time frames. All in all, these fundamental statistical results enable crucial insight into how stock prices behave differently across distinct variables and time frames.

3.3 Autoregressive Data Setup

To facilitate Machine Learning modeling, the stock closing price data must be supplemented with an array of temporal variables. The overall autoregressive data setup process is primarily structured according to the method of Omar et al. (2022). In their research, Omar et al. (2022) use a lagged price variable to forecast the dependent variable, defined as the next day's closing price (lag shift -1). However, given the focus shift towards stock characteristics (Aggressive and Defensive) in this study, the inclusion of variables such as rolling-window statistics and price percentage changes is necessary to help the models capture and differentiate the volatility aspect across different stock data (Sinha, 2021). Furthermore, the added features can help capture mid-term trends (rolling windows) and percentage-based movement of the stock prices (returns). The key features generated and included in this study are as follows:

Table 2 | *Descriptive Statistics of AAPL, PG, and S&P 500*

Features	Descriptions	Economic Interpretation
lag_1, lag_2, lag_3	Closing prices from one, two, and three trading days prior	Capture short-term memory and autoregressive structure
rolling_mean_5, rolling_std_5	5-day moving average and rolling standard deviation.	Reflect short-term trend and variation around the mean
rolling_mean_10, rolling_std_10	10-day moving average and rolling standard deviation.	Reflect long-term trend and variation around the mean
pct_change_1	One-day percentage change	Capture immediate momentum or reversal
pct_change_5	Five-day percentage change in price	Captures medium-term directional movement

To guarantee comparability across data points, all predictors are normalized using the StandardScaler module from scikit-learn, since the regression-based model used in the current study is particularly sensitive to feature scaling. Furthermore, following the methodologies outlined by Omar et al. (2022), the datasets for both the 5-year and 10-year intervals will be partitioned, with 75% allocated for model fitting and training, and the remaining 25% designated as test data to assess model performance.

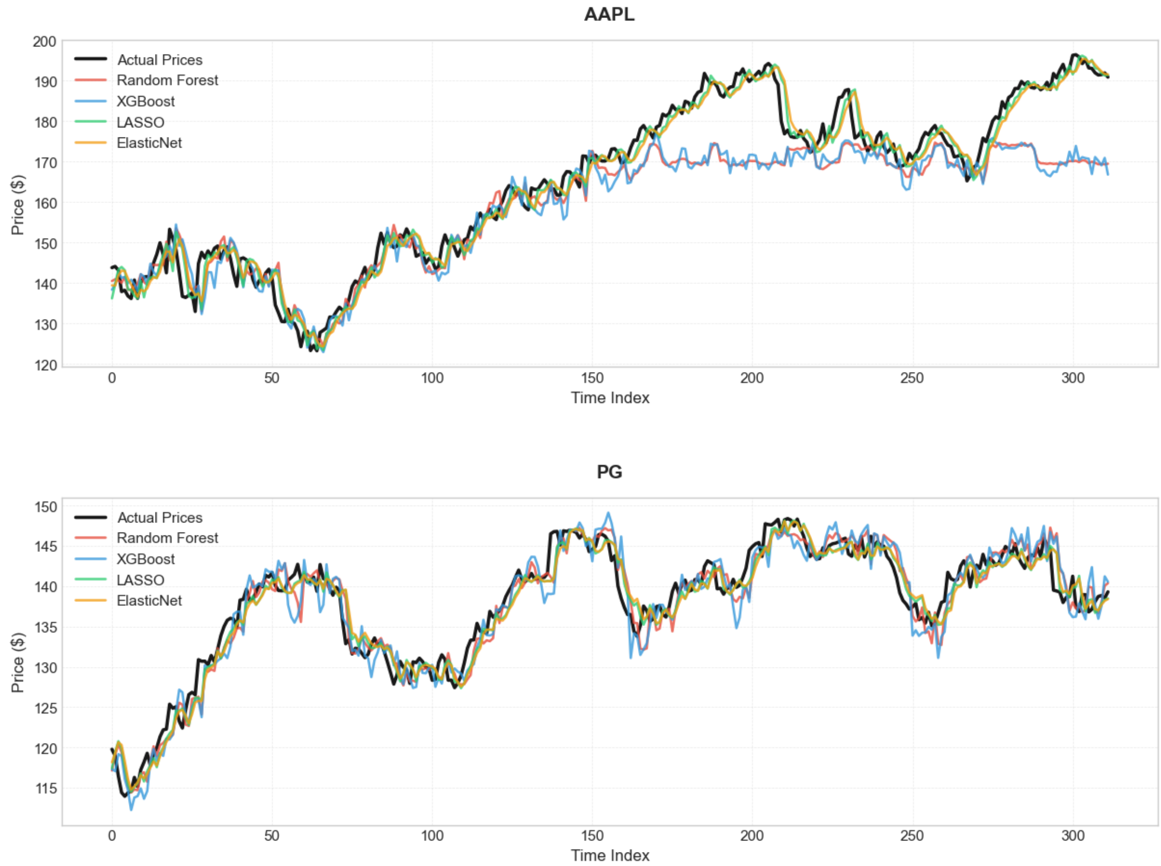
4. Results and Discussion

4.1 Time Frame: 5-Year

Table 3 | *Model Forecasting Performance (5-Year Period: 2019-2023)*

Stock	Model	MAE	RMSE	MAPE (%)	R^2
AAPL	RF	7.28	10.16	4.15	0.74
	XGBoost	7.55	10.28	4.32	0.73
	LASSO	2.71	3.53	1.70	0.97
	ElasticNet	3.00	3.77	1.88	0.96
PG	RF	1.75	2.22	1.28	0.91
	XGBoost	2.02	2.57	1.48	0.88
	LASSO	1.51	1.92	1.10	0.93
	ElasticNet	1.61	2.03	1.18	0.93

Figure 1 | *Comparison Between Actual and Predicted Stock Price (5-Year Period: 2019-2023)*



Error metrics for models trained on the short-to-medium-term (5-Year) dataset are shown in **Table 3**, accompanied by a visual comparison in **Figure 1**, which shows the actual and predicted prices for both AAPL and PG over the 5-year timeframe.

Table 3 illustrates that linear regularization methods, including LASSO and Elastic Net, surpass the tree-based approach for both AAPL (Aggressive) and PG (Defensive) stocks. The LASSO model performs best at forecasting the more volatile stock (AAPL), with the lowest mean absolute error (MAE = 2.71) and root mean square error (RMSE = 3.53), and an R^2 of 0.97. The Elastic Net model follows closely, exhibiting slightly higher error and an R^2 of 0.96, signifying a robust model fit and predictive accuracy. On the other hand, the ensemble methods, including both random forests and XGBoost models, show a fairly significant jump in error values above seven and a substantial drop in R^2 values compared to the linear regularization methods.

In predicting a more defensive stock (PG), all models yield results that are overall significantly close. In forecasting a relatively stable stock, the performance of both tree-based methods (random forest and XGBoost) improves substantially, with MAE values dropping to around 1.7-2.0, down from error values greater than 7 in the forecasting of AAPL stock. Although the tree-based models demonstrate strong performance and accuracy with R^2 values of 0.91 and 0.88, the LASSO model still yields the lowest overall error with an MAE of 1.51 and an R^2 of 0.93, followed closely by Elastic Net with a similar R^2.

The visual comparison in **Figure 1** reinforces these error results by showing that the forecasted values from both LASSO and Elastic Net are closely aligned with the actual price of AAPL stock. In contrast, those from random forest and XGBoost tend to deviate from the actual price during significant price spikes or dips.

4.2 Time Frame: 10-Year

Table 4 | *Model Forecasting Performance (10-Year Period: 2014-2023)*

Stock	Model	MAE	RMSE	MAPE (%)	R^2
AAPL	RF	27.00	31.84	16.04	-2.42
	XGBoost	27.81	32.54	16.55	-2.57
	LASSO	3.00	3.85	1.92	0.95
	ElasticNet	3.31	4.19	2.12	0.94
PG	RF	11.89	13.77	8.48	-2.18
	XGBoost	11.78	13.65	8.40	-2.12
	LASSO	1.59	2.12	1.18	0.92
	ElasticNet	1.76	2.32	1.31	0.91

From **Table 4**, it is apparent that both the random forest and XGBoost models experience a severe increase in overall error measures. The significantly larger values of MAE (>20) and RMSE (>30) indicate instability in the model's forecasting capabilities over a longer time frame. Furthermore, the negative R^2 values for both random forests and XGBoost models suggested that the models were overfitting the data and had poor generalization. In contrast, both LASSO and Elastic Net exhibit more consistent performance across short- and long-term forecasting. For both aggressive and defensive stocks, the LASSO model still outperforms the Elastic Net with an MAE value of 3.00, an RMSE value of 3.85, and an R^2 of 0.95 for the AAPL stock, while for the PG stock, the MAE is 1.59, the RMSE is 2.12, and the R^2 is 0.92.

Figure 2 | *Comparison Between Actual and Predicted Stock Price (10-Year Period: 2014-2023)*

Figure 2 illustrates the severe underperformance of tree-based models (random forest & XGBoost) compared to a linear regularization model (LASSO & Elastic Net) in forecasting both aggressive and defensive stock prices over the period of 10 years. The figures show that the predicted prices from LASSO and Elastic Net closely tracked the actual prices throughout the entire time frame. In contrast, both random forests and XGBoosts diverged significantly from the exact prices and failed to capture meaningful price predictions.

4.3 Discussion

The findings presented in each model's performance results substantiate the critical role of stock volatility in shaping the outcome of price forecasting using the machine learning method. The overall results from the modeling comparison between AAPL (Aggressive) and PG (Defensive) stocks show that model performance increases as stock price volatility decreases (forecasting PG stock prices). The results from both of the tree-based models (random forest

& XGBoost) in the 5-year forecasting window further support this claim by presenting the most significant change in error measures, with random forest and XGBoost having an MAE score around 7 in forecasting AAPL (Aggressive) stock, to an MAE score around 1 when forecasting PG (Defensive) stock. Furthermore, although not as significant, the same pattern of improvement is also present in both linear regularization models (LASSO & Elastic Net), where the MAE score decreases from around 2-3 in forecasting AAPL (Aggressive) stock to 1 when forecasting PG (Defensive) stock.

In addition, the inclusion of the time horizon aspect in the dataset significantly affects machine learning performance, especially tree-based models (random forest & XGBoost). From the results presented, it is apparent that both tree-based models severely deteriorate when forecasting a dataset with a long-term time window (10 years). The decline in model accuracy indicates that tree-based models, such as random forests and XGBoost, included in this study encounter difficulty in capturing nonstationary long-term data in which the relationship between predictor variables and the target may change over time. Conversely, both linear regularization models (LASSO & Elastic Net) are able to maintain a stable performance in both short-term (5-year) and long-term (10-year) datasets. This relatively stable model performance is achieved by minimizing overfitting and penalizing excessive coefficient growth, which adheres to the principle of shrinkage estimation (Sinha, 2021; Tibshirani, 1996).

5. Conclusion

This study extended the work of Omar et al. (2022) by investigating the performance of machine learning models in forecasting stocks with different volatility levels, rather than different time periods. We compared two tree-based models (Random Forest, XGBoost) and two linear regularization models (LASSO, Elastic Net) in predicting the prices of an aggressive stock (AAPL) and a defensive stock (PG) over 5-year and 10-year horizons.

The key finding is that model performance is highly sensitive to both stock volatility and the data time frame. Contrary to expectations that complex models are universally superior, our results show that simpler, regularized linear models (LASSO and Elastic Net) were the most robust and accurate. They consistently delivered the lowest errors and highest R^2 values for both volatile and stable stocks across short and long-term horizons. In contrast, the tree-based models performed well only in specific conditions, namely, for the stable PG stock in the short-term window. Their performance severely deteriorated with the high volatility of AAPL and over the 10-year period, where they overfit the data and failed to generalize.

In summary, for stock price forecasting, simpler linear models with regularization can provide more reliable and consistent predictions than complex tree-based ensembles, especially over longer periods and for volatile assets. This indicates that the optimal model choice for investors and analysts is not one of complexity, but of fit to the asset's risk profile and the investment horizon.

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