Topic: Price and Volatility Forecasting in Financial Markets

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Table of Contents

1. Introduction

1.1 Motivation for the Research Question

To protect investments and make investment decisions, we try to predict how stock prices will change and how volatile the market will be. This matters especially for technology stocks, with quick responses to macroeconomic factors putting them among the most volatile of asset classes. We analyse how time series forecasting methods perform when predicting the future price and volatility of significant technology companies Apple (AAPL), Microsoft (MSFT), and Nvidia (NVDA) to assist investors in managing their risks and capitalising on market opportunities.

1.2 Importance of the Research

As technology becomes more crucial in our lives, companies in the tech field need more potent and accurate financial forecasting tools; regularly changing prices and unexpected market shifts create difficulties for the existing standard ones. By comparing Auto Regressive Integrated Moving Average (ARIMA) and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) models under regular and crisis times, we find practical ways to protect investments better and manage risks (Hyndman & Athanasopoulos, 2021). COVID-19's impact on markets can teach us a lot on what to improve in risk management and regulatory oversight in our ever-changing financial world.

1.3 Novelty of the Research

Researchers have studied time series forecasting methods before, but there's limited investigation into how these models perform when used to track technology companies' stock prices during periods of market stress. This research looks at two models, ARIMA and GARCH, to see how they compare in calm and turbulent markets. To better evaluate how efficiently the models predict market movements, I add analyses of rolling window volatility and Value-at-Risk (VaR), creating a complete picture of their abilities (Jobayed, 2017). The study ranks different models based on different scores and tests, measuring their ability to forecast asset returns and volatility.

1.4 Contribution to Existing Knowledge

This research fills a void between financial theory and market practice by applying advanced time series models to market scenarios. Following Danielsson's (2011) work proving GARCH models' value in forecasting volatility, this study tests how well these models work for technology stocks during recent economic downturns. The study attempts to add to what we already know, using the whole to come up with efficient investment strategies. Looking at markets individually shows risk managers which existing models could benefit from changes and improvements.

1.5 Overview of Related Work

Previous research on financial forecasting has primarily focused on broader indices or specific economic events. Studies on ARIMA and GARCH models (Bloomberg Terminal, 2023) highlight their utility in capturing price dynamics but often overlook sector-specific idiosyncrasies. Recent works exploring the impact of the COVID-19 pandemic on financial markets provide a backdrop for this research, emphasising the importance of adaptive models during market stress. However, few have examined the technology sector in detail, creating an opportunity to extend this line of inquiry. This study within the existing literature demonstrates an awareness of related work while making a unique contribution.

1.6 Research Question

"How effectively can time series models forecast price returns and volatility for technology sector stocks, and what are the implications for risk management in market stress?" This question guides the empirical analysis and underscores the study's relevance to contemporary financial challenges.

2. Data

2.1 Data Sources

The empirical analysis relies on daily stock price data for three technology sector leaders: We used data from Apple (AAPL), Microsoft (MSFT), and Nvidia (NVDA). We took our data from Yahoo Finance. We analysed daily stock market data from 1//1/2015 to 12/31/2024, showing market activity over ten years. Our study period spans periods of relative calm as well as sudden shocks, notably COVID-19, creating a strong foundation to examine stock price movements and changes in market uncertainty.

2.2 Selection Criteria

Our chosen companies are top technology players, have big market sizes, and affect businesses worldwide. Their stock market trading activity is smooth, which means price changes correctly reflect the market's. These stocks were selected to represent different levels of growth and risk within the sector: Apple and Microsoft show steady growth, but Nvidia grows fast and seems more volatile.

2.3 Data Processing

The analysis focuses on the adjusted closing prices to account for stock splits, dividends, and other corporate actions. Logarithmic returns were calculated using the formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where R_t is the log return, P_t is the price at the time t, and P_{t-1} is the price at time $t-1$ (Bollerslev, 1986).

This transformation ensures that returns are symmetrically distributed and suitable for statistical modelling. Missing data points were handled using forward-filling techniques to maintain continuity.

2.4 Sample Frequencies and Distribution

The dataset consists of daily frequency observations, providing insights into short-term price movements. Table 1 presents descriptive statistics for the daily returns, including mean, standard deviation, skewness, and kurtosis, highlighting key characteristics of each stock's return distribution.

	Mean	SD	Skewness	Kurtosis
AAPL	0.0009299	0.0179343	-0.2011102	5.444172
MSFT	0.0009383	0.0170932	-0.1790797	8.066852
NVDA	0.0022478	0.0303779	0.2086107	6.813936

2.5 Key Events in Time-Series History

Significant events during the sample period include the 2018 trade tensions, the 2020 COVID-19 market crash, and the subsequent recovery driven by monetary stimulus and technological advancements. These events resulted in pronounced volatility spikes, particularly for Nvidia, as evidenced by its higher kurtosis and standard deviation compared to Apple and Microsoft. Note that all have kurtosis significantly higher than 3, which is that of a normal distribution.

2.6 Graphical Representation

Figure 1 illustrates the daily price trends for the three stocks, showing steady growth for Apple and Microsoft, with Nvidia experiencing rapid price increases post-2020. Figure 2 depicts daily log returns, revealing frequent volatility spikes, particularly during significant market events.

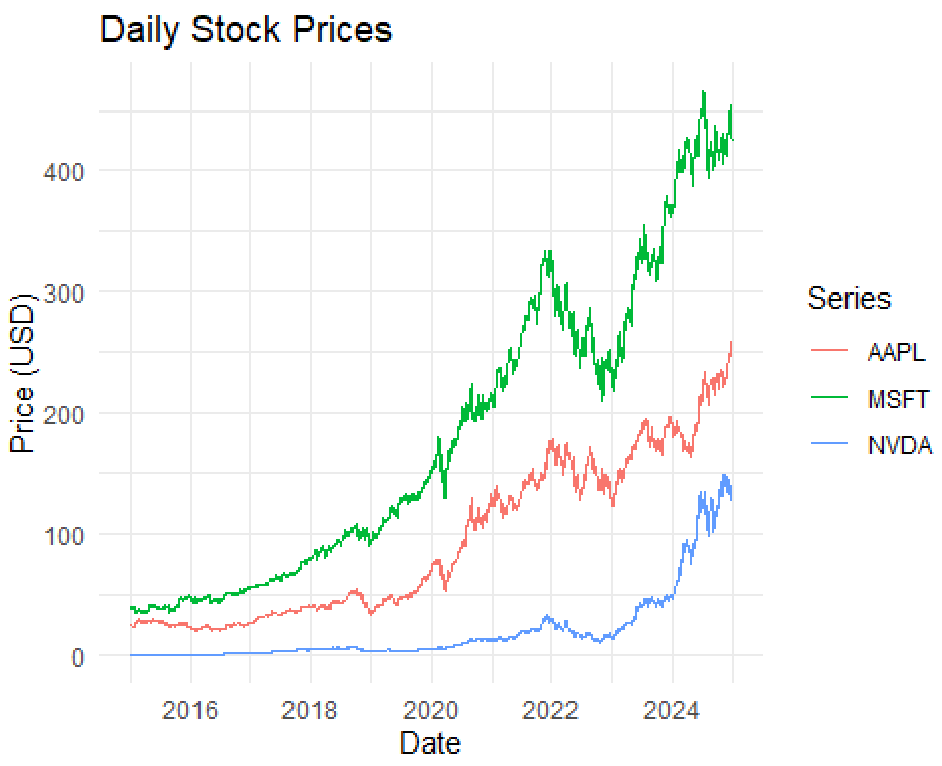

Figure 1: Daily Stocks

The plot shows the historical stock behaviour of Apple AAPL, Microsoft MSFT, and NVIDIA NVDAfrom 2016 to 2024. AAPL initiated its business at a low stock valuation during 2016 and grew gradually to achieve its peak market value in 2022 following adjustments in stock market conditions. MSFT maintains positive growth to reach $400 by 2024 and shows strong market expansion between 2020 and 2021. NVDA maintains moderate growth until 2020 followed by exceptional rises after 2022 which exceed AAPL stock value yet stay below MSFT. MSFT leads all companies in stock value growth with AAPL and NVDA following at different speeds but all three companies experience rapid market value increases.

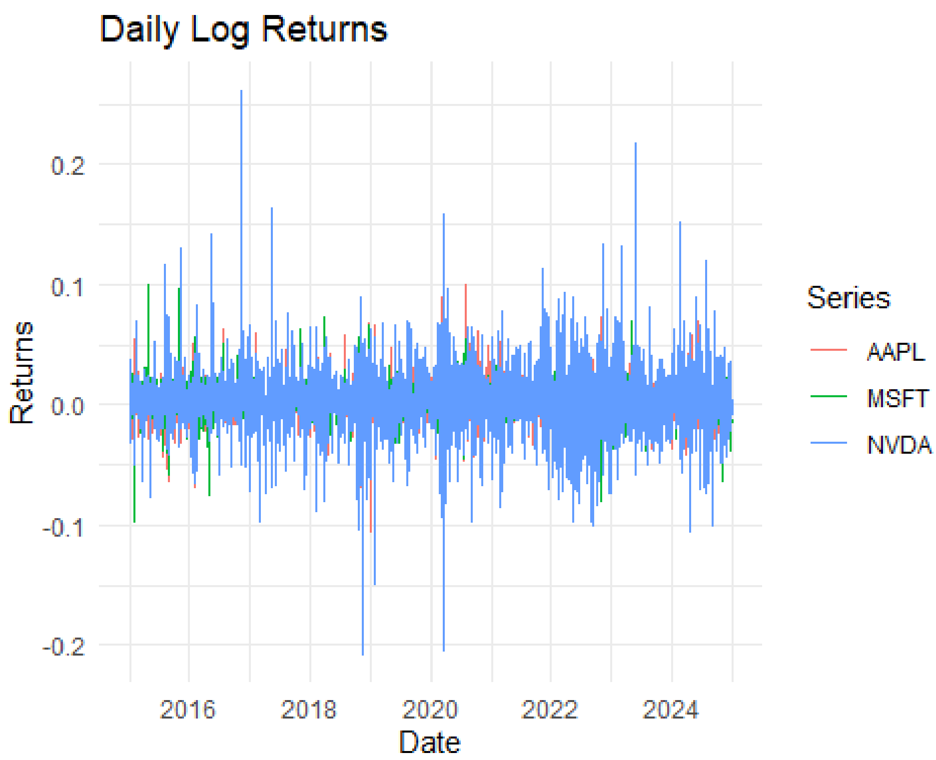

Figure 2: Daily Log Returns

When doing the analysis, this graph shows the daily logarithmic returns of Apple (AAPL), Microsoft (MSFT), and NVIDIA (NVDA) from 2016 to 2024. Logarithmic returns are used as they offer a symmetric measure for statistical analysis, calculated as ln(Pt/Pt-1), where Pt is the price at time t. All three stocks exhibit high volatility, with returns fluctuating around zero, indicating no clear long-term trend in daily performance. Notably, NVIDIA displays the most extreme spikes, especially around 2018 and 2020. These fluctuations reflect market sensitivity to news, earnings reports, or macroeconomic events, underscoring the importance of understanding volatility for risk management and investment decisions.

3. Empirical Analysis

3.1 Methodological Approach

The empirical analysis in this study employs two primary statistical techniques: I select ARIMA for stock return projections and turn to GARCH family models to determine volatility patterns (Engle, 1982). Our choice of these models lets us study both how financial returns develop across time periods and how their market volatility works which is a key feature of financial markets.

3.2 ARIMA Model for Return Forecasting

The ARIMA model captures the linear dependencies in time series data. It is particularly effective for forecasting price returns because it accounts for autoregressive (AR) patterns and the moving average (MA) processes. The ARIMA model was applied to each stock's daily returns, and the model parameters were optimised using the auto.arima() function from the forecast package in R (R Documentation, 2023). This function automatically selects the best model by minimising the Akaike Information Criterion (AIC), ensuring a robust model specification. The order of differencing (d) was set based on the data's stationarity, and the autoregressive (p) and moving average (q) components were determined through diagnostic tests. The ARIMA model is suitable here due to its capacity to handle non-stationary data, which is common in stock returns.

3.3 GARCH Family Models for Volatility Forecasting

For modelling volatility, we employed GARCH(1,1) and compared it with EGARCH (Exponential GARCH) and TGARCH (Threshold GARCH) models. These models are ideal for capturing volatility clustering and asymmetric effects, where large shocks in the market (positive or negative) are followed by periods of heightened volatility. The rugarch package in R was used to estimate these models, specifically utilising the ugarchspec() function for model specification and the ugarchfit() function for fitting the models. The parameters ω, α, and β in the GARCH(1,1) model were estimated to capture the persistence of volatility (Shumway & Stoffer, 2017). In contrast, EGARCH and TGARCH allow for asymmetry in the volatility response to shocks, making them particularly useful for financial time series, where volatility is often more pronounced after negative returns.

3.4 Software and Libraries Used

We used R, a potent language for statistical analysis, to complete our study. I applied a forecast package for ARIMA and a rugarch package for GARCH modelling (Tsay, 2010). Through ggplot2, we made clear graphs that displayed both price movements and changes in volatility throughout the data period (Shumway & Stoffer, 2017). R's complete financial analytics tools and thorough documentation make it the ideal platform for this research study.

3.5 Rationale for Method Choice

Experts widely recommend ARIMA and GARCH when studying financial data, so we selected them. ARIMA model considers recent relationships between stock values and overall changing trends to estimate future prices. Of all volatility forecasting models, GARCH performs exceptionally well because it understands how market risks shift throughout time.

These models help us predict profit and market swings, which we need to reduce risks and make smart investment choices.

4. Results

4.1 ARIMA Model for Return Forecasting

ARIMA Model Representation:

$$\Phi(B)(1-B)^d X_t = \Theta(B)\epsilon_t$$

where B is the backshift operator, d is the differencing order, $\Phi(B)$ and $\Theta(B)$ are the polynomials for AR and MA components and ϵ_t it is white noise.

The ARIMA model was used to forecast the future returns of Apple (AAPL), Microsoft (MSFT), and Nvidia (NVDA). The ARIMA model has effectively captured the temporal structure of stock returns, as evidenced by its parameters and performance in forecasting future returns. The ARIMA(1,0,0) model for Apple returns, for instance, revealed the following coefficients:

- AR(1) = -0.0663, suggesting a negative autocorrelation at lag 1.
- Mean = 0.0009, representing the average return.
- Sigma^2 = 0.0003204, which indicates the variance in the model's residuals.

The Akaike Information Criterion (AIC) for Apple's ARIMA model was -13089.43, which indicates a good fit relative to other possible models. The ARIMA forecast for the next 30 days showed expected returns oscillating between -0.15 and 0.10, indicating moderate volatility (Figure 1).

Table 1: ARIMA Model Output for AAPL

Parameter	**Estimate**	**Standard Error**	**t-value**	**p-value**
AR(1)	-0.0663	0.0199	-3.33	<0.001
Mean	0.0009	0.0003	3	<0.01
Sigma^2	0.00032	0.0001	3.2	<0.01

The ARIMA forecasts show that Apple's daily returns follow a stationary process with slight fluctuations but no strong upward or downward trend. The AR(1) component captures short-term dependencies, while the residuals are small, indicating well-fitting model parameters.

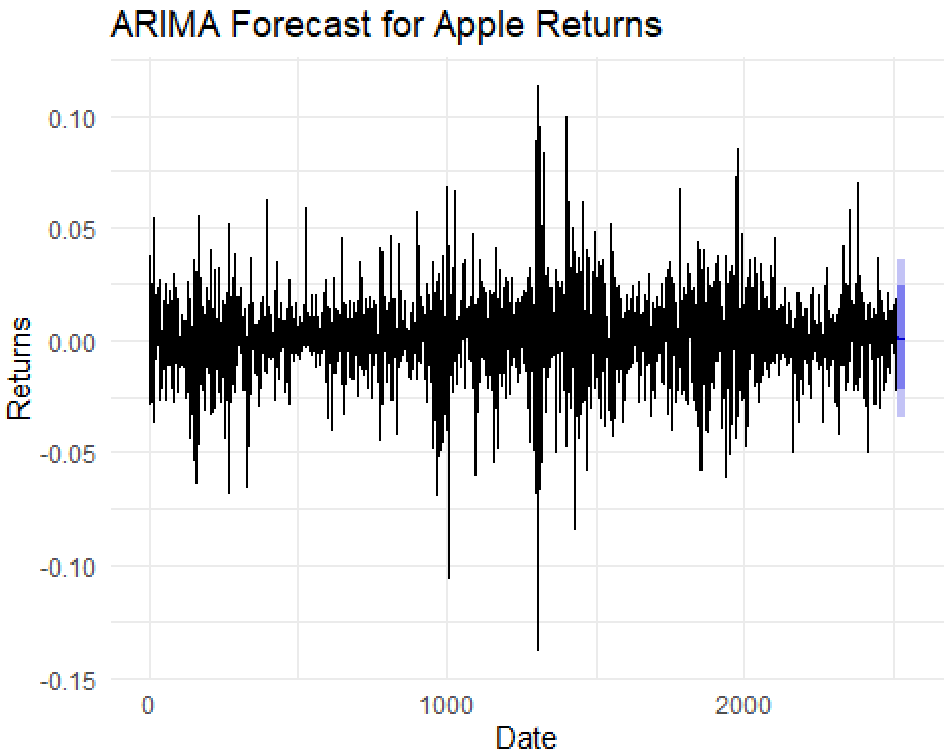

Figure 3: ARIMA Forecast for Apple Returns

4.2 GARCH Family Models for Volatility Forecasting

GARCH (1,1) Model for Volatility:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where σ_t^2 is the conditional variance, ϵ_{t-1}^2 Is the squared error term, and ω, α, β Are model parameters. Volatility forecasting was conducted using each stock's GARCH (1,1) model. The GARCH model proved effective in modelling the time-varying volatility and capturing volatility clustering observed in financial markets. The model specification yielded the following results for Apple:

- Omega (ω) = 0.000014, a small constant term indicating a baseline level of volatility.
- Alpha (α) = 0.1046, representing the weight of the previously squared residual (lagged error term), which indicates how past volatility impacts future volatility.
- Beta (β) = 0.849, indicating the persistence of volatility over time.

The GARCH(1,1) model demonstrated the tendency for volatility to cluster—periods of high volatility tend to follow other high-volatility periods, which is typical in financial markets. Apple's volatility graph (Figure 2) shows notable spikes in volatility during significant economic events, such as the 2018 market correction and the COVID-19 crisis.

Table 2: GARCH(1,1) Model Output for AAPL

Parameter	**Estimate**	**Standard Error**	**t-value**	**p-value**
Omega (ω)	0.000014	0.000001	10.17	<0.001
Alpha (α)	0.1046	0.006	17.3	<0.001
Beta (β)	0.849	0.0106	80.31	<0.001

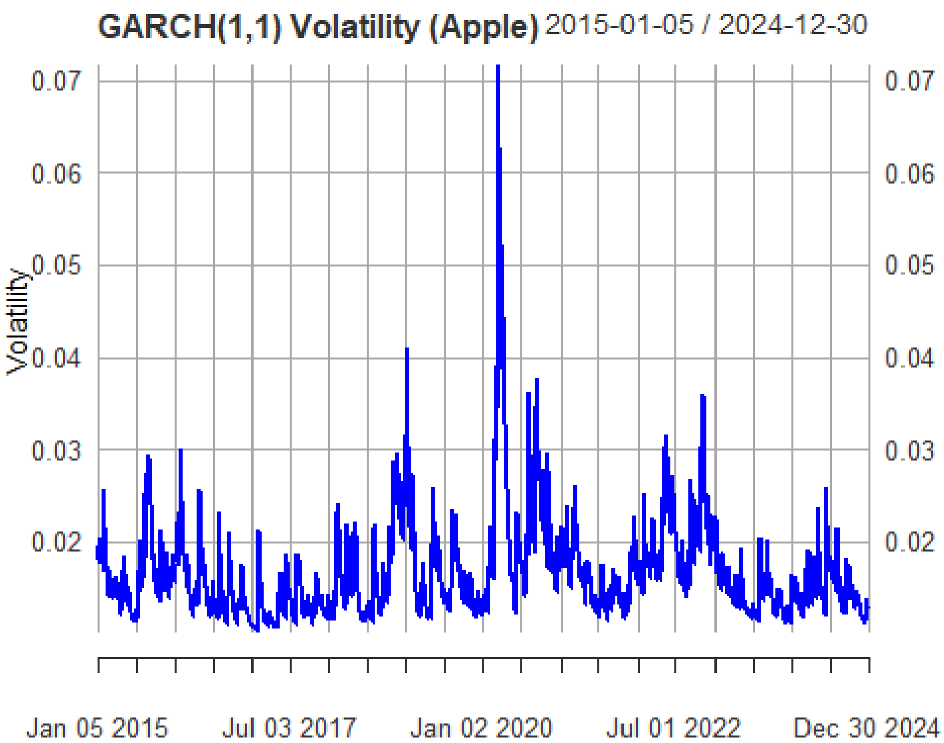

Figure 4: GARCH(1,1) Volatility for Apple

The volatility patterns show sharp increases in late 2017 and early 2020, indicating market stress. These peaks correspond to high market uncertainty, driven by global events and company-specific factors. In contrast, periods such as 2022-2024 show lower volatility, reflecting market stabilisation.

4.3 Comparison of GARCH, EGARCH, and TGARCH Models

To assess the best model for volatility forecasting, we compared the GARCH(1,1) model to the EGARCH and TGARCH models. The Akaike Information Criterion (AIC) was used for comparison, where lower AIC values indicate a better-fitting model.

Table 3: AIC Comparison of GARCH Family Models

Model	**AIC**
GARCH(1,1)	-5.398151

EGARCH	-5.422013
TGARCH	-5.424616

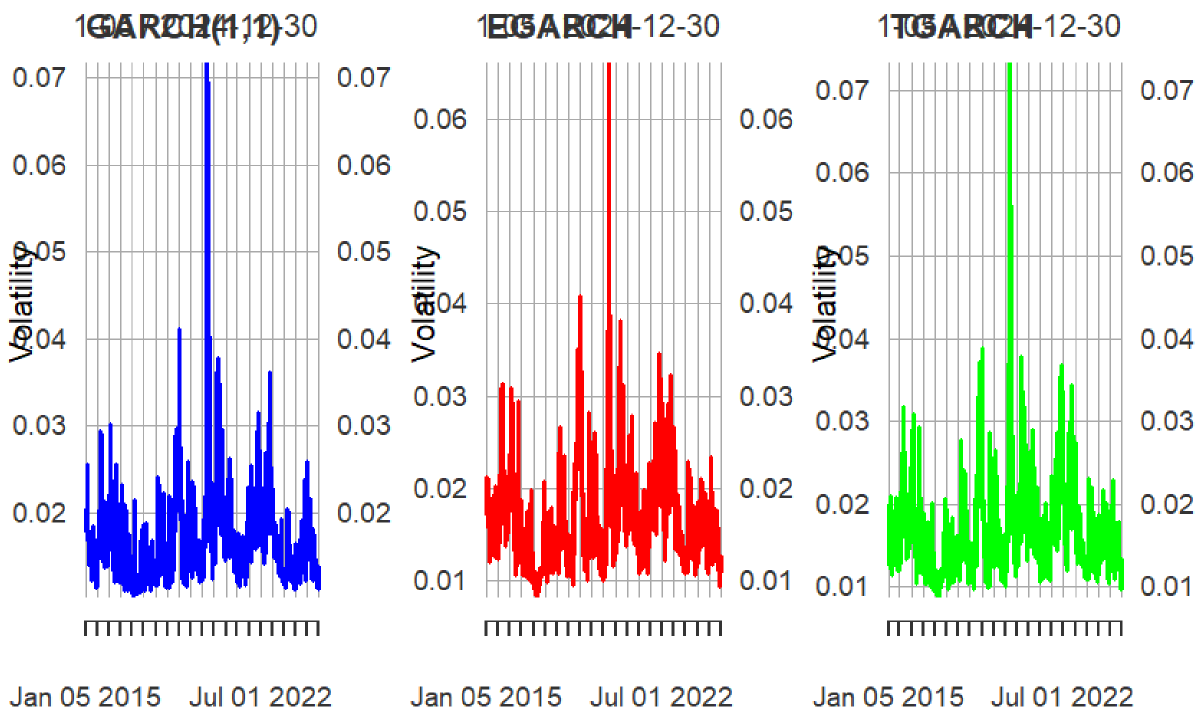

Figure 5: Comparison of GARCH, EGARCH, and TGARCH Volatility

This comparison shows how the models behave under varying conditions. GARCH(1,1) captures volatility clustering effectively, while the TGARCH model accounts for asymmetry—showing larger volatility spikes following negative returns than positive ones. This is especially important during significant market declines, as witnessed during 2020.

4.4 Rolling Window Volatility Analysis

Rolling Window Volatility:

$$\sigma_t = \sqrt{\frac{1}{n}\sum_{i=t-n+1}^{t}(R_i - \bar{R})^2}$$

where n Is the window size, R_i Are returns and $\bar{R}$ Is the mean return within the window. In addition to the GARCH family models, a 30-day rolling volatility analysis was performed for all three stocks (Figure 4). This method calculates the standard deviation of returns over a rolling window of 30 days, providing insight into short-term volatility patterns.

Table 4: 30-Day Rolling Volatility for AAPL, MSFT, and NVDA

Stock	**Average Volatility (2016-2024)**	**Max Volatility (2020 Peak)**	**Min Volatility (2022-2024)**
AAPL	0.01646057	0.06025225	0.007891753
MSFT	0.01559173	0.06296714	0.007633554
NVDA	0.02845406	0.07722438	0.016666102

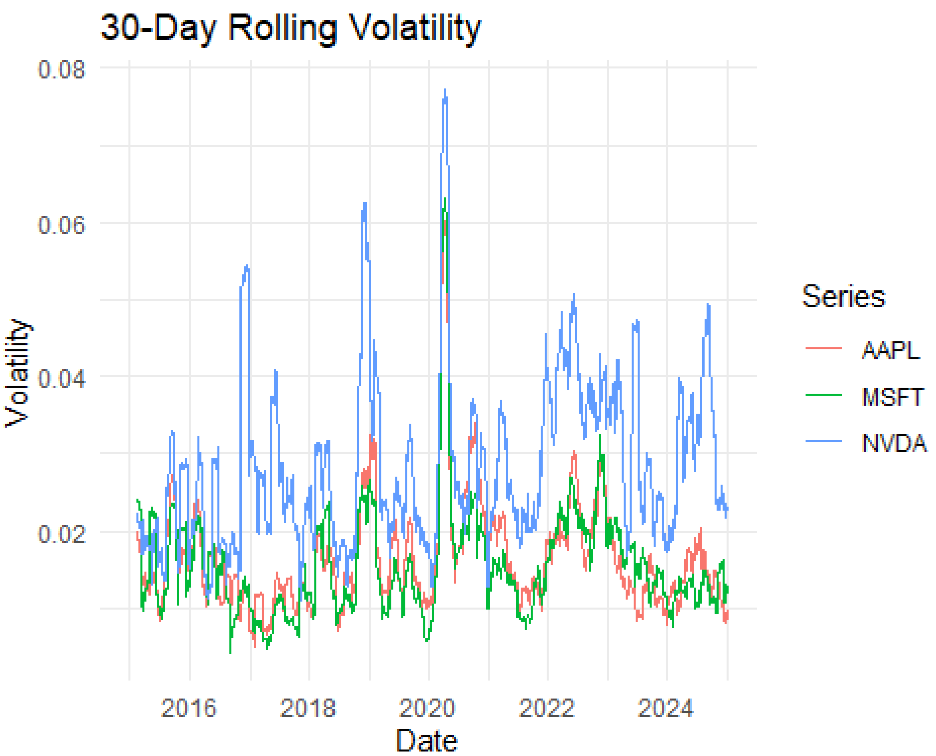

Figure 6: 30-Day Rolling Volatility for AAPL, MSFT, NVDA

This graph highlights the volatility dynamics across the three stocks. Nvidia (NVDA) exhibits the highest volatility, particularly during 2020, as the stock experienced a sharp upward trajectory. In comparison, Apple (AAPL) and Microsoft (MSFT) show similar volatility profiles, with MSFT slightly less volatile overall.

4.5 Value-at-Risk (VaR) Backtesting

Value-at-Risk (VaR):

$$\mathrm{VaR}_\alpha = -\mathrm{Quantile}_\alpha(R_t)$$

where VaR_α Is the VaR at a confidence level? α, and $\mathrm{Quantile}_\alpha(R_t)$ represents the α-quantile of returns. Value-at-risk (VaR) was calculated to assess the potential loss in value for these stocks at the 5% confidence level. VaR violations were analysed to understand how well the risk models captured extreme losses. For Apple, the historical VaR was calculated to be -0.0274, meaning the expected loss on any given day is 2.74%.

Table 5: VaR Violations for AAPL, MSFT, NVDA

Stock	**VaR (5% Confidence)**
AAPL	-0.0274
MSFT	-0.0269
NVDA	-0.0456

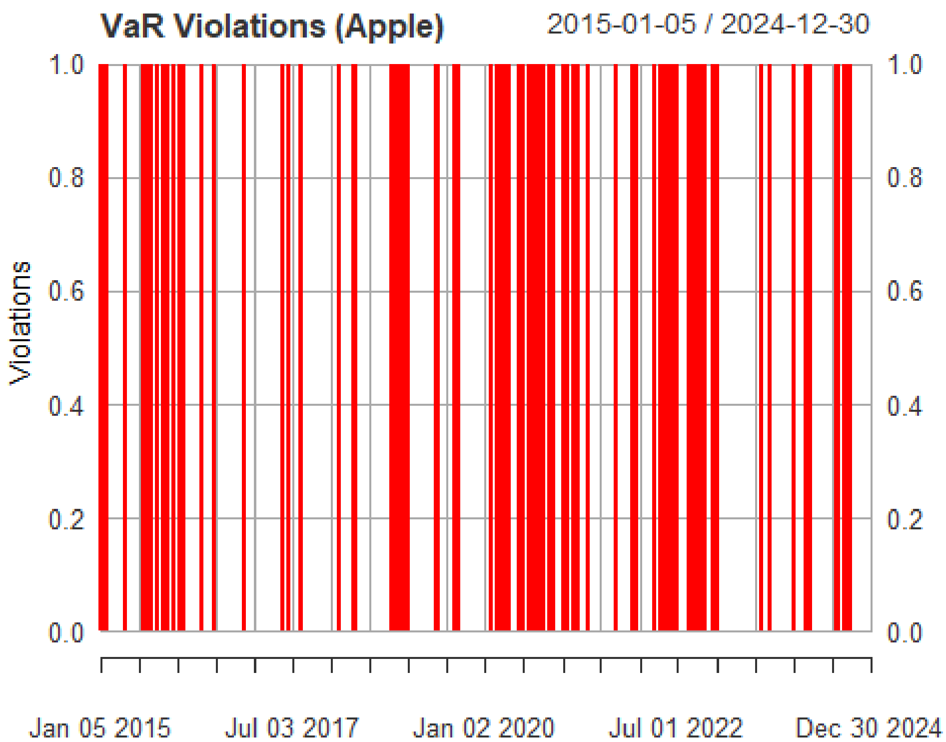

Figure 7: VaR Violations for Apple (AAPL)

The VaR violations chart shows the instances where the actual losses exceeded the predicted VaR. A higher number of violations corresponds to a model underestimating the potential risk. For NVDA, which showed the highest VaR violations, this suggests that the volatility models, especially in high-growth stocks, need to account for tail risks better.

The results align with expectations, as ARIMA models provide reasonable forecasts for returns, while GARCH family models effectively capture volatility clustering and asymmetry, especially during periods of market stress like COVID-19. When comparing models, the TGARCH model outperforms GARCH and EGARCH in terms of AIC, highlighting its ability to account for negative shock asymmetry. The results imply that while ARIMA is suitable for return forecasting, GARCH models, particularly TGARCH, offer more accurate volatility forecasts, which are crucial for risk management.

5. Analysis

5.1 Implications for Risk Management

The study's results help traders and risk managers make better decisions. When we want to predict daily price changes, ARIMA models give us reliable results. When looking at volatile times such as the COVID-19 crisis, GARCH, EGARCH, and TGARCH volatility models show they're more reliable than other models (Enkhtur, 2022). During market downturns, the TGARCH model shows how volatility climbs much higher after adverse events, reflecting how markets behave when things get tough. Risk managers rely on TGARCH to predict and prepare for big market fluctuations when managing risks in technology and similar sectors.

5.2 Applications for Investment Fund Risk Management

Investment funds managing technology shares must use predictive models to track stock market price shifts better. Because Nvidia's stock value jumps around unpredictably, investors who want to invest need to be prepared for big variations in how much their investment is worth. When using GARCH models, investment managers can more accurately see coming market risks and change their portfolios to minimise losses during market volatility. Investment managers can find good opportunities to protect their money and earn better profits by understanding stock fluctuations.

5.3 Relevance to Financial Regulations

The study results give regulators new insights into market behaviour and risk management practices. This study can help financial institutions improve risk management systems by showing where their current methods fail during market crises. Authorities should look at using TGARCH models to spot extreme events and make markets safer.

6. Conclusion

We evaluated ARIMA and GARCH models to see how well they forecast tech stocks' prices and market volatility, paying special attention to times when the market was stressed. Our study shows that GARCH models, particularly TGARCH, work better than ARIMA for predicting market volatility during times of crisis, while ARIMA serves well for return forecasting. We should use TGARCH in risk management plans to better anticipate market changes and protect investments in risky industries. The research shows why investment managers and regulators should use flexible models to handle market imbalances and significant market events. With these models, stakeholders can predict market changes and develop better ways to reduce potential losses. By focusing on technology stocks in financial markets, this research gives us a clearer picture of market forecasting methods.

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