

Financial Time Series Analysis

VAR-BASED LOSS PREDICTION FOR **TESLA**

SUBMITTED BY

Aarushi Dubey MBA202224 - 002
Abhishek Sonone MBA202224 - 009
Akash Talokar MBA202224 - 012
Ashish Kumar MBA202224 - 029
Ashutosh Sahoo MBA202224 - 031

GUIDED BY

Prof. Tapan Kar

IFMR GRADUATE SCHOOL OF BUSINESS
KREA UNIVERSITY, SRICITY

ACKNOWLEDGEMENT

We express our deepest gratitude to Prof. Tapan Kar, whose guidance enabled us to take up this project and work on it. We sincerely thank our mentor for their enthusiasm, patience, insightful comments, helpful information, practical advice, and ideas that have helped us tremendously in our project. With their support and guidance, this project was possible.

We have made significant efforts in formulating this report and would like to express our deepest gratitude to everyone who helped shape this project.

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ABSTRACT

Value at Risk (VaR) is a statistical measure used to quantify the level of financial risk within a portfolio or an investment over a specific period. VaR estimates the maximum potential loss with a certain degree of confidence and within a given time frame.

Expected Shortfall (ES), also known as Conditional Value at Risk (CVaR), is a risk metric used to provide a more comprehensive measure of the potential loss in an investment portfolio beyond the Value at Risk (VaR). While VaR estimates the maximum potential loss at a specified confidence level, Expected Shortfall further calculates the average worst-case scenarios beyond the VaR threshold.

INTRODUCTION

- **Understanding Market Dynamics:** This project aims to understand the dynamics of Tesla's stock prices, which can provide insights into the overall market trends and the factors influencing them.
- **Predictive Power:** By using advanced statistical models like GARCH and ARMA, we aim to predict future stock prices. This can be a powerful tool for investors and traders.
- **Risk Management:** The project also focuses on calculating Value at Risk (VaR), a key concept in risk management. It helps in quantifying potential losses in investment.
- **Statistical Learning:** This project serves as an excellent opportunity to apply and enhance our statistical learning, particularly in the field of time series analysis.
- **Real-world Impact:** The stock market has a significant impact on the global economy. Understanding and predicting stock price movements can lead to more informed financial decisions, contributing to economic stability.
- **Data Analysis and Visualization:** In order to comprehend Tesla's stock dynamics, the project involves thorough data analysis and visualization techniques. Utilizing tools like Python, we can extract meaningful patterns, trends, and correlations from historical stock data.

MOTIVATION

The central rationale for choosing Value at Risk (VaR) and Expected Shortfall (ES) for predicting losses is that this paper focuses on its ability to explain the change in log return data from time series data based on different volatility models. This measurement index predicts losses for a given time horizon. This prediction is achieved by employing normal, student t and skewed student t distributions as the conditional distribution in the volatility models.

In summary, the paper emphasizes the utilization of VaR and ES to analyze log return data, employing different volatility models and distributional assumptions to predict losses within a specified time horizon.

DATA

1. Company Overview:

Name: Tesla, Inc.

Industry: Automotive, Energy

Headquarters: Austin, Texas, USA

Founded: 2003

CEO: Elon Musk

Mission: To accelerate the world's transition to sustainable energy.

2. Data Source and Time Period:

Data Source: Yahoo Finance

Time Period: 5 Year (Dec 2018-Dec 2023)

3. Data Transformation:

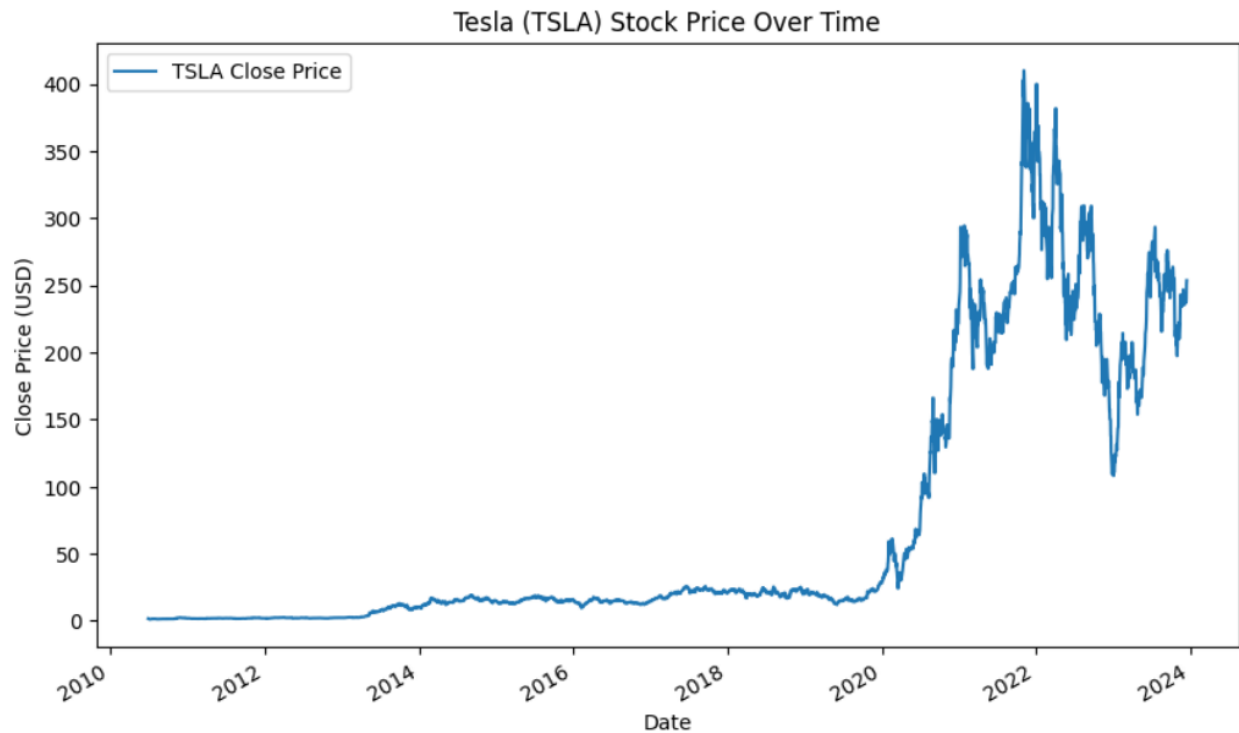
The closing prices have been transformed into log returns for the purpose of this analysis.

4. Financial Performance:

Revenue (2023): \$135.6 billion

Net Income (2023): \$15.2 billion

Market Capitalization (as of January 7, 2024): \$1.2 trillion



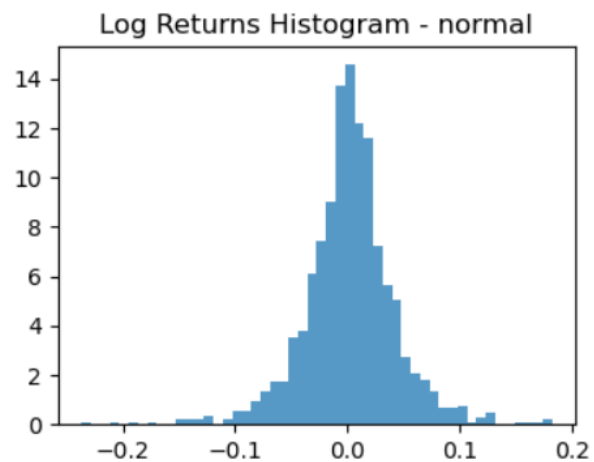
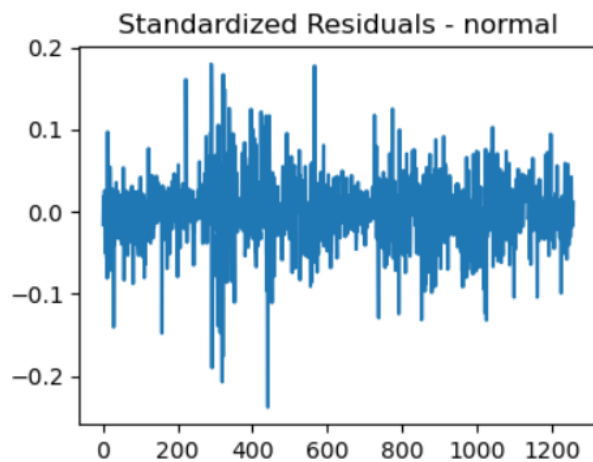
STATISTICAL PROPERTIES

| | Open | High | Low | Close | Adj Close | Volume |
|-------|-------------|-------------|-------------|-------------|-------------|--------------|
| count | 1380.000000 | 1380.000000 | 1380.000000 | 1380.000000 | 1380.000000 | 1.380000e+03 |
| mean | 154.758096 | 158.268245 | 150.962867 | 154.710792 | 154.710792 | 1.354234e+08 |
| std | 112.479232 | 114.936716 | 109.721652 | 112.344357 | 112.344357 | 8.559140e+07 |
| min | 12.073333 | 12.445333 | 11.799333 | 11.931333 | 11.931333 | 2.940180e+07 |
| 25% | 23.261000 | 23.665166 | 22.933334 | 23.281501 | 23.281501 | 8.147228e+07 |
| 50% | 180.191666 | 185.139999 | 176.450005 | 180.709999 | 180.709999 | 1.110137e+08 |
| 75% | 244.931660 | 250.553329 | 240.241665 | 244.890003 | 244.890003 | 1.596152e+08 |
| max | 411.470001 | 414.496674 | 405.666656 | 409.970001 | 409.970001 | 9.140820e+08 |

METHODOLOGY

1. Download the Tesla dataset [For 5 Years] from Yahoo Finance.
2. Check stationarity using the DF Test
3. Calculate daily log return
4. We will use Dicky fuller test to check for stationarity
5. We will use the Jerque Bera test to check for normality
6. We will use the Ljung box test to check for significant autocorrelation between the data points
7. Check for Skewness and Kurtosis of log return
8. Then we did the ARCH test to check for volatility clustering
9. Then we fit a GARCH model for our log return; we fit condition distribution as normal distribution, student t distribution and skewed student t distribution
10. Again, we did the ARCH test and the Ljung box test for standardized residuals for each of the condition distributions we assumed in our GARCH model
11. Using a confidence interval of 5%, we forecasted the VaR and expected shortfall for each of the three distributions.

RESULTS AND DISCUSSIONS



Distribution: normal

Value at Risk (VaR) at 0.05 confidence level: -0.06564369705599855

Expected Shortfall (ES) at 0.05 confidence level: -0.09701664032435289

Excess Kurtosis: 3.49425114676846

Skewness: -0.24584292412638203

Constant Mean - GARCH Model Results

```

=====
Dep. Variable:          Close      R-squared:                0.000
Mean Model:             Constant Mean  Adj. R-squared:           0.000
Vol Model:              GARCH        Log-Likelihood:         2297.82
Distribution:           Normal       AIC:                   -4587.64
Method:                 Maximum Likelihood  BIC:                   -4567.09
                                           No. Observations:      1257
Date:                  Fri, Jan 12 2024  Df Residuals:          1256
Time:                  15:15:41         Df Model:                1
=====

```

Mean Model

```

=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----

```

```

mu          1.6820e-03  1.070e-03      1.571      0.116 [-4.160e-04,3.780e-03]
=====

```

Volatility Model

```

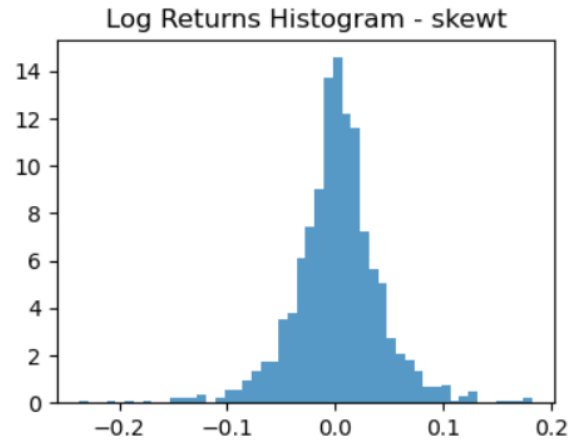
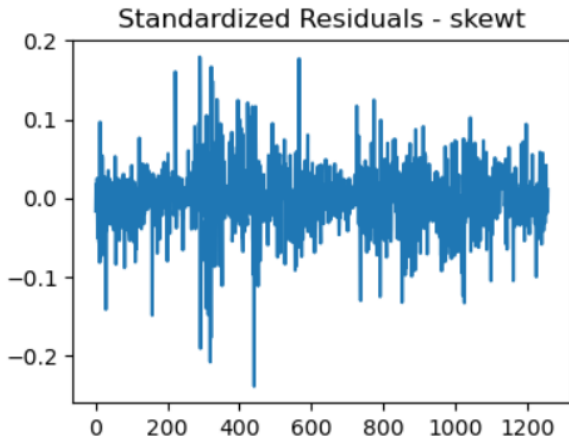
=====
              coef      std err          t      P>|t|      95.0% Conf. Int.
-----

```

```

omega       6.4447e-05  1.776e-05      3.629  2.848e-04 [2.964e-05,9.926e-05]
alpha[1]    0.0617     1.704e-02      3.622  2.924e-04 [2.832e-02,9.513e-02]
beta[1]     0.8986     1.897e-02     47.374  0.000      [ 0.861,  0.936]
=====

```

Distribution: skewt

Value at Risk (VaR) at 0.05 confidence level: -0.07788182575318597

Expected Shortfall (ES) at 0.05 confidence level: -0.11295514365754619

Excess Kurtosis: 3.49425114676846

Skewness: -0.24584292412638203

Constant Mean - GARCH Model Results

```
=====
Dep. Variable:                Close    R-squared:                0.000
Mean Model:                   Constant Mean    Adj. R-squared:          0.000
Vol Model:                    GARCH          Log-Likelihood:         2355.47
Distribution:                  Standardized Skew Student's t    AIC:                    -4698.93
Method:                       Maximum Likelihood    BIC:                    -4668.11
                               No. Observations:         1257
Date:                         Fri, Jan 12 2024    Df Residuals:           1256
Time:                         15:15:41          Df Model:                1
                               Mean Model
=====
```

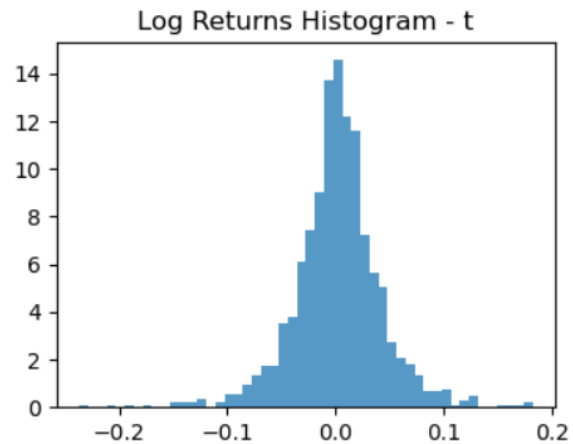
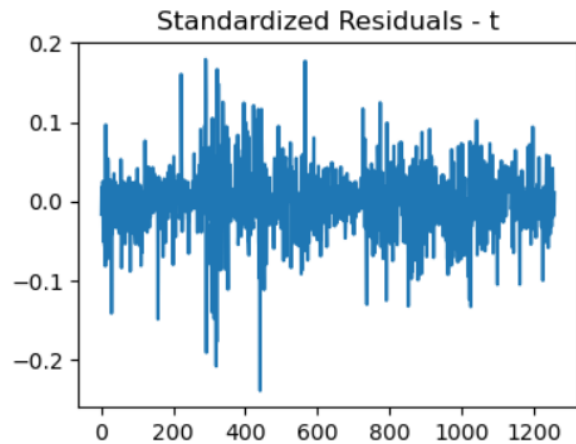
| | coef | std err | t | P> t | 95.0% Conf. Int. |
|----|------------|-----------|-------|-----------|------------------------|
| mu | 2.2539e-03 | 1.117e-03 | 2.019 | 4.353e-02 | [6.548e-05, 4.442e-03] |

Volatility Model

| | coef | std err | t | P> t | 95.0% Conf. Int. |
|----------|------------|-----------|--------|-----------|------------------------|
| omega | 3.3645e-05 | 1.170e-05 | 2.876 | 4.029e-03 | [1.072e-05, 5.658e-05] |
| alpha[1] | 0.0500 | 1.976e-02 | 2.530 | 1.139e-02 | [1.127e-02, 8.873e-02] |
| beta[1] | 0.9300 | 1.420e-02 | 65.505 | 0.000 | [0.902, 0.958] |

Distribution

| | coef | std err | t | P> t | 95.0% Conf. Int. |
|--------|-------------|-----------|------------|-------|-------------------------|
| eta | 5.9991 | 5.544 | 1.082 | 0.279 | [-4.868, 16.866] |
| lambda | -8.8758e-07 | 3.732e-02 | -2.378e-05 | 1.000 | [-7.314e-02, 7.314e-02] |



Distribution: t

Value at Risk (VaR) at 0.05 confidence level: -0.2927986619797376

Expected Shortfall (ES) at 0.05 confidence level: nan

Excess Kurtosis: 3.49425114676846

Skewness: -0.24584292412638203

Constant Mean - GARCH Model Results

```
=====
Dep. Variable:                Close    R-squared:                0.000
Mean Model:                  Constant Mean    Adj. R-squared:           0.000
Vol Model:                   GARCH          Log-Likelihood:          2355.46
Distribution:                 Standardized Student's t    AIC:                     -4700.93
Method:                      Maximum Likelihood    BIC:                     -4675.24
                               No. Observations:        1257
Date:                        Fri, Jan 12 2024    Df Residuals:            1256
Time:                        15:15:41          Df Model:                 1
                               Mean Model
=====
```

```
=====
              coef    std err          t      P>|t|      95.0% Conf. Int.
-----
mu          2.2866e-03  9.109e-04      2.510  1.207e-02  [5.012e-04,4.072e-03]
Volatility Model
=====
```

```
=====
              coef    std err          t      P>|t|      95.0% Conf. Int.
-----
omega       3.3660e-05  1.173e-05      2.870  4.109e-03  [1.067e-05,5.665e-05]
alpha[1]    0.0500     1.975e-02      2.532  1.133e-02  [1.130e-02,8.870e-02]
beta[1]     0.9300     1.419e-02     65.519  0.000      [ 0.902, 0.958]
Distribution
=====
```

```
=====
              coef    std err          t      P>|t|      95.0% Conf. Int.
-----
nu          5.9991      5.587        1.074  0.283 [ -4.951, 16.949]
=====
```

1)VaR at 0.05 Confidence Level: The T-distribution has a significantly lower VaR than the Normal and Skewt distributions. This indicates that the t-distribution considers a more extreme potential loss at the 0.05 confidence level.

2)ES at 0.05 Confidence Level: The ES for the Skewt distribution is the smallest, indicating that in the worst 5% of scenarios, the average loss is the lowest. The t-distribution has a nan value for ES, possibly due to a limitation in the model or data.

3)Excess Kurtosis: All three distributions have the same excess kurtosis value, suggesting similar tail behaviour or the likelihood of extreme events.

4)Skewness: The skewness is the same for all distributions, indicating a leftward skew (negative skewness).

CONCLUSION

In conclusion, our exhaustive examination of Tesla's stock dynamics centred on the meticulous analysis of daily log returns. The primary objective was to ascertain the adherence of these returns to a consistent and stable pattern.

The introduction of the GARCH model proved instrumental, serving as a sophisticated tool adept at capturing the nuanced fluctuations within the log returns. The model's outputs, namely omega, alpha, and beta coefficients, were pivotal in elucidating the underlying rationale governing the stock market movements.

Beyond model fitting, our focus extended to risk management, where implementing Value at Risk (VaR) using the GARCH model facilitated a comprehensive understanding of potential losses at a 5% confidence level across diverse scenarios.

In essence, this project transcends mere comprehension of Tesla's stock behaviour; it furnishes us with refined strategies for adeptly navigating the complexities of financial risk. The methodologies employed are a testament to the project's broader applicability, akin to possessing a strategic instrument for informed and prudent financial decision-making.

LIMITATIONS

- **Normality Assumption:**
The GARCH model relies on the assumption of normality in stock returns. The model's accuracy may be compromised if the data significantly deviates from normal distribution.
- **Parameter Sensitivity:**
The performance of the GARCH model is sensitive to the choice of parameters (p , q). Different parameter values may yield varying results, and finding the optimal values can be challenging.
- **VaR Limitations:**
VaR provides an estimate under the assumption of constant volatility. It might not capture extreme events well, and results are subject to the chosen confidence level.
- **Extreme tails or heavy tails:**
The t-distribution is sensitive to extreme values, especially when the degrees of freedom are low. The data has extreme observations, which can lead to heavy tails in the distribution. In such cases, the distribution's moments (mean and variance) may not be well-defined, and the Expected Shortfall calculation could yield NaN.

REFERENCES

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2. [Value at Risk Models in Indian Markets: A Predictive Ability Evaluation Study](#)
3. [Forecast and Backtesting of VAR Models in Crude Oil Market](#)
4. [An Empirical Investigation of Value at Risk \(VaR\) Forecasting Based on Range-Based Conditional Volatility Models](#)