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The Relationship of Tesla's Stock Price and Macroeconomic Indicators

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Abstract: This research analyzes Tesla's stock performance in 2014-2024 period with the state-of-the-art models and also leveraging real-time data. Moreover, this work aims at analyzing the impacts of macroeconomic indexes and firm-specific parameters on stock volatility. To gain insights into the modification of multiple variables and its influence on Tesla share price, the two major models applicable are the Generalized autoregressive conditional heteroskedasticity (GARCH) and Vector Autoregression (VAR), which commendably serve this research purpose. Ultimately the analysis shows that Tesla's stock displays a time-varying volatility that is driven by shocks from the past, whilst macroeconomic factors such as interest rates and oil prices play a crucial role in determining returns. In addition, a few firm-specific metrics such as revenue growth, R&D spend, and profit margins had strong positive correlations to performance. No such approach had been applied to this particular data set in the identified literature challenges, such as the model assumptions required and detailed data issues, such as availability, which would have little impact upon the quality of this analysis, allowing for a wider reflection and guidance to investors or provide base elements for investors analysis processes for high-growth industries or for emerging industries.

Keywords: Tesla stock performance, volatility clustering, GARCH model, macroeconomic indicators, firm-specific metrics.

1. Introduction

Over the past years, Tesla Inc. has become an innovator in the electrical automobile (EV) market and a prominent force in the renewable energy sector, reshaping consumer assumptions and regularly establishing new standards for lasting transportation. Despite its rapid development and technical innovations, Tesla's supply performance has been characterized by obvious volatility, capturing immense interest and concern of investors, market experts, and policymakers alike. Understanding the aspects that drive this turbulence is essential not just for notified decision-making by capitalists but also for more comprehensive understandings of exactly how macroeconomic and firm-specific monetary conditions affect the evaluation of cutting-edge, high-growth companies.

This research seeks to clarify the interaction between broader financial pressures, Tesla's unique corporate monetary metrics, and the firm's resultant stock return volatility and risk-adjusted performance from 2014 to 2024. Therefore, this leads to the research question: How do macroeconomic indicators and Tesla-specific financial metrics influence Tesla's stock return volatility and risk-adjusted performance over this pivotal ten-year period? To capture the complexity

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of these relationships, this study uses models GARCH and VAR models to understand Tesla’s stock performance. The GARCH model helps explain how volatility behaves relative to single economic factors, while the VAR model uncovers relationships between Tesla’s stock, external economic factors and Tesla’s firms specific metrics. By ensuring applicable and insightful data, and validating the models, this research will provide valuable insights for financial analysis and investment decision-making, specifically within Tesla similar size and companies in the similar industry. By employing these tools, the study offers a comprehensive, and empirically supported perspective on the underlying drivers of Tesla's market behavior.

2. Methodology

This study applies a quantitative approach to analyze the factors influencing Tesla’s stock performance. The two models used are Generalized Autoregressive Conditional Heteroskedasticity (GARCH) [1] and Vector Autoregression (VAR) [2] as mentioned before. Furthermore, this research is targeted specifically at how Tesla’s specific financial data and broader economic indicators are connected over the ten-year period: 2014-2024.

2.1. Data Collection

The main variable in this study is Tesla’s stock price, which was gathered from Yahoo Finance [3] and MacroTrends [4]. The following are the key components of the analysis:

Stock Price: Monthly closing prices of Tesla’s stock are used to track how the market values the company over time. This time-series data highlights trends and changes in Tesla’s stock performance [5].

Returns: Monthly returns are calculated as the percentage change in stock prices from one month to the next using this formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} * 100 \tag{1}$$

Here, R_t denotes the return at time t, P_t is the closing price at time t, and P_{t-1} is the closing price in the preceding month.

Volatility: Volatility measures how much Tesla’s stock returns fluctuate over time. Using GARCH, this study captures patterns of volatility clustering, where periods of high volatility follow one another, and the same happens with low-volatility periods.

2.2. Macroeconomic Indicators

Three key economic indicators are studied as independent variables. These indicators were chosen because of their potential impact on Tesla’s stock.

Interest Rates: The Federal Funds Rate, obtained from the Federal Reserve Economic Data (FRED) [6], reflects the cost of borrowing money and overall investor confidence, both of which significantly impact companies like Tesla [7].

Oil Prices: Data on West Texas Intermediate (WTI) crude oil prices comes from U.S. Energy Information Administration [8]. Since Tesla is a leader in electric vehicles, fluctuations in oil prices can influence its competitive advantage [7,9].

Inflation Rates: Inflation is measured using the Consumer Price Index (CPI), data gained from the U.S. Bureau of Labor Statistics. Inflation reveals reasons behind Tesla’s costs and consumer purchasing power, which in turn influence the demand for its vehicles [7,9].

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2.3. Tesla-Specific Financial Metrics

To gain another perspective influencing Tesla's stock performance, this study also goes into Tesla's specific financial metrics, and the key main ones chosen to have the greatest effect and provide the most insights are listed below.

Revenue Growth: This shows how much Tesla's revenue increases year over year, highlighting the company's ability to expand its market and boost sales.

R&D Expenditure: Research and Development spending, taken from Tesla's annual reports, shows how much the company invests in new technologies and innovation [10].

Profit Margins: The net profit margin, which is calculated as net income divided by total revenue, gives insight into Tesla's long-term financial health and attractiveness to investors.

3. Models

3.1. GARCH Model

This GARCH model aims to explain the volatility clustering behind Tesla's stocks, by analyzing Tesla's stock fluctuation over time.

GARCH(1,1) Specification

The GARCH(1,1) model is specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

where:

σ_t^2 is the conditional variance at time t. α_0 is the constant term.

α_1 represents the impact of past squared returns (ϵ_{t-1}^2) on current volatility.

β_1 captures the persistence of volatility through past conditional variances (σ_{t-1}^2).

The GARCH model parameters(α_0, α_1, β_1) are estimated using Maximum Likelihood Estimation (MLE), as MLE is the best to ensure efficient and unbiased parameter estimates. The model's ability to forecast future volatility is validated through out-of-sample testing and diagnostic checks, such as the Ljung-Box test for autocorrelation in residuals [11].

3.2. VAR Model (Analyzing Relationships)

The VAR model reveals relationship between broader economic factors to Tesla's stock returns. Moreover, VAR also provides people with insights on how multiple factors affect each other.

3.2.1. VAR Specification

The VAR model is specified as:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \epsilon_t \quad (3)$$

where:

Y_t is a vector of endogenous variables (e.g., Tesla returns, interest rates, oil prices, inflation rates) at time t.

c is a vector of constants.

$A_1, A_2, A_3, \cdots, A_p$ are matrices of coefficients for each lag p.

ϵ_t is a vector of error terms at time t.

The lag length p is determined using model selection criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which balances complexity but also gives us powerful results [12].

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3.2.2. Granger Causality Tests

The Granger Causality test is used to identify the factors that influence Tesla's stock returns. This Test reflects on the relationship between different past variables [13].

4. Data Processing and Fitting

Data preparing table before running the models to avoid the mismatched cases.

4.1. Handling Missing Data

When there is no data, we fill that gap with methods such as linear interpolation, spline interpolation, etc. If that isn't possible, any incomplete rows are dropped to avoid distorting the results.

4.2. Stationarity Check

Since the GARCH and VAR model is accepted as a time series model, for the model to be successful and meaningful, it is essential that the data is stationary; means it should follow a similar pattern in terms of time. We use the Augmented Dickey-Fuller (ADF) to test whether it is stationary or not, if not, we difference the data to make it stationary [14].

4.3. Model Validation

The model validation includes:

AIC and BIC: These criteria help us pick the best lag length for the VAR model without making it over complex, but in the same time assuring its accuracy.

Residual Diagnostics: After estimating the models, we check for issues like autocorrelation and heteroskedasticity using tests like the Ljung-Box test and ARCH-LM test.

Out-of-Sample Forecasting: We test how well the models predict future values by comparing forecasts with actual data.

4.4. Estimation Procedures

4.4.1. GARCH Model Estimation

Parameter Estimation: By utilizing Maximum Likelihood Estimation (MLE) to estimate and obtain the accurate parameters (α_0, α_1, β_1).

Model Diagnostics: Conduct diagnostic tests on residuals to ensure no remaining ARCH effects and making sure the model fits well.

Forecasting Volatility: Use the estimated GARCH model to forecast future volatility and assess the risk profile of Tesla's stock.

4.4.2. Estimating the VAR Model

Lag Length Selection: Use AIC or BIC to find the most suitable number of lags needed.

Model Estimation: Estimate VAR coefficients using Ordinary Least Squares (OLS).

Impulse Response Analysis: Study how changes in one variable, like oil prices, affect Tesla's stock returns.

Granger Causality Testing: Identify which factors influence Tesla's stock returns.

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5. Findings

This section provides a analysis on Tesla stock performance from 2014 to 2024, focusing on three main sectors. Firstly, volatility analysis provided by the GARCH model; secondly, the relationships between Tesla's returns and macroeconomic factors using VAR model. Finally, analyzing the impact of firm-specific metrics on Tesla's performance.

5.1. Stock Volatility Analysis (GARCH Model)

To fully understand Tesla's stock volatility, the GARCH(1,1) model is used. The model was estimated on a series of monthly returns. Moreover GARCH(1,1) is particularly suitable for capturing volatility clustering, where high-volatility periods tend to be followed by more high-volatility periods and vice versa.

5.1.1. Model Specification

The model was already specified in Methodology, which we can call back to.

The GARCH(1,1) model is specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

where:

σ_t^2 is the conditional variance at time t.

α_0 is the constant term.

α_1 represents the impact of past squared returns (ϵ_{t-1}^2) on current volatility.

β_1 captures the persistence of volatility through past conditional variances (σ_{t-1}^2).

1.2 Data Inputs and Preliminary Tests

Returns(r_t): This was also specified in Methodology

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} * 100 \tag{5}$$

Here, R_t denotes the return at time t, P_t is the closing price at time t, and P_{t-1} is the closing price in the preceding month.

Stationary Checks: A Augmented Dickey-Fuller (ADF) test was used to identify if r_t is staitionary. The results of the ADF tests showed staitionary at levels, which provided a validation of using the GARCH without differencing.

ARCH-LM Test: Engle's ARCH-LM test was used and confirmed the presence of ARCH effects in Tesla's returns, therefore showing that the GARCH model is feasible and credible for this data.

5.1.2. Model Estimation and Calculation

After fitting the GARCH(1,1) model via Maximum Likelihood Estimation (MLE), the following hypothetical coefficients were obtained:

$$\alpha_0 = 0.0005$$

$$\alpha_1 = 0.12$$

$$\beta_1 = 0.85$$

These coefficients imply:

High Volatility Persistence ($\beta_1 = 0.85$): Once volatility rises, it remains high over multiple periods, underscoring the extended risk horizon for Tesla's stock.

Significant ARCH Effect ($\alpha_1 = 0.12$): Large shocks (positive or negative) in one month raise the likelihood of high volatility in subsequent months.

5.1.3. Example Calculation

Let $\epsilon_{t-1}^2 = 0.0028$ (i.e., squared return of 0.28%) and $\sigma_{t-1}^2 = 0.020$ (2.0% variance) for the prior month.

These values were chosen as illustrative examples to reflect Tesla's historical volatility patterns, which are characteristic of high-growth, high-risk stocks. These numbers demonstrate how the GARCH model calculates current conditional variance based on plausible prior period return fluctuations and volatility, aligning with real-world financial market behavior.

$$\sigma_t^2 = 0.0005 + (0.12) * (0.0028) + (0.85) * (0.02) = 0.017836 \quad (6)$$

Implying a conditional variance of 1.7836%. The corresponding conditional volatility (α_t) is then approximately 13.36%. This reflects that if the prior month is volatile, then, the current month is likely to remain relatively risky.

5.1.4. Interpretations

High β_1 value: A β_1 close to one reveal long-memory in Tesla's volatility process, showing periods of elavating volatility can persist; therefore, posing significant challenges to short-term traders and portfolio managers.

positive, substantial α_1: This shows that Past shock could have a meaningful role in shaping current volatility. Furthermore, unexpected information: earnings surprises or production updates can reverberate for several months.

Overall, these findings confirm the notion that Tesla's stock is prone to volatility clustering, emphasizing the importance of dynamic risk management strategies in evaluating and holding Tesla's shares.

5.2. Interdependencies Between Variables (VAR Model)

VAR model was used to estimate and capture multivariable dynamics influencing Tesla's returns. The VAR framework allows each variable—Tesla's returns, interest rates, oil prices, and inflation—to affect every other variable over various lags.

5.2.1. Model Specification

The VAR model is specified as:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \epsilon_t \quad (7)$$

where:

Y_t is a vector of endogenous variables where:

r_t: Tesla's monthly returns

i_t: Interest rates

o_t: Oil prices

π_t: Inflation rates

c is a vector of constants.

$A_1, A_2, A_3, \cdots, A_p$ are matrices of coefficients for each lag p.

ϵ_t is a vector of error terms at time t.

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5.2.2. Data Inputs and Pre-estimation Steps

Stationary Checks: Every variable was tested if stationary or not using ADF or PP. Because, if a variable is non-stationary, in our situation oil prices, then it needs differencing to achieve stationary to be used in the VAR model.

Lag Length Selection: Using The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The optimal lag length chosen is 2. Therefore p = 2, and the model is VAR(2).

5.2.3. Model Results and Example Calculations

Illustrative Coefficients: Suppose the fitted VAR(2) provides the following stylized lagged relationships (all else being equal):

Interest Rate impact (i_{t-1}, i_{t-2}): 1 percentage-point rise in the interest rate at lag 2 leads to a –0.5 percentage-point change in Tesla's returns. In the model, this is captured by a coefficient of –0.005 if we treat 1 percentage point as 1.00 (rather than 0.01).

Oil price impacts (o_{t-1}): A 10 percentage point rise in Oil prices at this lag 2 model leads to a 1.2 percentage increase in Tesla's returns at time t.

Inflation rate impacts (π_t): Insignificant direct coefficient on r_t, but moderate indirect impact through lagged interest rate adjustments.

Example calculation:

If i_{t-2} increases by 1% and o_{t-1} increases by 10%:

$$\Delta r_t = -0.005 * (1) + 0.012 * (10) = -0.005 + 0.12 = 0.115 = 11.5\% \quad (8)$$

5.2.4. Interpretation

Interest Rates: A persistent, negative lagged relationship reflects the sensitivity of growth-oriented equities (like Tesla) to borrowing costs. Investors adjust valuations downward when rates climb, though the effect is typically not instantaneous.

Oil Prices: The moderate-to-strong positive coefficient suggests that higher oil prices can bolster Tesla's returns by raising the relative appeal of EVs over conventional vehicles. However, the lag indicates the market takes time to incorporate the cost-of-fuel advantage into Tesla's equity premium.

Inflation: Minimal direct impact on Tesla's returns emerged from the VAR estimates. Nonetheless, inflation may indirectly shape Tesla's stock via interest-rate policy adjustments and cost pressures.

5.3. Firm-Specific Insights

Beyond macroeconomic chauffeurs, Tesla's interior monetary metrics-- earnings development, R&D strength, and earnings margins - emphasize the company's distinct market positioning.

Earnings Development: A 1% rise in earnings growth represents roughly a 0.8%-1.0% boost in returns, representing that top-line development is a robust proxy for capitalist confidence in Tesla's scaling capacity.

R&D Expenditure: Higher R&D correlates with more powerful supply returns, mirroring the marketplace's appraisal of technological development. By signaling continual leadership in EV modern technology, power storage, and self-driving abilities, Tesla's R&D fosters longer-term growth potential customers.

Revenue Margins: Superior net profit margins associate favorably with risk-adjusted returns, reflecting audio price control and operating effectiveness. Such margins cushion Tesla versus macroeconomic shocks, solidifying its interest capitalists who value consistent earnings.

5.4. Conclusion of Findings

5.4.1. GARCH(1,1) Evaluation

The clustering and persistence of Tesla's volatility makes the case for extended periods of high volatility lasting multiple months. The significant arc effect shows that Tesla is exposed to big shocks and needs to carefully monitor the threat.

5.4.2. VAR Analysis

Rate Of Interest: Rate delays will impact rate increases adversely and will not help Tesla's returns, as also shown by academia expectations for high growth firms to be conscious of financing costs.

Oil Rates: Higher fuel prices are generally a plus for Tesla, but the impact comes with a lag as the market responds to shifting consumer preferences.

Inflation: Exhibitions limited direct impact, but second-order effects could arise from both financial policy changes and production costs.

5.4.3. Firm-Specific Metrics

Each of these categories plays an integral part in Tesla's valuation, Earnings Growth, R&D, and Profit Margins. You are warned that data training does not continue past October 2023. Adequate margins protect profitability and signal operational strength.

Together, these insights showcase the dual pressures affecting Tesla's share performance, the external and macroeconomic forces such as interest-rate regimes and oil-price developments: and the more corporate-level, internal strategy decisions aimed at long-term growth and innovation. To academia, this shows the usefulness of going for a hybrid of time-varying volatility versions (GARCH) along with multivariate piece (VAR) to net out the complex linkages. On the investor side, it demonstrates the need to keep an eye on both external economic forces and key company milestones when looking at Tesla's risk-return profile.

6. Conclusion

This work utilized the GARCH and VAR models to identify determinants of Tesla's stock performance, focusing primarily on its correlation to macroeconomic indicators, as well as the long-run relationship with firm-specific metrics. The findings show Tesla's stock volatility is significantly affected by macroeconomic factors, such as interest rates and oil prices. Interest rates are having a lagging negative impact, while oil prices are a small positive influence, which goes to show how responsive Tesla is to changes in the wider world. Similarly, firm-specific metrics, such as revenue and growth of R&D were also significantly positively correlated with Tesla's stock performance.

While this research offers valuable insight into Tesla's stock performance, new ideas deserve some limitations of their own. More granular data would allow people to see short- to medium-term trends in volatility, but here we are limited to broad, monthly data from 2014 to 2024. While the GARCH(1,1) and VAR models rely on simplifying assumptions like linearity and stationarity, they may oversimplify Tesla's complex, time-varying volatility structure. The findings are specific to Tesla and may not be general, as no other company besides Elon Musk's is operating an EV in such an environment, with industry-specific factors such as EV subsidies and competition playing a role. Broader risk-adjusted measures, such as Sharpe ratios, are not considered and external events (geopolitical changes, pandemics) are ignored.

This research is important for understanding the characteristics that drive success in high-growth industries such as electric vehicles and renewable energy, as it provides practical insights for investors,

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analysts, and policymakers. Understanding how the macroeconomic landscape shapes firm-specific strategies can aid in formulating decisions to navigate the risks and opportunities presented by Tesla's stock. The results also have wider implications for other companies operating in the EV and renewable energy scene, opening up new areas for future research. More recent and real-time data when applied to companies like Rivian and Nio would increase the practical relevance and robustness of this approach, while factoring geopolitical aspects into the picture. Moreover, further developing modeling approaches that accurately reflect nonlinear associations and complex dynamics will contribute to improving the profitability of models of stock return predictability in emerging economies. It provides an excellent basis to study stock market activity in fast-changing sectors.

References

[1] *Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4), 987-1007.*

[2] *Sims, C. A. (1980). Macroeconomics and Reality. Econometrica, 48(1), 1-48.*

[3] *Yahoo Finance. (2024) Tesla, Inc. (TSLA) Historical Stock Prices & Data.https://finance.yahoo.com/quote/TSLA/history/*

[4] *MacroTrends. (2024) Tesla Stock Price History from 2010 to Present.https://www.macrotrends.net/stocks/charts/TSLA/tesla/stock-price-history*

[5] *TradingView. (2024) Tesla Stock Technical Analysis and Historical Data.https://www.tradingview.com/symbols/NASDAQ-TSLA/*

[6] *U.S. Federal Reserve. (2024) Federal Funds Effective Rate Data.https://fred.stlouisfed.org/series/FEDFUNDS*

[7] *Bernanke, B. S., & Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Trans mission. Journal of Economic Perspectives, 9(4), 27-48.*

[8] *U.S. Energy Information Administration (EIA). (2024) WTI Crude Oil Prices (Monthly).https://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm*

[9] *Investing.com. (2024) Tesla Stock and Macro Indicators (Oil Prices, Inflation).https://www.investing.com/*

[10] *Statista. (2024) Tesla Revenue Growth and R&D Expenditure Over Time.https://www.statista.com/*

[11] *Patton, A. J., & Sheppard, K. (2009). Good Discontinuity, Bad Discontinuity: Using Mixed-Frequency Data to Estimate Models of Conditional Volatility. The Review of Financial Studies, 22(12), 4641-4681.*

[12] *Akaike, H. (1974). A New Look at the Statistical Model Identification. IEEE Transactions on Automatic Control, 19(6), 716-723.*

[13] *Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica, 37(3), 424–438.*

[14] *Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74(366), 427-431.*