The Return Predication and Risk Assessment of Tesla

Yongyuan Qu

yq2361@columbia.edu

Abstract Tesla has emerged as a prominent corporation in recent years, driven by its development of innovative electric vehicles, including the Model 3, Model X, and Model Y. The company's core mission is to promote zero-emission transportation and accelerate the transition from fossil fuels to sustainable energy sources such as electricity. As a result, Tesla's stock has attracted significant attention from investors and experienced substantial appreciation. However, the onset of the COVID-19 pandemic led to delays in vehicle deliveries and broader economic downturn in the United States, contributing to a decline in Tesla's stock price and a corresponding erosion of investor confidence. By 2023, Tesla's business operations began to recover, prompting our team to develop multiple forecasting models to predict future stock prices based on historical volatility and relevant financial factors. This study aims to identify the optimal modeling approach that captures the relationship between future stock prices and associated risks.

To achieve this objective, we propose three distinct models: Model I: Multi-Factor Model; Model II: Time Series Model; and Model III: Random Forest Model.

Model I adopts a multi-factor framework grounded in the **Fama-French three-factor model**. The selected factors include Small Minus Big (SMB), which captures the size effect by comparing returns of small-market-capitalization firms with those of large-cap firms; High Minus Low (HML), which reflects the value premium by contrasting firms with high and low book-to-market ratios; and Momentum (Mom), which represents the "winner minus loser" effect, wherein stocks with strong past performance continue to exhibit superior returns in the near term.

Model II employs an Autoregressive Integrated Moving Average (ARIMA) specification, which integrates autoregressive (AR) and moving average (MA) components. ARIMA models are widely used for short- to medium-term stock price forecasting by leveraging historical price patterns. The selected model, **ARIMA (1,0,1)**, was determined after removing seasonality and confirming stationarity in the data, thus eliminating the need for differencing. Model selection was further validated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), alongside visual inspection of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the stationary series.

Model III utilizes a **Random Forest regression algorithm**, an ensemble learning method based on bootstrap aggregating (bagging). This technique involves constructing multiple decision trees from resampled datasets and employing random node splitting to enhance model robustness. Predictions are aggregated by averaging or weighted averaging across individual trees, yielding the final regression output.

For sensitivity analysis, we compute rolling means and standard deviations of historical returns to simulate current-day returns. This approach enables the estimation of percentage changes over a moving window, thereby providing insight into the sensitivity of current returns to fluctuations in underlying market conditions.

Keywords Recurrent neural network, ARIMA, Cross Validation, Bootstrap Resampl

ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

1 Introduction

1.1 Background of Tesla

Tesla was founded in 2003 and the company wants to fully achieve the self-drive technology and get rid of the traditional cars which depend on fossil fuels. Tesla believes that electric vehicles would have better performance than traditional cars. In recent years, Tesla is a more and more popular product in the world and many people begin to choose tesla as their choice.

(a) Tesla Model X

(b）Elon Musk

Figure 1.Target

(a) **Tesla Model X**: Model X is the best SUV to drive, and the best SUV to be driven in. Clean, powerful yet invisible cabin conditioning; (b) **Elon Musk**: He is the founder, CEO, and Chief Engineer at SpaceX; angel investor, CEO, and Product Architect of Tesla, Inc.; founder of The Boring Company; and co-founder of Neuralink and OpenAI.

1.2 Approach

To forecast the future performance of Tesla, this study begins with data preprocessing, followed by a retrospective assessment of historical volatility using time series analysis. Subsequently, predictive models are developed, and a risk management framework is constructed to quantify associated uncertainties.

1) Standardize the dataset with time series.
2) Clean and Preprocessing data
3) Apply ARIMA and multi-factor models
4) Apply Random Forest model to predict the price
5) Combine the regression with the validity of the model
6) Create Sensitivity to measure the different risks
7) Make a conclusion

2 Our Assumption

Assumption 1: Assume there is no transaction cost during trading and all information is frictionless.

Justification: Assuming transaction cost is zero in our model because it would a dummy variable and will causes the mean squared error. Information is also frictionless, which each investor can get the same news of the stock and prevent the effects of insider trading to cause the fluctuation of the stock.

Assumption 2: ignore any political policy in the market that may dramatically affect the price fluctuation of Tesla.

Justification: Policy is an unstable factor that can severely affect models.

Assumption 3: Assume that there is no worldwide economic crisis that may affect the price of Tesla from 2023.5 to 2024.3.

Justification: Economic crisis will lead to a big fluctuation in the price of bitcoin and gold and other dummy variables will appear.

Assumption 4: Assume that there are some inter-relationships between the price of volatility and stock price.

Justification: Such that predict the volatility of the stock using some of the information of Tesla.

Assumption 5: There exists a potential linear relationship between the prior volatility of Tesla and the stock price between the current volatility of Tesla and its stock price.

Justification: This assumption is just for the regression model.

3 Model Preparation

3.1 Notation

Table 1. Notations

Symbol	Description
Y_i-Tesla	ith return of Tesla
S_i-Tesla	Skew of Tesla
$\hat{Y}_i$-Tesla	Predicted ith return of Tesla
K_i-Tesla	Kurtosis of Tesla
X *std*_ Tesla	Standard deviation of Tesla
Wt	Weight of Tesla

Table 2. Other Symbols

Symbol	Description
MAE	Mean absolute Error
RMSE	Root Mean Squared error
MSE	Mean Squared error

Notes: we will also discuss other variables in the specific parts.

3.2 Data Overview

3.2.1 Data Collection

Table 3. Data Collection

Database	Data Sources	Data Type
Tesla	Yahoo Finance	Float
Benchmark	S&P 500	Float

4 Model I: Multi-Factor Model

4.1 Model Establishment

Factor analysis provides a systematic method for identifying firm characteristics or trading anomalies associated with excess returns. These factors are typically categorized as either macroeconomic or style-based. In this section, we employ the Fama-French four-factor model to gain a comprehensive understanding of how specific style factors—namely, firm size, book-to-market equity, excess market return, and momentum—are associated with the return performance of the selected stocks.

4.2 Test the Model

4.2.1 Fama-French Four Factors Model

Small Minus Big (SMB) is a size effect based on the market capitalization of a company. SMB measures the excess return of small-cap companies over big-cap companies and it is a factor in the Fama French stock pricing model that says whether smaller companies outperform larger ones over the long-term. When small stocks have good performance than large stocks, the number will be positive from excess return.

High Minus Low (HML) is a value premium; it represents the spread in returns between companies with a high book-to-market value ratio and companies with a low book-to-market value ratio.

Momentum (Mom) is when stocks that have outperformed in the past tend to exhibit strong returns going forward. It follows the idea that stocks that have recently risen or fallen in price will continue that trend over the term.

4.2.2 Model Evaluation

Dep. Variable:	TSLA-RF	R-squared:	0.298
Model:	OLS	Adj. R-squared:	0.297
Method:	Least Squares	F-statistic:	425.5
Date:	Tue, 20 Feb 2024	Prob (F-statistic):	4.46e-79
Time:	22:25:41	Log-Likelihood:	-2711.5
No. Observations:	1005	AIC:	5427.
Df Residuals:	1003	BIC:	5437.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2262	0.114	1.993	0.047	0.003	0.449
Mkt-RF	1.5775	0.076	20.627	0.000	1.427	1.728

Omnibus:	101.640	Durbin-Watson:	2.035
Prob(Omnibus):	0.000	Jarque-Bera (JB):	660.701
Skew:	0.155	Prob(JB):	3.39e-144
Kurtosis:	6.960	Cond. No.	1.49

Figure 2. Single Factor Model Data

By having a regression on Tesla for one regression of CAPM Model during the period, when looking at the coefficient of market risk premium, Tesla has the number of 1.5775 significant at 95% level, an abnormal daily return of 0.2262% significant at 95% level, and R squared number of 0.298, which suggests that Tesla may not have a higher volatility level than whole systematic risk of market. Tesla's high beta coefficient of 1.5775 indicates that the stock has a high systemic risk relative to the overall market. That means Tesla's stock could be more volatile when the overall market goes up or down. A unit of increase in beta coefficient from Tesla will bring to the 1.5775% increase in expected return. It is likely to suffer from market volatility also, while performs not exactly

ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

well than market with a positive alpha following, and have a 29.8% systemic risk suggesting high market risk with relatively less proportion following with market change. This is attractive to investors looking for high-risk, high-return investments. However, the R-squared value is only 29.8 percent, suggesting that the market model explains only a small portion of Tesla's stock movement, and there are other factors at play.

Multiple Regression Assumptions check

1st Durbin-Watson serial correlation test (range between 0-4)

```
In [29]: err1=reg_TSLA_multifactor.resid
         err1

Out[29]: Date
         2020-01-03     3.416005
         2020-01-06     0.921764
         2020-01-07     3.770140
         2020-01-08     3.477657
         2020-01-09    -3.272256
                         ...
         2024-01-25   -12.600518
         2024-01-26    -0.379156
         2024-01-29     1.337213
         2024-01-30     1.935425
         2024-01-31     0.675537
         Length: 1026, dtype: float64

In [30]: sm.stats.stattools.durbin_watson(err1)

Out[30]: 2.0090964282062376
```

Figure 3. DW Test

Since the test statistics is close to 2, we cannot reject the null hypothesis that there is no serial correlation in the residual.

2nd Breusch Pagan Heteroskedasticity (Null hypothesis: Error variances are all equal)

```
In [31]: #Breusch Pagan Heteroskedasticity

         #Null hypothesis: Error variances are all equal
         sm.stats.diagnostic.het_breuschpagan(err1,x3)

Out[31]: (10.026047888607186,
          0.03999118715911032,
          2.51891174793269,
          0.039824558206770194)
```

Figure 4. BP Test

For both Tesla, since p value for both Lagrage multiplier and f test is larger than 5%, we cannot reject the null hypothesis that there is no Heteroskedasticity in the data.

3rd Check of Multicollinearity Problem

```
In [34]: x3.corr()

Out[34]:
```

	const	Mkt-RF	SMB	HML	Mom
const	NaN	NaN	NaN	NaN	NaN
Mkt-RF	NaN	1.000000	0.232162	-0.044111	-0.199106
SMB	NaN	0.232162	1.000000	0.007829	-0.235267
HML	NaN	-0.044111	0.007829	1.000000	-0.275567
Mom	NaN	-0.199106	-0.235267	-0.275567	1.000000

Figure 5. Check of multicollinearity

Four Factor Analysis Results:

OLS Regression Results

Dep. Variable:	TSLA-RF	**R-squared:**	0.365
Model:	OLS	**Adj. R-squared:**	0.363
Method:	Least Squares	**F-statistic:**	146.7
Date:	Sun, 10 Mar 2024	**Prob (F-statistic):**	3.79e-99
Time:	20:04:31	**Log-Likelihood:**	-2712.7
No. Observations:	1026	**AIC:**	5435.
Df Residuals:	1021	**BIC:**	5460.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.2027	0.107	1.902	0.057	-0.006	0.412
Mkt-RF	1.4677	0.076	19.404	0.000	1.319	1.616
SMB	0.8373	0.143	5.853	0.000	0.557	1.118
HML	-0.7487	0.092	-8.181	0.000	-0.928	-0.569
Mom	0.1254	0.080	1.566	0.118	-0.032	0.283

Omnibus:	96.936	**Durbin-Watson:**	2.009
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	604.164
Skew:	0.105	**Prob(JB):**	6.42e-132
Kurtosis:	6.753	**Cond. No.**	2.24

Figure 6. Model Results

Expanding the one-factor Capital Asset Pricing Model (CAPM) to a four-factor framework provides a more nuanced understanding of Tesla's return dynamics. The estimation results reveal several key insights. First, the regression constant, or Jensen's alpha, is positive and statistically significant in both models when estimated over the COVID-19 period. Tesla exhibits a daily abnormal return of approximately 0.2027%, indicating a risk-adjusted performance that consistently outperforms the broader market. Second, the coefficient for the market risk premium—a measure of the stock's systematic risk, or beta—exceeds one, confirming Tesla's higher volatility relative to the market. Specifically, a one-unit change in the daily market risk premium corresponds to a 1.4677% change in Tesla's expected return. Crucially, by incorporating additional style factors (size, value, and momentum), the four-factor model yields a more precise estimate of this market beta compared to the simpler CAPM, while reaffirming Tesla's elevated sensitivity to market movements.

Tesla's small minus big factor is positive, showing it is a stock with relatively less size of capitalization. Although it is a company with a huge market cap, its stock has performed similar to the stock of smaller market cap companies. This phenomenon may be because investors see Tesla as a fast-growing innovative business, which makes its stock behave like a small company in some ways. In addition, it also reflects the market's optimistic expectations about Tesla's future growth potential, especially the long-term growth prospects provided by its leading position in electric vehicles and renewable energy.

In high minus low coefficients, Tesla show the excess return is from the company's small book-to-market equity value, and the stock behave more like one of growth stock. This shows that investors are willing to pay a premium for expected future growth based on Tesla's performance in technology innovation, product development, and market expansion. Tesla's character as a growth stock is further confirmed here, and its performance is not constrained by traditional value factors, but rather driven by its potential future growth.

In momentum coefficients, Tesla displays a trend the rate of change in price movement over a period of time during the period but may follows the risk level trend mentioned in previous session. A stock's past performance often influences its future performance. Tesla's strong momentum may be related to its innovation leadership in the market, positive earnings reports and favorable industry trends. This sustained upward price trend presents opportunities for investors seeking short - to medium-term profitability, although it also comes with higher volatility and risk.

Integrating market risk premium, size (SMB), value (HML), and momentum factors provides a holistic view

ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

of Tesla's risk-return profile. The analysis confirms Tesla's nature as a high-risk, high-reward asset, characterized by exceptional returns accompanied by substantial volatility. Consequently, these findings underscore the necessity for investors to adopt a robust, multi-factor risk management framework that accounts for the collective influence of these drivers on Tesla's stock price dynamics.

In conclusion, through the performance of Tesla stock in the Fama-French four-factor model, it is a stock with high growth potential but also accompanied by high volatility. The high growth potential of Tesla's stock has attracted investors looking for returns that beat the market average, but that potential has also come at the cost of high volatility. This volatility reflects the sensitivity of Tesla's stock price to internal developments, changes in market conditions, and macroeconomic factors. Therefore, when considering investing in Tesla, investors need to be able to accept the high level of risk that comes with pursuing high returns.

5 Model II: Time Series Model

5.1 ARIMA Model- Autoregressive Integrated Moving Average

Conditions: p=1, d=0, q=1

The ARIMA model, standing for AutoRegressive Integrated Moving Average, is a forecasting technique that is widely used for time series data analysis. This model aims to describe the autocorrelations in the data with an approach that integrates three key concepts: autoregression (AR), differencing (I - Integrated), and moving average (MA).

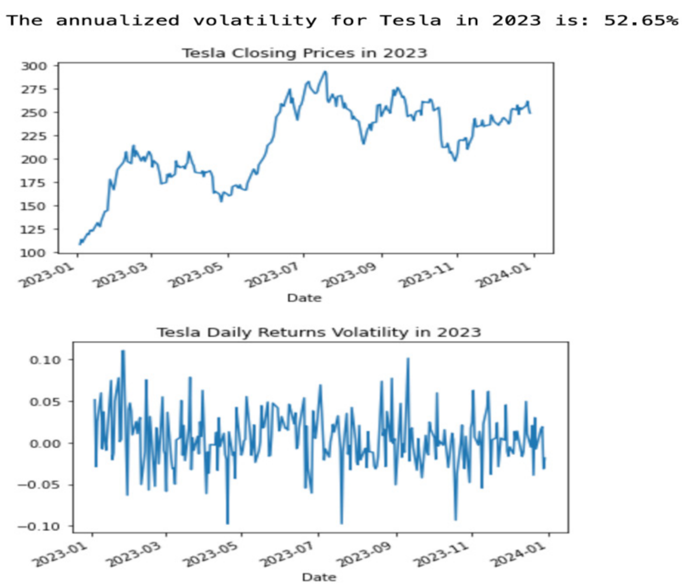


Figure 7. Annualized Volatility

The inclusion of market, size, value, and momentum factors in a unified framework offers a more complete characterization of Tesla's risk and return dynamics. The empirical evidence points to a pronounced high-risk, high-reward profile, wherein the potential for exceptional returns is coupled with significant volatility. This finding underscores the multifaceted nature of Tesla's systematic risk and highlights the imperative for investors to implement a comprehensive risk management strategy that explicitly considers the joint effects of these factors on share price behavior.

```
ADF Statistic: -3.4095068603551564
p-value: 0.010639021353960406
Critical Values:
        1%: -3.458
        5%: -2.874
        10%: -2.573
time series is stationary
```

Figure 8. ADF Test

Initial visualization of monthly volatility data indicated strong seasonality. After applying a seasonal adjustment procedure to remove this component, the Augmented Dickey-Fuller (ADF) test confirmed that the resulting time series is stationary.

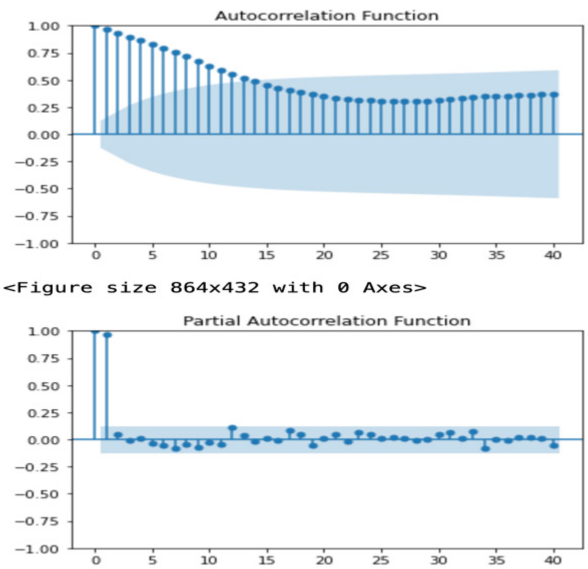


Figure 9. ACF and PACF

5.2 Model Evaluation

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  250
Model:                 ARIMA(1, 0, 1)   Log Likelihood                -843.144
Date:                Mon, 22 Jan 2024   AIC                           1694.289
Time:                        17:20:21   BIC                           1708.374
Sample:                             0   HQIC                          1699.958
                                - 250
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        158.8567     51.002      3.115      0.002      58.894     258.819
ar.L1          0.9958      0.006    174.267      0.000       0.985       1.007
ma.L1         -0.0011      0.051     -0.022      0.982      -0.102       0.099
sigma2        48.8251      2.677     18.239      0.000      43.578      54.072
===================================================================================
Ljung-Box (L1) (Q):                   0.17   Jarque-Bera (JB):               162.80
Prob(Q):                              0.68   Prob(JB):                         0.00
```

Figure 10. ARIMA Model Result

Estimation results from the SARIMA model reveal several important characteristics of Tesla's volatility dynamics. Both the constant term and the autoregressive (AR) coefficient are statistically significant at the 5% level. The magnitude of the SARIMA coefficient, which exceeds those estimated from alternative specifications, indicates that volatility is highly persistent and exhibits significant clustering—a phenomenon where periods of high volatility tend to be followed by similarly volatile periods. This finding is further corroborated by the diagnostic plot, which visually illustrates the evolution and magnitude of Tesla's volatility over the sample period. Regarding model performance, the relatively low Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values suggest that the SARIMA specification achieves a favorable balance between goodness-of-fit and parsimony, indicating strong predictive capability.

ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

5.3 Results

After backtesing, Mean Square Error is 428.82 which is lower than the other models and give us a relative benchmark for arbitraging.

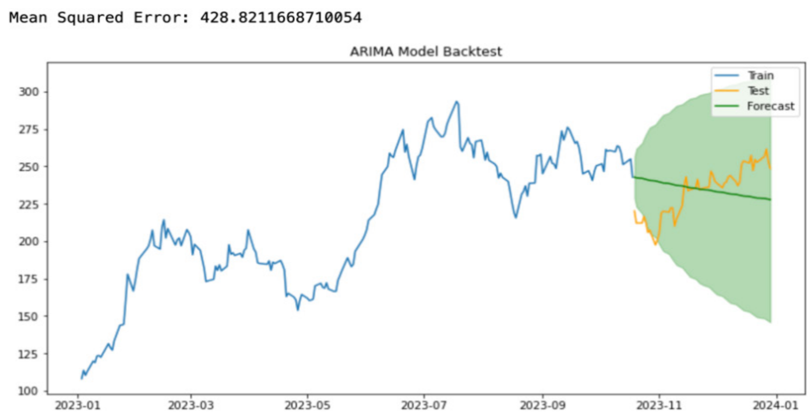


Figure 11. ARIMA Model Backtest

Using the confidence interval, our team conclude the following possible prices after applying ARIMA model.

95% Confidence Interval:	lower y	upper y
250	185.023602	212.414092
251	179.233861	217.865585
252	174.778897	221.983737
253	171.020093	225.407157
254	167.709249	228.384039
255	164.718717	231.042028
256	161.972467	233.457144
257	159.420840	235.679043
258	157.029252	237.742302
259	154.772461	239.672156
260	152.631364	241.487704
261	150.591083	243.203817
262	148.639754	244.832353
263	146.767736	246.382948
264	144.967061	247.863563
265	143.231054	249.280869
266	141.554053	250.640521
267	139.931206	251.947365

Figure 12. Forecast Stock Prices

6 Model III: Random Forest Model

6.1 Model Structure

In Random Forest, each decision tree is independent and trained on a randomly selected subsample, which effectively reduces the risk of overfitting. In addition, it can handle high-dimensional data and large-scale datasets and has a strong fitting ability for data with nonlinear relationships. Considering the volatile and nonlinear nature of financial markets, this research attempts to predict stock prices using Random Forest, which can capture complex nonlinear relationships between features without any transformation of the input data. This feature that is particularly useful in stock market forecasting, where relationships between variables can be highly nonlinear. Although stock price forecasting is inherently affected by numerous unpredictable factors such as industry trends and market sentiment, Random Forests are still considered valuable tools because they are more robust to overfitting than individual decision trees, especially when a large number of trees are used, and the model parameters are correctly tuned.

However, while random forests are more robust to overfitting than individual decision trees, the overall model may still be complex and difficult to interpret compared to simpler models. This complexity makes it challenging to understand how decisions are made, which is a key aspect in financial applications. Furthermore, despite its robustness, there's still a risk of overfitting, especially if the model is not properly validated or if the data is not representative of future market conditions.

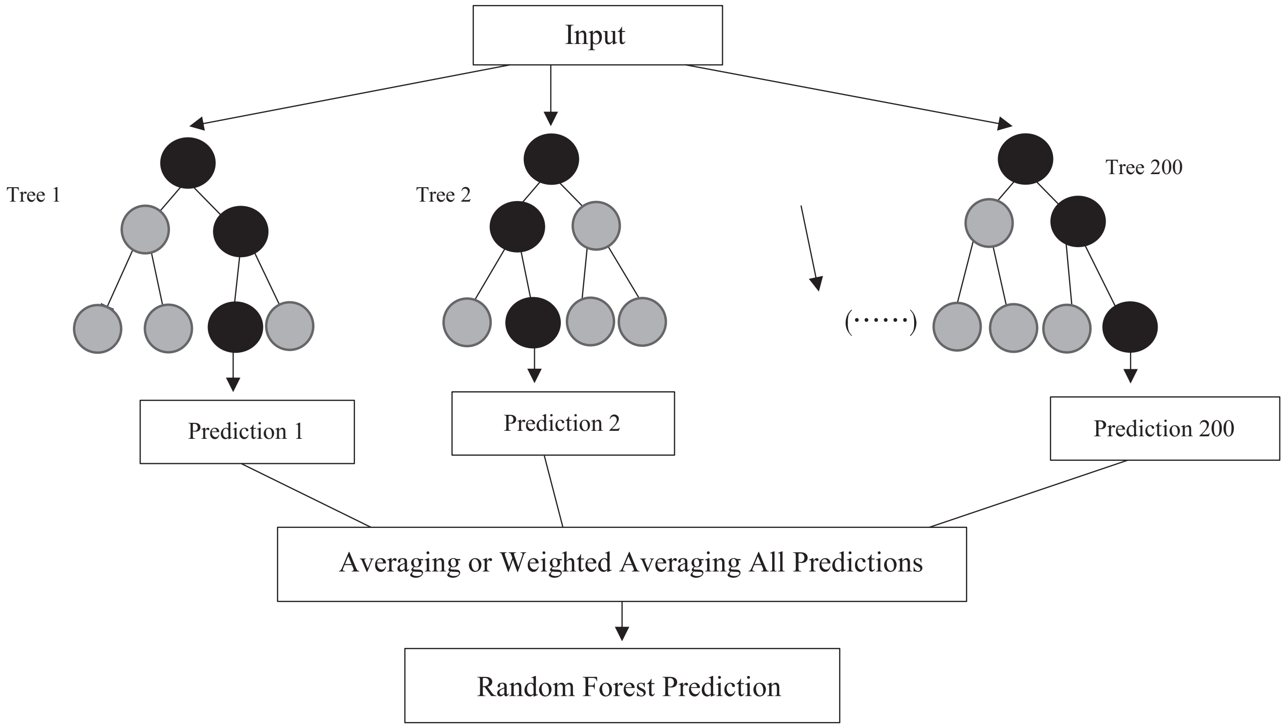


Figure 13. Random Forest

6.2 Predicting the price

The original data set contains four dependent variables: Open, High, Low, and Volume. Considering the characteristics of the financial markets, the researchers of this program added two features: 5-day moving average and 10-day moving average. Moving averages help in identifying the underlying trend in stock prices by smoothing out daily price fluctuations.

To evaluate the predictive accuracy of the regression model, we employ two standard metrics: the Mean Squared Error (MSE) and the coefficient of determination (R^2). A lower MSE indicates smaller average deviations between predicted and actual closing prices, while an R^2 value closer to 1 signifies that a larger proportion of the variance in the dependent variable is explained by the model.

On the training dataset, our model achieves an MSE of 4.1028 and an R^2 of 0.9972. The exceptionally high R^2 indicates that 99.72% of the variance in closing prices is captured by the independent variables, suggesting that the model fits the training data remarkably well. However, while such strong in-sample performance is desirable, it also raises a potential concern regarding overfitting. An R^2 approaching unity may indicate that the model has learned not only the underlying signal but also the noise specific to the training sample. Consequently, these metrics alone are insufficient to validate the model's predictive power. To assess its generalizability, it is imperative to evaluate the model's performance on a holdout test dataset, comparing out-of-sample MSE and R^2 to determine whether the model can accurately forecast unseen data.

ISSN 3106-5783 (Print)   ISSN 3106-7042 (Online)

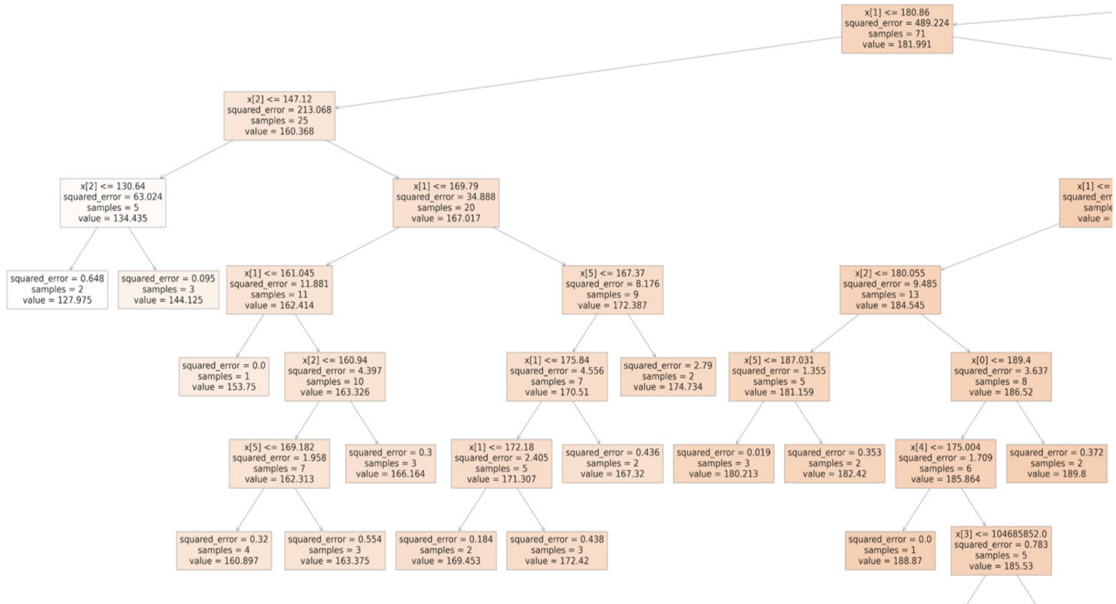


Figure 14. Part of Random Forest Predication

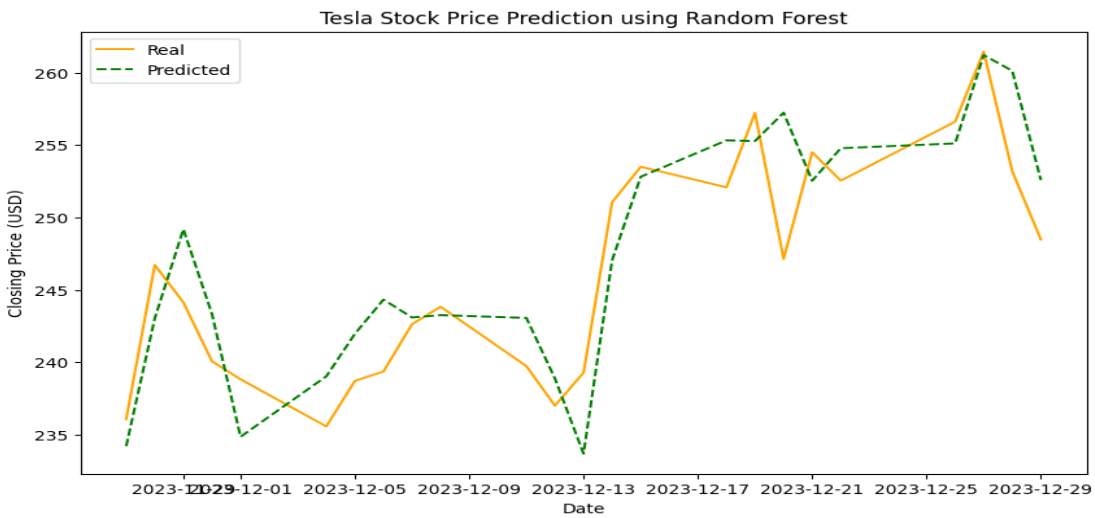
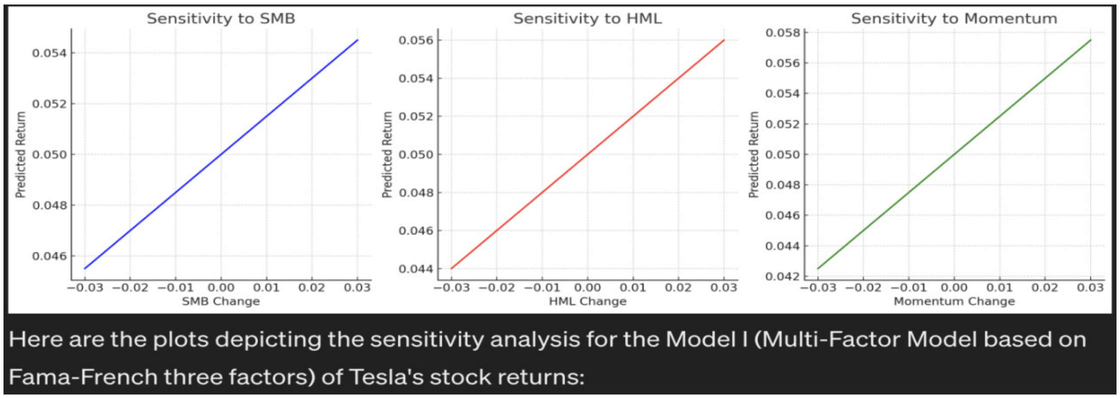


Figure 15. Predicated Trend

The MSE on the test set is 15.4604, indicating that the model's predictions deviate from the actual values to a certain extent. Compared to the training MSE of 4.1028, the higher test MSE suggests that the model does not predict as accurately on unseen data as it does on the training data. The R^2 value on the test set is 0.7238, indicating that approximately 72.38% of the variance in the dependent variable is predictable from the independent variables in your model when applied to unseen data. While this is a significant proportion, the drop from the training R^2 of approximately 99.72% to 72.38% on the test set indicates a decrease in predictive accuracy when the model encounters new data.

7 Sensitivity Analysis

7.1 Sensitivity Analysis on Model I: Multi-Factor Model



Sensitivity to SMB (Small Minus Big):

The plot shows a linear relationship between changes in SMB and the predicted. returns. As SMB increases, indicating better performance of small-cap stocks over large-cap stocks, Tesla's predicted returns increase accordingly.

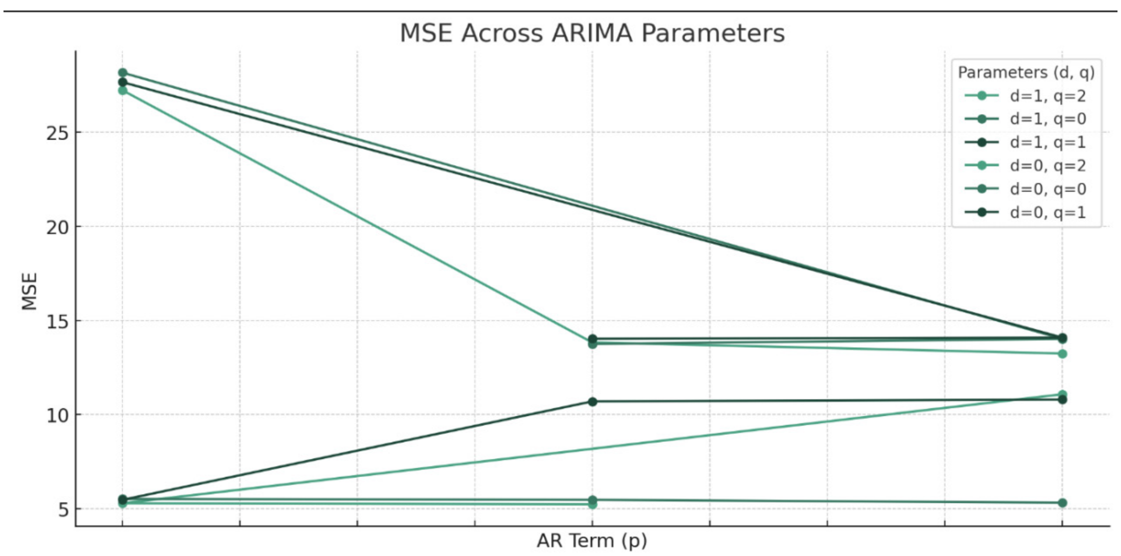
Sensitivity to HML (High Minus Low):

The impact of HML on the returns is also linear. An increase in HML, which reflects a greater return spread between high and low book-to-market stocks, leads to higher predicted returns for Tesla. This suggests that Tesla might benefit from market conditions favoring value stocks.

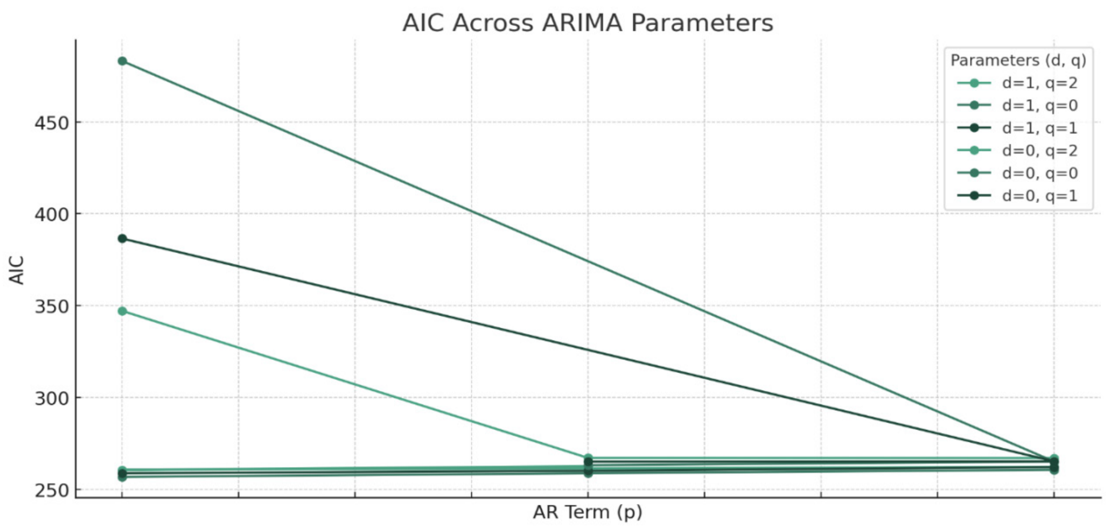
Sensitivity to Momentum (Mom):

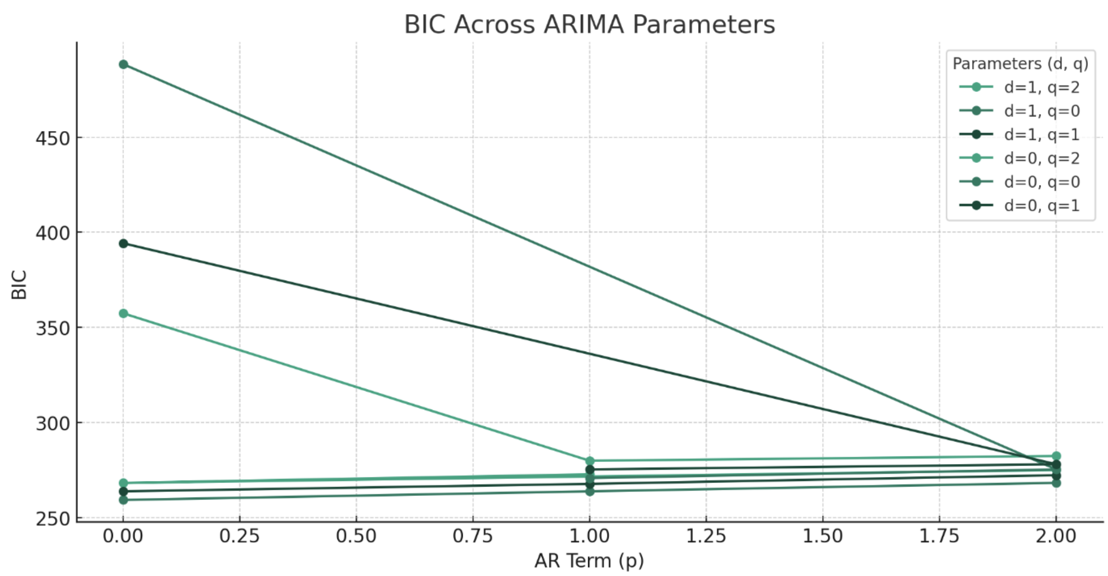
The sensitivity to Momentum indicates that as the past performance trend (Momentum) becomes more positive, the predicted returns increase. This reflects Tesla's sensitivity to ongoing market trends and past performance.

7.2 Sensitivity Analysis on Model II: Time Series Model



ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

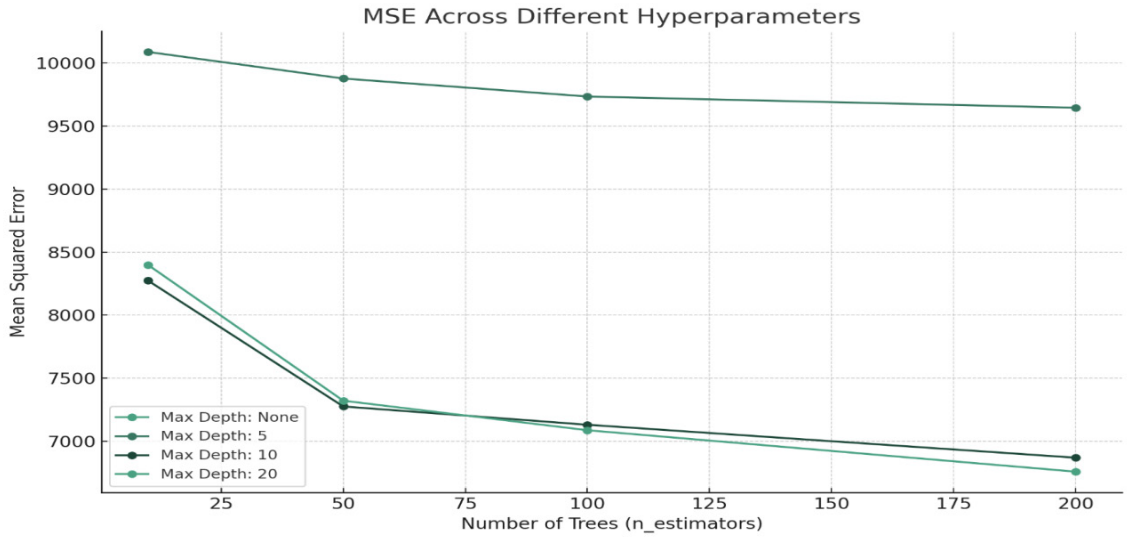


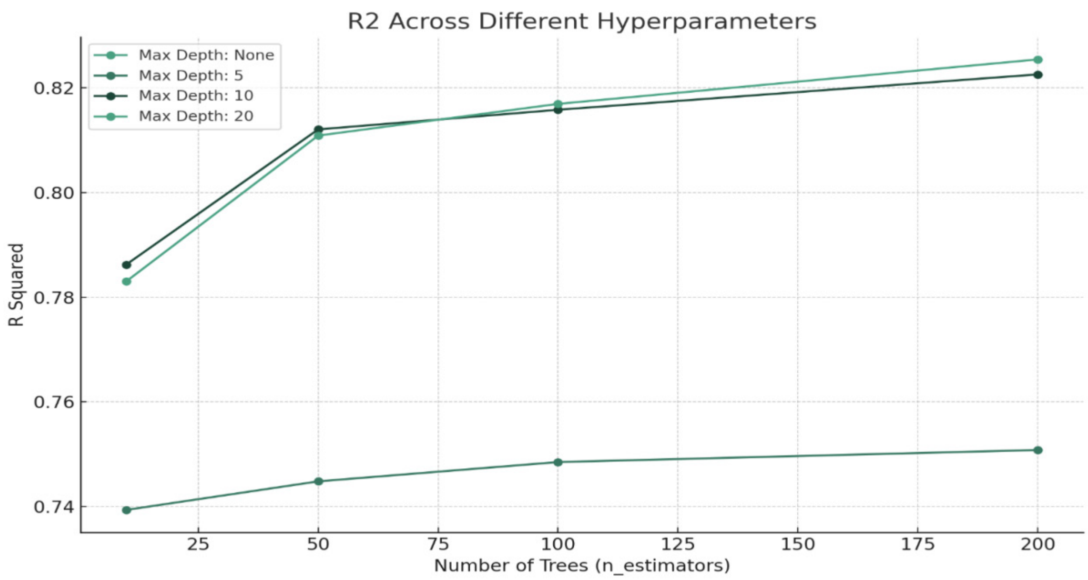


Here are the plots depicting the sensitivity analysis for the ARIMA model based on changes in the parameters.

1. MSE Across ARIMA Parameters: This plot shows how the Mean Squared Error varies with different values of the AR term p for combinations of differencing d and moving average term q. Lower MSE values are better, indicating that the model's predictions are closer to the actual data.
2. AIC Across ARIMA Parameters: This plot illustrates how the Akaike Information Criterion changes with p. Lower AIC values suggest a model that better balances goodness of fit with complexity.
3. BIC Across ARIMA Parameters: Similar to the AIC plot, this shows the Bayesian Information Criterion, which also penalizes model complexity but tends to prefer simpler models than AIC.

7.3 Sensitivity Analysis on Model III: Random Forest Model





Here are the plots depicting the sensitivity analysis for the Random Forest Model (Model III), based on different hyperparameters:

1. Mean Squared Error (MSE) Across Different Hyperparameters:

This plot illustrates how MSE changes with different numbers of trees (n_estimators) for various maximum tree depths (max_depth). Lower MSE values indicate better model performance, where predictions are closer to the actual data. Generally, more trees lead to lower MSE, particularly when no maximum depth is set, allowing the trees to fully grow.

2. R Squared (R^2) Across Different Hyperparameters:

This plot shows how R^2 changes with the number of trees. R^2 is a statistical measure of how close the data are to the fitted regression line, with higher R^2 values indicating better model performance. Similar to MSE, more trees and deeper trees tend to improve the R^2 score, signifying a model that explains a larger variance portion in the dataset.

8 Conclusion

It is evident that Tesla's stock exhibits high growth potential, albeit accompanied by significant volatility. The application of multiple financial models—including the Fama-French four-factor model, ARIMA for time series

ISSN 3106-5783 (Print) ISSN 3106-7042 (Online)

analysis, and Random Forest for machine learning regression—provides a multifaceted understanding of Tesla's stock performance and its sensitivity to market conditions. The analysis underscores Tesla as a potentially lucrative but highly volatile investment. The high volatility reflects Tesla's sensitivity to both internal developments and external economic conditions. For investors, this means a need for a balanced approach that considers both the promising growth potential and the significant risks. Effective risk management strategies are recommended, emphasizing the need for continuous monitoring of market conditions and regular model updates to adapt to new data. The insights gained from these models equip investors with a deeper understanding of how Tesla's stock might behave, enabling more informed investment decisions in a landscape shaped by innovation and market dynamics.

In closing, while Tesla presents an attractive investment opportunity with its strong market position and innovative edge, the associated risks demand a cautious and informed approach to capitalize on its potential benefits without falling prey to its inherent unpredictability.

References

[1] Chen, J. (n.d.). *What factor investing is and how the strategy works*. Investopedia. https://www.investopedia.com/terms/f/factor-investing.asp

[2] Zhu, L. (2020, April 13). *Council post: Lessons from tesla: Why smaller-cap tech-focused companies offer opportunity during Bear Market*. Forbes. https://www.forbes.com/sites/forbesfinancecouncil/2020/04/13/lessons-from-tesla-why-smaller-cap-tech-focused-companies-offer-opportunity-during-bear-market/?sh=3bd0f2094d22

[3] Dhaduk, H. (2021, July 18). *Stock market forecasting using time. series analysis with Arima Model*. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/07/stock-market-forecasting-using-time-series-analysis-with-arima-model/