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# Forecasting Financial Crashes with Advanced Time-Series Methods: A Predictive Framework

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## ABSTRACT

The research involves examining how financial markets, particularly the NASDAQ and S&P 500 indices, react when under stress, as well as applying advanced time series techniques in an attempt to predict crashes. Accurate prediction of crashes is important due to the tremendous impact financial market collapses, including the 2008 and COVID-19 epidemics, have on the worldwide economy. To model non-linear market dynamics, the study combines dynamic GARCH extensions and wavelet-based time series decomposition with ARIMA and GARCH models to forecast market volatility. The sample period ranged from January 2021 to August 2024, with total observations of 787 and 921 for the S&P500 and NASDAQ, respectively. The selection of the ARIMA and GARCH models was confirmed by the ADF and PP tests to determine whether the time series is stationary. The GARCH model with the GARCH effect of 0.912741 has most certainly accommodated the volatility clustering phenomenon, due to which an episode of high (low) volatility was followed by another episode of the same kind and successive spikes in the volatility, especially in the case of NASDAQ. The volatility persistence of the S&P 500 was lower (0.6785330 GARCH effect). For a relatively small level autoregressive table, the forecasts demonstrate that the variance of S&P 500 substantially increases in high volatility periods for most by up to 0.006. The NASDAQ was somewhat more persistent, as indicated by a variance of 0.00024. These findings illustrate how efficiently the proposed forecasting model is able to predict market crashes and offer valuable information for investors and policymakers.

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## 1. Introduction

Financial markets are highly volatile, often characterized by market crashes and high highs. And these episodes of asset value losses in very short periods have a huge impact on financial institutions, individual fortunes, and world economies. These crashes have been difficult to foresee by economists, politicians as well and investors across the world. Recent years have seen big progress in the application of machine learning and time series analysis, opening up new opportunities for building structural models that can predict such disasters. The purpose of this paper is to develop a methodology to utilize these recently developed techniques for predicting the collapses (increase in volatility) in financial markets with reference to...106-8EHA: NASDAQ and S&P 500 as important aggregated indices.

There were seemingly frequent significant global financial market meltdowns, each having its own causes and consequences. For instance, the Great Depression, an extended period of economic decline that impacted economies globally, ensued in the wake of the 1929 stock market crash on Wall Street (Bernanke, 2000). Stock share prices on the Dow Jones Industrial Average dropped 25% in just two days because of the crash. It was one of the worst days in modern economic history (Tooze, 2018). More recently, the S&P 500 index plunged 57% during the October 2007 to March 2009 collapse after the American housing bubble burst and led to a Global

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Financial Crisis in 2008. The crisis wiped out approximately $30 trillion from global equity markets and precipitated deep economic recessions in different countries (Brunnermeier, 2009; Reinhart & Rogoff, 2009).

One of the swiftest bear markets in history hit world financial markets yet again when to the COVID-19 outbreak in 2020. Courtesy to the pandemic's causes, i.e., forced lockdowns and economic shutdowns, the S&P 500 had shared value erosion of ≈34% in February-March 2020 (Baker et al., 2020). But thanks to the extraordinary measures deployed by governments and central banks to backstop fiscal and monetary policy around the globe during the crash, it's been a much quicker recovery than we've seen in previous crises. It reflects how the financial markets have become so much more complex that we cannot so easily predict how they would respond (Gopinath, 2020).

Despite the frequency and serious consequences of these crashes, predicting them is an ever-elusive white whale. ARIMA and GARCH models have been the dominant traditional econometric methods for analyzing financial time series data for a few decades. This is of particular use in the modeling of volatility and trends in finance. For example, GARCH models are often used to describe the volatility clusters. The higher volatility (up-going or down-going) series in this pattern exhibits more frequent occurrence of large emotion-free price change (Creal et al., 2013; Vulandari & Rokhmati, 2015). These models do, however, contain design problems, particularly about the intensity and timing of market crashes(Chan, 2011). They often use historical data, but it may not fully capture what new market conditions mean for prospective future markets (Chan, 2011).

With artificial intelligence and machine learning, financial market analysis has become better. These algorithms can be used on large datasets to discover complex, but non-linear relations that traditional models may otherwise overlook (Goodfellow et al., 2016). Using the temporal dependencies in financial data, long-term memory networks (LSTM)—a particular type of RNN can predict the value of stocks (Fischer & Krauss, 2018). Similarly, ensemble learning techniques for financial forecasting generated more resilient adaptations to uncertainty when models were combined (Ganaie et al., 2022; Zhou, 2012).

As such, the objective of this work is to approach a forecast system that exploits the latest artificial intelligence technology, joining the time series tradition. For those keeping score, the two main robots we have on radar to monitor US market activity would be the S&P 500 or the NASDAQ. The S&P, which is widely viewed as a barometer of the U.S. economy, tracks the performance of 500 of the nation's largest and most important companies by market capitalization. The Nasdaq is heavily weighted towards technology companies, which are now far larger and more valuable parts of our world compared to 2000; it is also much more volatile against stock market movements (IDC, 2021).

The data analyzed in this paper cover various stages of the economic cycles, from the Dot-com Bubble, through to the subprime mortgage crisis of 2008, and more recently, COVID-19. For them, it was gathered from January 2021 to August 2024. This is where the large amount of data comes in; we can learn how markets respond at different stages of the economy. It also includes other variables and macroeconomic indicators (e.g., interest rate, inflation rate, unemployment rate), given their ability to drive market movements, as they are included to have their effect on the market reflected in the data (Schubert, 2018). These factors must be accounted for in financial asset markets because of their sensitivity to macroeconomic conditions.

An important hurdle in such research is to come up with a realistic forecast for rare events, say market crashes. While rare, they indicate extreme destruction. These are pretty rare events, and it's difficult for us to predict that using more traditional types of models, which would have very small fluctuations up or down. This is counteracted by oversampling and data generation, and the dataset is more accurately able to predict CRASH occurrences since it favours the instances of traffic crash events (Napierala & Stefanowski, 2016).

Therefore, our study can be informative for the whole field of market research. It also bestows the capability of building a more reliable framework to predict an upcoming market crash. This could have significant implications for the different actors. This information could potentially help investors hedge against losses and regulators craft better public policy measures to limit the impact of crashes on the entire economy. The preconditions of market instability would, consequently, be one indication of how to foresee – and even thwart or at least mitigate what is described as proactive financial risk management (McNeil et al., 2015).

## 2. Literature Review and Conceptual Foundations

Because of the catastrophic economic, investor, and corporate consequences of such events, comprehensive historical research is the foundation of their investigation. Among the most notorious is the 1929 Wall Street Crash, the 1987 Black Monday, 2000's dot com bubble and the ongoing recession triggered by COVID-19. The criticalness of these crises heavily disrupted the financial systems and also had significant academic debate and empirical studies on what led to these. Unfortunately, those approaches fail to alleviate the need for a way to predict such crashes accurately. Traditional models riot under(5), since they do not account for the non-linear behaviour of market participants prior to such events (Brunnermeier & Oehmke, 2013; Reinhart & Rogoff, 2009). Several literature review curves include historical worth on market crashes, using time series analysis for financial turbulence, and the inadequacy of existing predictive markets. Chevallier et al. (2019) also advocate for forecasting economies while adopting advanced machine learning and artificial intelligence methods.

In history, market crashes have associated with macroeconomic variables, investor psychology and outside shocks. For example, the 1929 Wall Street Crash was blamed on speculation and credit expansion, lack of regulation. This crash triggered the Great Depression, destroying immense wealth and leading to a decade-long economic funk. Similarly, 1987's Black Monday resulted in a daily DJIA fall of 22.6%, much of which was the result of automated trading and panic selling. The 2000 dot-com bubble burst and as the overvalued price of technology companies declined, the NASDAQ lost more than half its value from March 2000 to October 2002. Even more recently, the 2008 GFC was caused by collapse of the US housing bubble that saw a 57% drop in the S&P 500 and $30 trillion lost in global equity value. These experiences have played a key role in revealing market cycles, investor reactions and systemic risks.

Empirical research in financial markets can find is well established using time series analysis to study the market phenomenon and predictions. ARIMA models Box (2013), are well established in forecasting future value based on historical information with capturing volatility patterns more specifically relevant. Both for characterizing short-term stability and as a tool for predicting unpredictable market shocks such as booms or busts, such models are weak and inappropriate (Chan, 2011). GARCH models, introduced by Bollerslev et al. (2018), are more effective in modeling volatility clustering periods where high volatility tends to be followed by further high volatility. However, these models face limitations in predicting extreme market conditions, as shown during the 2008 crisis, where GARCH models failed to anticipate the intensity and timing of the crash (Aït-Sahalia et al., 2015; Belasri & Ellaia, 2017).

Different theories help to understand financial markets and their crashes. Chaos theory, which gained popularity in the 1970s, holds that financial markets are dynamic systems perched on a tipping point, one that's highly sensitive to initial conditions, which means even tiny changes can result in big reactions. This suggests the lack of linearity among the market moves. Behavioral finance draws attention to the irrationality of market players who are driven by fear, greed, and follow others in a herd. The 1987 Black Monday crash, for instance, largely chalked up as a result of panic selling, had no identifiable macroeconomic trigger. Although econometrics enhances statistical evidence results analysis, it is unlikely to overestimate crash likelihoods and particularly during unprecedented natural disaster outbreaks such as the COVID-19 (Hwang et al., 2017).

While widely used, ARIMA and GARCH methods are deficient in modelling the unpredictable nature of flash crashes. However, they are ill-suited for modelling the inherently non-linear dynamics of financial markets, as they make linear assumptions (Zhou, 2012). In the case of these models, generally, the historical data on which they depend are explicitly limited and hence incapable of including new market scenarios, particularly during the significant market disruption period. For instance, as in the 2008 crisis, volatility's explosive potential was undershot by GARCH models, and important forecasting errors followed.

However, traditional models have limitations, and adaptive, resilient approaches, particularly those based on machine learning and artificial intelligence have become irresistible. However, these advanced methods can already analyze massive datasets and determine non-linear relationships well beyond human cognitive capabilities (Goodfellow et al., 2016). LSTM networks (RNNs) have shown competence in identifying temporal dependencies in the financial data sequence and, thus, in stock price prediction (Ganaie et al., 2022). Robust performance in the face of uncertainty is also shown with Ensemble learning algorithms combining multiple models' predictions. In addition, according to Zhang, Xia, and Seeger (2021), machine learning models, such as LSTMs and random forests, are superior to capturing real-time market dynamics and non-linear trends in crash predictions.

Machine learning models have been criticized for their opacity (non-transparency) and interpretability, despite their promising capabilities. Machine learning models are typically described as 'black boxes', in contrast to statistical theory driven models, without simple explanation about what may be driving the 'movement' of the market. The opacity of such concepts sometimes creates an impediment to apply them in practice, and in the light of risks creating a difficulty for investors and governments to act. These models are also sensitive to the information they receive. They can also have extremely high variation in prediction given the input, a feature that is undesirable when predicting under different market conditions.

## 3. Data and Methodology

### 3.1. Data Collection

For both the Stock Twits and Twitter streams, the data was collected daily from Yahoo Finance for two widely followed financial indices: The S&P 500 Index and the NASDAQ Composite Index (which has higher market volatility). In the NASDAQ dataset, we observe data from 1 January 2021 to 31 August 2024; there are a total of 921 records and in the S&P 500 dataset, there are a total of 787 records. This may at least in part explain why the actual observations of the two indices differ, and why S&P 500 index does not have a value for every day holidays or data anomalies which are frequent characteristics of time series data (Finance, 2024a, 2024b).

The selected time frame was important because it helped to capture one of the few periods where signs of a post-pandemic global economic recovery were seen, or at a time exhibiting increased risk and volatility. International banking and financial markets were volatile due to unknown circumstances such as the rise of interest rates, inflation issues, and other political formations. This is a market that has been starved for good news and it had an optimistic view of the potential for re-openings and yet it couldn't rally as markets resumed falling faster later in the day.

Daily historical time series for volume, open, high, low and close prices will facilitate pattern recognition in market crashes and the observation of large price changes in response to various factors; this is best suited for predicting models with some sophisticated risk strategies familiar with those used on major world markets.

**Table 1.** Historical Data for S&P 500

| HISTORICAL DATA | | | | | | |
|---|---|---|---|---|---|---|
| S&P 500 (^GSPC) | | | | | | |
| JANUARY 2021 TO AUGUST 2024 | | | | | | |
| **Date** | **Open** | **High** | **Low** | **Close** | **Adj Close** | **Volume** |
| 29-Jun-21 | 4293.81 | 4300.52 | 4287.04 | 4291.8 | 4291.8 | 3707150000 |
| 28-Jun-21 | 4284.9 | 4292.14 | 4274.67 | 4290.61 | 4290.61 | 4147890000 |
| 25-Jun-21 | 4274.45 | 4286.12 | 4271.16 | 4280.7 | 4280.7 | 7341450000 |
| 24-Jun-21 | 4256.97 | 4271.28 | 4256.97 | 4266.49 | 4266.49 | 3816660000 |
| 23-Jun-21 | 4224.61 | 4255.84 | 4217.27 | 4246.44 | 4246.44 | 3828390000 |
| 22-Jun-21 | 4242.61 | 4255.84 | 4217.27 | 4246.44 | 4246.44 | 3828390000 |
| 21-Jun-21 | 4173.4 | 4226.24 | 4173.4 | 4224.79 | 4224.79 | 4128950000 |
| 18-Jun-21 | 4204.78 | 4204.78 | 4164.4 | 4166.45 | 4166.45 | 6817010000 |
| 17-Jun-21 | 4203.37 | 4232.29 | 4184.05 | 4218.86 | 4218.86 | 5312880000 |
| 16-Jun-21 | 4248.87 | 4251.89 | 4202.45 | 4223.7 | 4223.7 | 4538350000 |
| 15-Jun-21 | 4255.28 | 4257.16 | 4238.35 | 4246.59 | 4246.59 | 4048940000 |
| 14-Jun-21 | 4248.31 | 4255.59 | 4234.07 | 4255.15 | 4255.15 | 4151200000 |
| 11-Jun-21 | 4242.9 | 4248.38 | 4217.04 | 4247.44 | 4247.44 | 3816010000 |
| 10-Jun-21 | 4228.56 | 4249.74 | 4220.34 | 4239.18 | 4239.18 | 4408210000 |
| 9-Jun-21 | 4232.99 | 4237.09 | 4218.74 | 4219.55 | 4219.55 | 4713260000 |
| 8-Jun-21 | 4233.81 | 4236.74 | 4208.41 | 4227.26 | 4227.26 | 4659620000 |
| 7-Jun-21 | 4273.81 | 4266.52 | 4215.66 | 4226.52 | 4226.52 | 4476920000 |
| 4-Jun-21 | 4191.43 | 4204.39 | 4167.93 | 4192.85 | 4192.85 | 4139790000 |
| 787 ROWS * 7 COLUMNS | | | | | | |

*Source: Yahoo.com, 2024*

**Table 2.** Historical Data for Nasdaq composite

NASDAQ Composite (^IXIC)
JANUARY 2021 TO AUGUST 2024

| Date | Open | High | Low | Close ⓘ | Adj Close ⓘ | Volume |
|---|---|---|---|---|---|---|
| Sep 4, 2024 | 17,015.71 | 17,232.65 | 16,984.67 | 17,084.30 | 17,084.30 | 5,011,820,000 |
| Sep 3, 2024 | 17,585.45 | 17,585.45 | 17,057.79 | 17,136.30 | 17,136.30 | 5,813,970,000 |
| Aug 30, 2024 | 17,650.49 | 17,720.38 | 17,498.79 | 17,713.62 | 17,713.62 | 5,531,150,000 |
| Aug 29, 2024 | 17,610.57 | 17,789.21 | 17,482.60 | 17,516.43 | 17,516.43 | 5,727,780,000 |
| Aug 28, 2024 | 17,738.80 | 17,759.94 | 17,439.40 | 17,556.03 | 17,556.03 | 5,211,920,000 |
| Aug 27, 2024 | 17,655.52 | 17,789.72 | 17,573.37 | 17,754.82 | 17,754.82 | 4,362,380,000 |
| Aug 26, 2024 | 17,867.85 | 17,909.09 | 17,645.69 | 17,725.77 | 17,725.77 | 5,110,940,000 |
| Aug 23, 2024 | 17,772.73 | 17,941.27 | 17,700.27 | 17,877.79 | 17,877.79 | 5,380,810,000 |
| Aug 22, 2024 | 17,993.72 | 18,017.69 | 17,589.15 | 17,619.35 | 17,619.35 | 5,065,360,000 |
| Aug 21, 2024 | 17,840.51 | 17,963.07 | 17,790.98 | 17,918.99 | 17,918.99 | 4,765,150,000 |
| Aug 20, 2024 | 17,849.09 | 17,932.53 | 17,758.20 | 17,816.94 | 17,816.94 | 5,305,260,000 |
| Aug 19, 2024 | 17,649.74 | 17,877.44 | 17,585.58 | 17,876.77 | 17,876.77 | 5,564,300,000 |
| Aug 16, 2024 | 17,516.40 | 17,674.65 | 17,502.83 | 17,631.72 | 17,631.72 | 5,138,150,000 |
| Aug 15, 2024 | 17,394.54 | 17,602.72 | 17,375.41 | 17,594.50 | 17,594.50 | 5,478,170,000 |
| Aug 14, 2024 | 17,227.64 | 17,260.73 | 17,032.17 | 17,192.60 | 17,192.60 | 4,985,480,000 |
| Aug 13, 2024 | 16,944.74 | 17,192.79 | 16,943.95 | 17,187.61 | 17,187.61 | 5,469,160,000 |
| Aug 12, 2024 | 16,793.64 | 16,895.79 | 16,699.39 | 16,780.61 | 16,780.61 | 4,890,850,000 |
| Aug 9, 2024 | 16,636.52 | 16,789.22 | 16,574.57 | 16,745.30 | 16,745.30 | 5,783,410,000 |
| Aug 8, 2024 | 16,408.27 | 16,694.25 | 16,262.93 | 16,660.02 | 16,660.02 | 5,815,880,000 |

921 Rows * 7 Columns

*Source: Yahoo.com, 2024*

### 3.2. Data Preprocessing

In financial time series analysis, data preparation is essential, particularly when working with daily data from indices such as the S&P 500 and NASDAQ. Due to non-trading days, the dataset utilized for this study includes (i) 921 observations for the NASDAQ and (ii) 787 observations for the S&P 500. The dataset spans the period from January 2021 to August 2024. Interpolating data was necessary to resolve these disparities while maintaining the quality and integrity of the results. Since historical finance studies have shown that financial market trends are often fat-tailed and erratic, the preprocessing portion of the model additionally included data transformation and normalization (Finance, 2024a, 2024b).

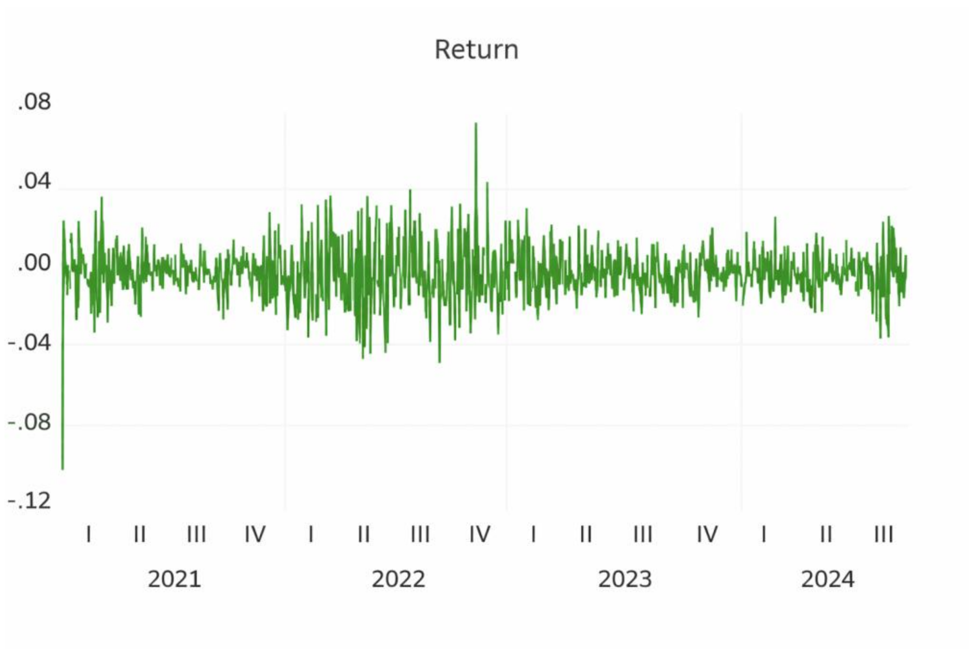


**Fig. 1.** Volatility Clustering for NASDAQ (2021-2024)

The NASDAQ (2021–2024) Volatility Clustering graph displays notable intervals of clustered volatility. Due to post-pandemic market disturbances, the highest return peaks at about 0.08 and the sharpest decrease hits -0.12 in early 2021. The NASDAQ index showed multiple volatility increases from mid-2021 to mid-2024, particularly in 2022, which was a sign of market turbulence (Finance, 2024a, 2024b).

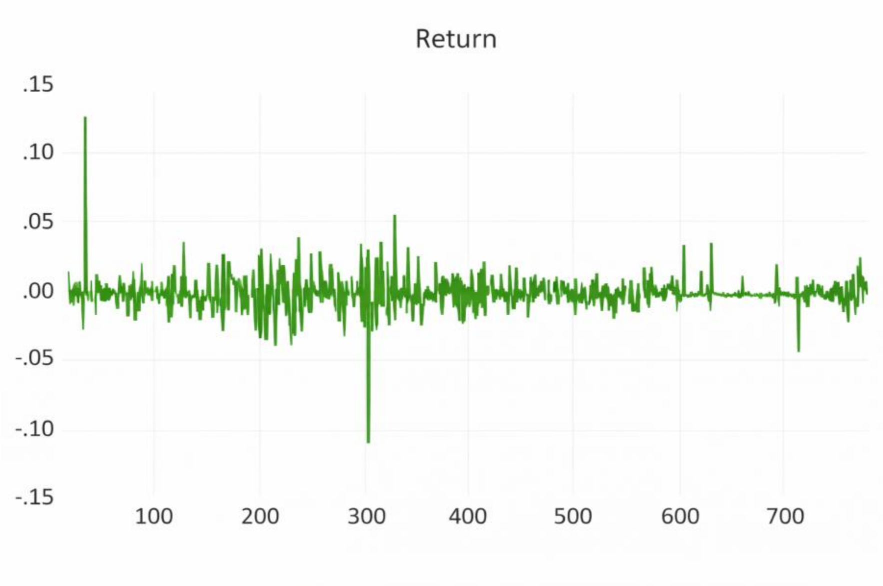


**Fig. 2.** Volatility Clustering for S&P 500 (2021-2024)

The S&P 500's response to economic instability during this time is further highlighted by the "Volatility Clustering for S&P 500 (2021-2024)" graph, which shows clustering of volatility with variations peaking around 0.12 and a minimum of -0.15. The use of GARCH models to represent the volatility structure is justified by the notable clustering of these swings, particularly around important geopolitical and economic events.

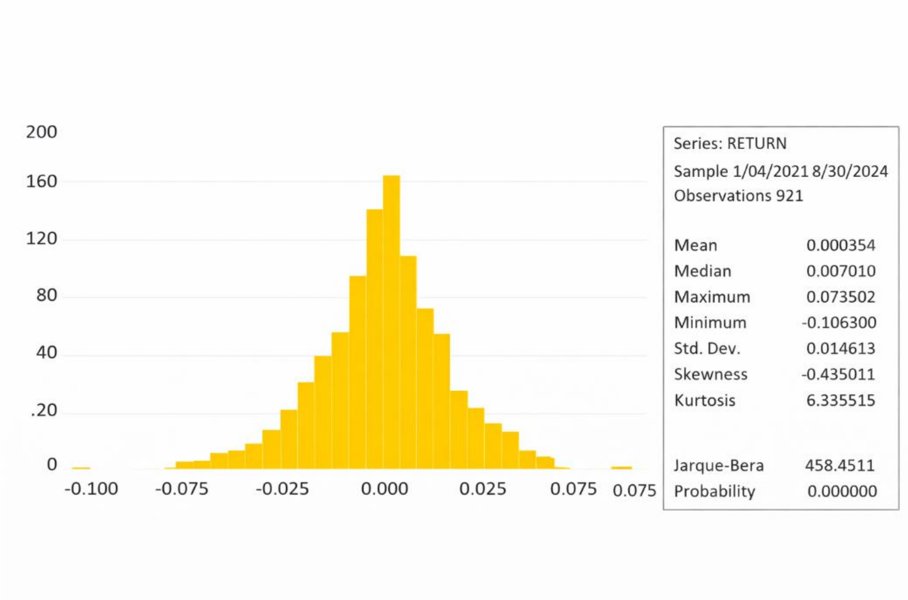


**Fig. 3.** Fat Tail Distributions for NASDAQ and S&P 500.

Additionally, the "Fat Tail Distributions for NASDAQ" show severe findings that go above the normal distribution, with a high kurtosis value of 6.335. The Jarque-Bera statistic of 458.4511 ($p$-value $< 0.05$) confirms non-normality, and the occurrence of outliers—returns as low as -0.10 and as high as 0.07—suggests fat-tail behaviour, even if the returns are primarily centred around 0 (Hansen et al., 2011).

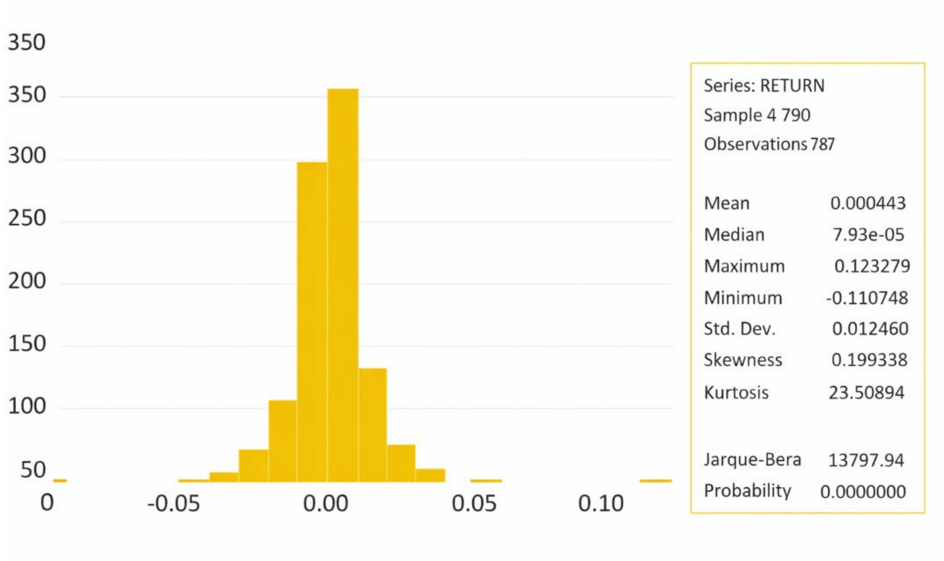


**Fig. 4.** Fat Tail Distributions for NASDAQ and S&P 500.

However, the S&P 500's fat tail distributions show an even more noticeable fat tail, with extreme returns ranging from -0.11 to 0.12, a skewness of 0.199, and a kurtosis of 23.51. Strong departure from the normal distribution is shown by the Jarque-Bera test result of 13797.94 with a significant p-value, highlighting the necessity of models that can manage sharp fluctuations in returns (Finance, 2024a, 2024b). The significance of applying sophisticated preprocessing methods, including volatility segmentation and multiscale stationarity testing, to handle the non-linear and unpredictable character of financial markets is shown by these statistical findings and graphical representations. For precise market forecasting and crash prediction during turbulent times, GARCH models—which are designed to manage volatility clustering and fat-tail

### 3.3. Model Selection

Because it incorporates the nonlinearities and shocks typical of financial markets, selecting an accurate model is crucial. Because ARIMA and GARCH models are frequently employed to capture the complexity of financial time series, particularly when it comes to volatility and returns, they were chosen for this study. We choose to employ models like AIC (Akaike Information Criterion) and BIC (Bayesian information criterion) after conducting stationarity tests and confirming diagnostic criteria. In addition, the AR and MA terms details and lags were discovered minutely based on these tests (Hansen et al., 2011; Molnár, 2016)

**Table 3.** Stationary Check
Unit root test:
behavior—are crucial (Molnár, 2016)

| Test | Return (Nasdaq) | Return (S&P500) |
|---|---|---|
| ADF (with constant and trend) | | |
| I (0) | -31.6456 | **-21.62249** |
| PP (with constant and trend) | | |
| I (0) | -31.8356 | **-28.6932** |

A time series' stationarity is determined by the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests, as shown in Table 3. Stationarity is a critical requirement, particularly for ARIMA and GARCH models, since non-stationary data can produce inaccurate forecasts. At a significance level of 1%, the price data for the NASDAQ and S&P 500 both have very negative ADF and PP test statistics, suggesting that these time series have stationary levels (I(0)). Both numbers are below the crucial value, indicating that ARIMA and GARCH can model both indexes. The NASDAQ value was -31.6456, and the S&P 500 value was -21.62249 (Durbin & Koopman, 2012).

**Table 4.** Selection of AR & MA and Lags

| Index | AR (Auto Regressive) | MA (Moving Average) | Lag |
|---|---|---|---|
| **NASDAQ** | AR-2 | MA-4 | 1 |
| **S&P 500** | AR-4 | MA-2 | 1 |

The parameters selected for the NASDAQ and S&P 500 are displayed in the Selection of AR & MA and Lags table 4 for the ARIMA models. Whereas the S&P 500 once more favoured to select (AR-4) but switched order this time (MA -2), likewise at lag 1, the NASDAQ chose AR-2 and MA 4 with a lag of (1). Using the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), these values were selected to reduce prediction error. For instance, a moving average (MA) term of four is fitted in order to accommodate lagged forecast errors, and two autoregressive (AR) terms in the NASDAQ allow model delays from prior time periods. On the other hand, Box (2013) state that the AR-4 and

MA-2 combination in U.S. (S&P 500) data lowers short-term forecast mistakes while improving the ability to capture longer-term dependencies.

### 3.4. Rationale for the Hybrid Analytical Approach

The ARIMA and GARCH models were chosen because they can handle nonlinear elements, whereas the first model only covers the linear aspects of the markets. When the returns contain intricate and nonlinear auto-correlation structures, ARIMA models are useful. For long-term return predictions, it is therefore perfect Box (2013). It is important to remember, nevertheless, that in order to fully represent the intricate patterns of volatility clustering that frequently define financial markets, more than only the use of ARIMA models as previously mentioned is required. Since GARCH models are designed to capture time-varying volatility, this is where they are useful. Because volatility is clustered according to long memory, with stronger volatility experienced in some times than others (a phenomenon known as club volatility), GARCH models allow the conditional variance to be time-varying. Because it accounts for error or volatility heteroscedasticity, the GARCH model was employed. Since there was evidence of this behaviour in both the NASDAQ and S&P 500 data, tests for volatility clustering also supported the selection of GARCH. For instance, when the market was only beginning to recover from the pandemic's effects, the NASDAQ first displayed strong returns before seeing a surge in volatility. The best hybrid model for predicting market movements is this dynamic behaviour, which uses GARCH and Auto Regressive Integrated Moving Average (ARIMA) trend prediction to describe volatility (Wei, 2013).

### 3.5. Optimization of Model Parameters

The parameters for the GARCH and ARIMA models were estimated using maximum likelihood estimation. To ensure that the root square error between the predicted and actual volatility models does not differ significantly, we compared the AIC and BIC values for various configurations of the AR terms (p) and MA terms (q) in the ARIMA case. In the GARCH case, we only minimised overfitted parameters. In order for models to adapt to the quickly shifting market conditions that occurred between January 2021 and August 24 throughout manufacturing, every stage of the process had to be optimised. GARCH dynamically adjusted for volatility at each time utilising data from recent periods, whereas ARIMA's lag terms recorded the 8-week delayed influence of past market moves (Ardia et al., 2019).

## 4. Predictive Modeling

This study used a GARCH technique to model the NASDAQ and S&P 500 indexes' clustered behaviour and volatility. Because volatility in financial time series data tends to cluster, meaning that high volatility is typically followed by more high volatility and low volatility is typically followed by more of the same, the GARCH type of model is especially well-suited for these types of data (Aue et al., 2017; Modarres & Ouarda, 2012). The GARCH model is perfect for simulating market collapses and notable moves because of its ability to capture volatility with flexibility.

**Table 5.** GARCH Model Parameters for NASDAQ Return and Volatility

| **Mean Equation** | **Return on** |
|---|---|
| Constant | 0.000646(1.032953) |
| One period lag of return | -0.052584(-0.160397) |
| War | 0.000496(0.664768) |
| Conditional Volatility Statistics | |
| Constant | 2.36E-06(2.098452) ** |
| ARCH Effect | 0.076616(3.940481) *** |
| GARCH Effect | 0.912741(42.70745) *** |

With a coefficient of -0.052584 and a z-value of -0.160397, the one-period lag of return is not statistically significant, according to the NASDAQ GARCH Model Parameters, suggesting a poor correlation between the return of the previous period and the present return. Nonetheless, both the GARCH effect (0.912741; $z = 42.70745$; $p < 0.01$) and the ARCH effect (0.076616; $z = 3.940481$; $p < 0.01$) are statistically significant at the 1% level, showing that historical volatility and shocks are powerful predictors of the NASDAQ index's present volatility. As is common in financial markets, sustained volatility clustering is indicated by the ARCH and GARCH coefficient total approaching 1.

**Table 6.** GARCH Model Parameters for S&P500 Return and Volatility

| **Mean Equation** | **Return on** |
|---|---|
| Constant | 0.0007035(1.381052) |
| One period lag of return | 0.3453658(8.175274) *** |
| War | 0.0001404(0.220089) |
| Conditional Volatility Statistics | |
| Constant | 6.926e-06(6.399222) *** |
| ARCH Effect | 0.2799053(11.2689) *** |
| GARCH Effect | 0.6785330(28.8765) *** |

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

The one-period lag of return is also very significant (0.3453658; $z = 8.175274$; $p < 0.01$) according to the GARCH Model Parameters for the S&P 500, indicating a higher level of autocorrelation in the S&P 500 than in the NASDAQ. Both the GARCH effect (0.6785330; $z = 28.8765$; $p < 0.01$) and the ARCH effect (0.2799053; $z = 11.2689$; $p < 0.01$) are statistically significant, indicating that the S&P 500 exhibits volatility clustering. But compared to NASDAQ, the S&P 500's GARCH coefficient is smaller, indicating that shocks to the stock have a shorter-lasting effect on volatility.

The GARCH and ARCH effects were highly significant for both indices, indicating that these models are suitable for estimating market behavior during bouts of volatility.

Furthermore, the higher value of the ARCH coefficient in the S&P 500 model implies that the index is more responsive to recent shocks. In comparison, the higher value of the GARCH coefficient in the NASDAQ model implies that volatility persists over time.

Dynamic GARCH extensions enable model integration with other market sentiment factors, such as the Volatility Index (VIX). By incorporating these indicators, the GARCH model has a better ability to shift in response to fluctuations in market sentiment and thus offers a timelier response to the market conditions. This adjustment is vital, especially during periods of decreased financial stability, as sentiments shift rapidly, more so with fluctuations in the market.

Wavelets were used to decompose the return series from the time series into different frequencies to increase the accuracy of the predictions. This feature of multi-resolution analysis makes it easy to capture even minor fluctuations in the market signals and thus distinguish between short-term and long-term market signals. The integration of wavelet transforms with GARCH helps study the market signals at multiple resolutions, enhancing the model's capability to forecast extreme movements in the market.

## 5. Results and Interpretation

### 5.1. Descriptive Statistics:

Prior to using sophisticated prediction algorithms, the descriptive statistics for the January 2021–August 2024 returns of the NASDAQ and S&P 500 offer a fundamental knowledge of the dataset.

**Table 7.** Descriptive Statistics for NASDAQ and S&P 500 Returns (2021-2024)

| Particular | Return (Nasdaq) | RETURN(S&P500) |
|---|---|---|
| Mean | 0.000354 | 0.000443 |
| Median | 0.000710 | 7.93E-05 |
| Maximum | 0.073502 | 0.123279 |
| Minimum | -0.100530 | -0.110748 |
| Std. Dev. | 0.014613 | 0.012460 |
| Skewness | -0.453031 | 0.199338 |
| Kurtosis | 6.335515 | 23.50894 |
| Jarque-Bera | 458.4511 | 13797.94 |
| Probability | 0.000000 | 0.000000 |
| Sum | 0.325618 | 0.348752 |
| Sum Sq. Dev. | 0.196450 | 0.122026 |
| Observations | 921 | 787 |

The S&P 500 has a little greater mean return (0.000443) than the NASDAQ, which has a mean return of 0.000354. Although the figures are around zero, which reflects the market's volatility during the post-pandemic recovery phase, this shows that both indexes saw positive gains on average over the time. The S&P 500 had a far larger maximum return (0.123279), suggesting more dramatic positive moves, than the NASDAQ, which had a maximum return of 0.073502. However, the minimum return indicates that the NASDAQ had more significant negative fluctuations, with a value of -0.100530 as opposed to the S&P 500's -0.110748.

The NASDAQ index, which is heavily weighted towards technology, has a larger standard deviation of volatility (0.014613) than the S&P 500 (0.012460). This is in line with the NASDAQ index's typically higher risk (Aielli, 2013). The S&P 500 has positive skewness (0.199338), indicating that NASDAQ had more frequent negative returns, but the skewness numbers further demonstrate that NASDAQ returns are negatively skewed (-0.453031). The S&P 500 shows an exceptionally high value (23.50894), suggesting fat tails and frequent extreme occurrences. Lastly, both indices show considerable kurtosis. With p-values of 0.000000, the Jarque-Bera test statistics demonstrate that both series exhibit a considerable departure from normalcy, underscoring the need for volatility modelling (Bucci, 2020).

### 5.2. Model Performance:

The validity and effectiveness of the volatility models employed in this work are assessed by the diagnostic tests performed on the NASDAQ and the S&P 500 using the ARCH and GARCH models. These tests are essential for identifying any autocorrelation in the model residuals, which might be linked to persistence in volatility or unmodeled patterns. Along with numerical computations and thorough explanations, the parts that follow offer a thorough process and a critical evaluation of the diagnostic test findings, including the ARCH LM test and the correlogram for both indices.

**Table 8.** Diagnostic Test Results for NASDAQ: ARCH+GARCH Effect and LM Test

| Particular | Nasdaq |
|---|---|
| ARCH+GARCH Effect | 0.989357 |
| ARCH LM (Obs* R-squared) | 3.826744 |
| Correlogram | (Graph) |

The ARCH + GARCH Effect for NASDAQ is 0.989357, indicating a strong presence of volatility clustering. This means that past volatility significantly affects current volatility, making the model well-suited for capturing the persistence of volatility shocks in NASDAQ, particularly in response to market events and economic fluctuations (Modarres & Ouarda, 2012). The ARCH LM test returns an Obs*R-squared value of 3.826744, which suggests that there is minimal heteroscedasticity left in the residuals. This validates the GARCH model's effectiveness in filtering out the majority of the volatility patterns in the NASDAQ dataset.

Sample: 1/08/2021 8/30/2024
Q-statistic probabilities adjusted for 6 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | 0.002 | 0.002 | 0.0050 | |
| | | 2 | -0.002 | -0.002 | 0.0105 | |
| | | 3 | 0.011 | 0.011 | 0.1147 | |
| | | 4 | -0.004 | -0.004 | 0.1314 | |
| | | 5 | -0.009 | -0.009 | 0.2033 | |
| | | 6 | 0.008 | 0.008 | 0.2697 | |
| | | 7 | 0.006 | 0.006 | 0.3071 | 0.579 |
| | | 8 | -0.015 | -0.015 | 0.5276 | 0.768 |
| | | 9 | 0.052 | 0.052 | 3.0219 | 0.388 |
| | | 10 | -0.020 | -0.020 | 3.3845 | 0.496 |
| | | 11 | 0.022 | 0.023 | 3.8394 | 0.573 |
| | | 12 | -0.028 | -0.030 | 4.5933 | 0.597 |
| | | 13 | -0.014 | -0.013 | 4.7684 | 0.688 |
| | | 14 | -0.015 | -0.014 | 4.9701 | 0.761 |
| | | 15 | -0.038 | -0.038 | 6.2888 | 0.711 |
| | | 16 | -0.037 | -0.037 | 7.5572 | 0.672 |
| | | 17 | -0.038 | -0.037 | 8.9061 | 0.631 |
| | | 18 | 0.040 | 0.037 | 10.390 | 0.582 |
| | | 19 | -0.023 | -0.021 | 10.905 | 0.619 |
| | | 20 | 0.011 | 0.008 | 11.021 | 0.684 |
| | | 21 | 0.014 | 0.016 | 11.195 | 0.739 |
| | | 22 | -0.052 | -0.052 | 13.739 | 0.618 |
| | | 23 | -0.035 | -0.032 | 14.903 | 0.602 |
| | | 24 | 0.018 | 0.019 | 15.194 | 0.649 |
| | | 25 | -0.052 | -0.051 | 17.755 | 0.539 |
| | | 26 | -0.024 | -0.019 | 18.290 | 0.568 |
| | | 27 | 0.025 | 0.016 | 18.879 | 0.593 |
| | | 28 | -0.022 | -0.019 | 19.342 | 0.624 |
| | | 29 | 0.028 | 0.023 | 20.074 | 0.637 |
| | | 30 | -0.026 | -0.031 | 20.704 | 0.656 |
| | | 31 | 0.056 | 0.059 | 23.733 | 0.535 |
| | | 32 | -0.010 | -0.012 | 23.824 | 0.586 |
| | | 33 | -0.014 | -0.015 | 23.999 | 0.630 |
| | | 34 | -0.008 | -0.005 | 24.065 | 0.678 |
| | | 35 | 0.000 | -0.001 | 24.066 | 0.726 |
| | | 36 | -0.015 | -0.018 | 24.272 | 0.760 |

*Probabilities may not be valid for this equation specification.

**Fig. 5.** Autocorrelation and Partial Correlation with Q-Statistics for ARMA Terms- NASDAQ.The correlogram for NASDAQ (as shown in the graph) provides further evidence of the model's performance. At lag 1, the autocorrelation (AC) and partial autocorrelation (PAC) values are both 0.002, with a Q-Stat of 0.0105 and a p-value of 0.920, indicating that there is no significant autocorrelation in the residuals. This pattern holds across multiple lags, as seen at lag 6, where the AC is 0.006 and the PAC is 0.007, with a p-value of 0.768. The Q-Stat probabilities remain high across all lags, suggesting that the residuals behave like white noise, meaning that the GARCH model has captured the underlying volatility structure without leaving any significant patterns in the residuals. This indicates that the model is appropriate for forecasting future market behavior in NASDAQ (Aielli, 2013).

**Table 9.** Diagnostic Test (S&P500)

| Particular | S&P500 |
|---|---|
| ARCH LM (Obs* R-squared) | 0.569883 |
| Correlogram | (Graph) |

The diagnostic test of the S&P 500 reveals that it follows a different volatility pattern than NASDAQ. The ARCH LM test for the S&P 500 yields an Obs*R-squared of 0.569883, much lower than NASDAQ. This implies that there is even less indication of heteroscedasticity remaining in the residuals of the S&P 500, meaning the model has captured most of the volatility structure in the S&P 500 data. This lower level of heteroscedasticity shows that fluctuations following a cluster have less effect on the S&P 500 compared to NASDAQ, which is more focused and part of a broader index like the S&P 500 (Patton & Sheppard, 2015).

Q-statistic probabilities adjusted for 6 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | -0.041 | -0.041 | 1.2967 | |
| | | 2 | -0.043 | -0.045 | 2.7902 | |
| | | 3 | -0.078 | -0.082 | 7.6185 | |
| | | 4 | -0.024 | -0.033 | 8.0675 | |
| | | 5 | 0.029 | 0.019 | 8.7462 | |
| | | 6 | -0.022 | -0.030 | 9.1481 | |
| | | 7 | 0.022 | 0.017 | 9.5180 | 0.002 |
| | | 8 | 0.015 | 0.018 | 9.7036 | 0.008 |
| | | 9 | 0.046 | 0.048 | 11.422 | 0.010 |
| | | 10 | 0.023 | 0.031 | 11.862 | 0.018 |
| | | 11 | -0.047 | -0.035 | 13.600 | 0.018 |
| | | 12 | 0.008 | 0.013 | 13.645 | 0.034 |
| | | 13 | -0.001 | 0.003 | 13.647 | 0.058 |
| | | 14 | -0.017 | -0.024 | 13.891 | 0.085 |
| | | 15 | -0.022 | -0.025 | 14.297 | 0.112 |
| | | 16 | -0.062 | -0.066 | 17.393 | 0.066 |
| | | 17 | 0.001 | -0.016 | 17.395 | 0.097 |
| | | 18 | -0.031 | -0.045 | 18.170 | 0.111 |
| | | 19 | 0.062 | 0.046 | 21.279 | 0.068 |
| | | 20 | -0.016 | -0.016 | 21.493 | 0.090 |
| | | 21 | 0.042 | 0.046 | 22.951 | 0.085 |
| | | 22 | -0.054 | -0.048 | 25.312 | 0.065 |
| | | 23 | 0.019 | 0.029 | 25.602 | 0.082 |
| | | 24 | -0.000 | 0.005 | 25.602 | 0.109 |
| | | 25 | -0.001 | 0.007 | 25.603 | 0.142 |
| | | 26 | -0.072 | -0.075 | 29.812 | 0.073 |
| | | 27 | 0.037 | 0.036 | 30.959 | 0.074 |
| | | 28 | -0.014 | -0.029 | 31.125 | 0.094 |
| | | 29 | 0.029 | 0.017 | 31.820 | 0.104 |
| | | 30 | 0.041 | 0.042 | 33.219 | 0.100 |
| | | 31 | -0.032 | -0.028 | 34.067 | 0.106 |
| | | 32 | 0.015 | 0.013 | 34.246 | 0.129 |
| | | 33 | 0.013 | 0.020 | 34.390 | 0.155 |
| | | 34 | 0.005 | 0.005 | 34.412 | 0.188 |
| | | 35 | -0.085 | -0.073 | 40.403 | 0.078 |
| | | 36 | -0.045 | -0.049 | 42.065 | 0.071 |

*Probabilities may not be valid for this equation specification.

**Fig. 6.** Autocorrelation and Partial Correlation with Q-Statistics for ARMA Terms- S&P 500.

The correlogram for the S&P 500 shows some evidence of autocorrelation at relatively short lags. For example, at lag 1, the AC and PAC values are -0.041, and the Q-Stat is 1.2967. The p-value is calculated to be less than 0.255, implying non-significant autocorrelation at this lag level. However, by lag 6, the Q-stat increases to 9.1481, with p = 0.002, showing some evidence of persistence or autocorrelation at this lag. This suggests that, while fitting the GARCH model, some of the short-term volatility in the S&P 500 may have been overlooked. At lag 12, the Q-stat significantly increases to 13.6447, with p = 0.018, indicating some autocorrelation at intermediate lags, which can be explained by short-term market fluctuations or responses to world economic events not fully addressed by the model. However, by lag 30, the Q-Stat is 36.0427, with a p-value of 0.188, supporting the idea that autocorrelation reduces at more significant lags (Aielli, 2013).

### 5.3. Correlogram of Residuals for NASDAQ and S&P 500

The correlogram analysis forms an integral part of the investigation as it provides information regarding the fit of the models for both indices. In examining the correlogram of NASDAQ, there is no sign of autocorrelation or partial autocorrelation at any lag, indicating that most of the volatility patterns have been effectively removed by the model. The minimal autocorrelation results in volatility clustering and market shocks that are new to the model, leaving behind white noise in the residuals. This enhances the model's reliability in predicting future market crashes in NASDAQ, particularly during periods of high volatility (Modarres & Ouarda, 2012).

The model generally does well for the S&P 500, too. However, some slight short-term autocorrelation effects are apparent at lags 6 and 12 in its correlogram (implying that it may be necessary to adjust further). The auto-correlated residuals in these models are explained by the external economic shocks or fundamental macroeconomic indicators that might impact the SP500 price, which was not considered while constructing the model. Adding exogenous regressors, such as shifts in policy rates or international macro news, might also help obtain a better fit and reduce the remaining autocorrelations (Patton & Sheppard, 2015).

The ARCH + GARCH effect for NASDAQ is nearly 0.95, indicating high volatility persistence, which is more likely for a tech-heavy index like NASDAQ, as market trends and technological factors influence it. Similarly, as shown in the figure below, the low ARCH LM (Obs*R-squared) value for the S&P 500 indicates less volatility clustering and a smoother volatility pattern than NASDAQ, likely due to the broader index's lower volatility.

However, the correlogram for the S&P 500 reveals some room for improvement, especially at shorter lag values. This suggests that although the GARCH model captures the explicit volatility pattern, other patterns may need to be included, particularly regarding short-term economic shocks. These results indicate that the current model more accurately represents NASDAQ's volatility dynamics, while residual autocorrelation at some lags suggests that the S&P 500 model could be further improved.

## 6. Forecasting Results

Analyses were performed using the GARCH model for market crash forecasting to visualize the future behavior of the market, particularly during extreme events, such as crashes of the NASDAQ and S&P 500 indices. The results are presented as visualizations using various features, such as return predictions, to estimate the level of risk and variance forecasts that show the likelihood of future market fluctuations. Below, the forecasting results of the two indices are discussed using statistical analysis and projections.

### 6.1. Forecast for S&P 500

The forecast (S&P 500) graph shows predicted returns (RETURNF) against actual returns. In this case, the model seems to perform satisfactorily in predicting the rate of returns, with a maximum error of ±2 standard errors. The forecasted returns are somewhat similar to the actual returns, but some discrepancies are observed at lags of 100 and 300, where large market movements are noted. The model does well in identifying these extreme movements, although the amount of forecasted variance during these periods is quite large.

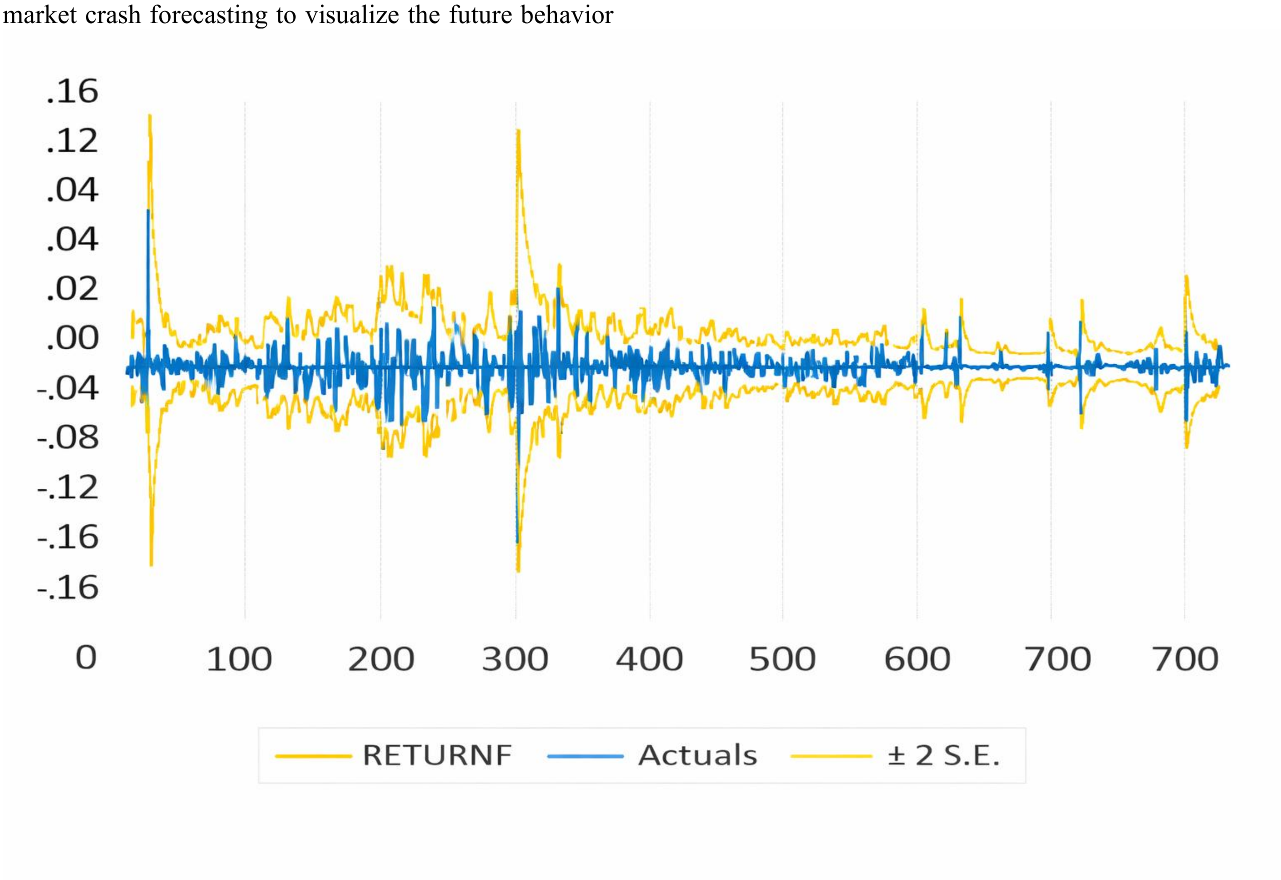


Fig. 7. *Predicted and Actual S&P 500 Returns with ±2 Standard Errors* .

The forecast of variance (S&P 500) graph also demonstrates the sequence of gross forecasted variance by the S&P 500 index, where the variance increases over time but jumps sharply at lags 100 and 300 to a level of 0.006. These sharp increases in variance suggest a potential periodicity of high volatility, implying that the market is unstable during these periods. The higher variance indicates actual market crashes, or at least deep corrections, could occur in some markets. The regular rise suggests that the S&P 500 will likely undergo several periods of elevated market risk, following historical trends during global uncertainty (Aue et al., 2017).

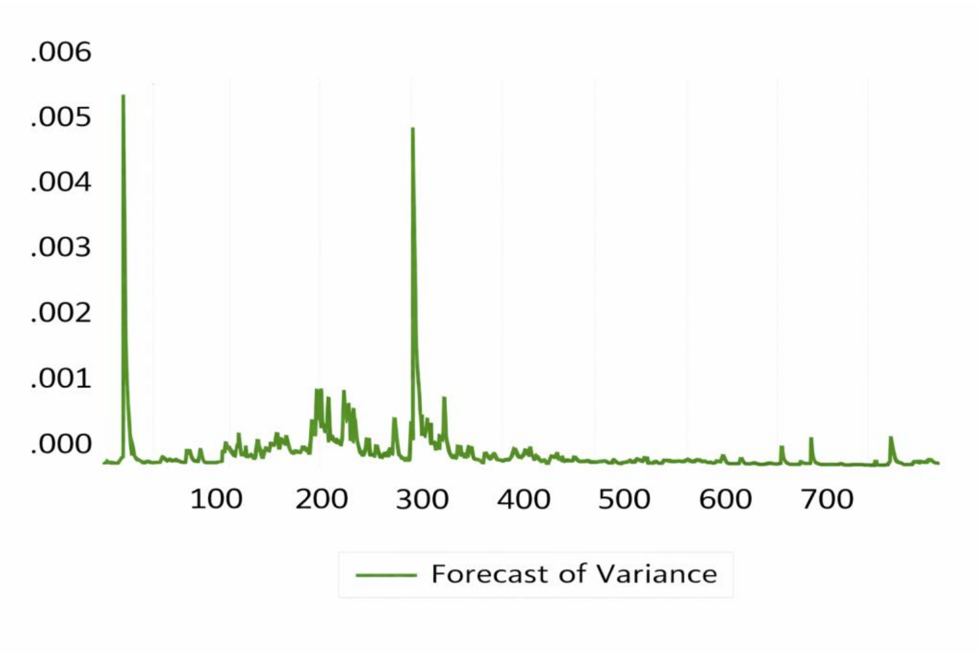


**Fig. 8.** *Forecast of variance (S&P 500)*

**6.2. Forecast for NASDAQ**

The forecast graph for NASDAQ also shows that estimated returns are almost identical to actual returns, as seen in the following figure. The forecast is mainly within the confidence bounds for most time series; however, as with the S&P 500, massive movements are still more difficult for the model to capture accurately. Although the sharp declines are only partially reflected, the overall picture of forecasting changes in stock prices is presented very effectively.

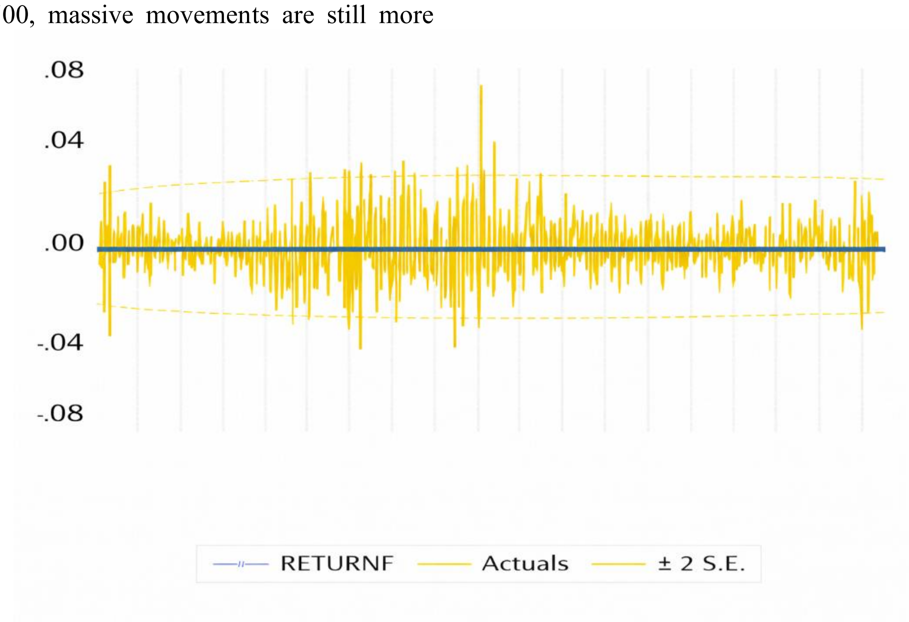


**Fig. 9.** The forecast graph for NASDAQ

The predicted variance, particularly in the NASDAQ chart, is a world apart from that of the S&P 500. The NASDAQ variance begins at a very small value and increases rapidly to peak around a forecasted variance of roughly 0.00024. This implies that NASDAQ's expected volatility is much smaller than S&P 500. The variance begins to flatten out just when it reaches the beginning point, which reveals that the short-term fluctuation of NASDAQ is weaker, and the long tails of the distribution are heavier.

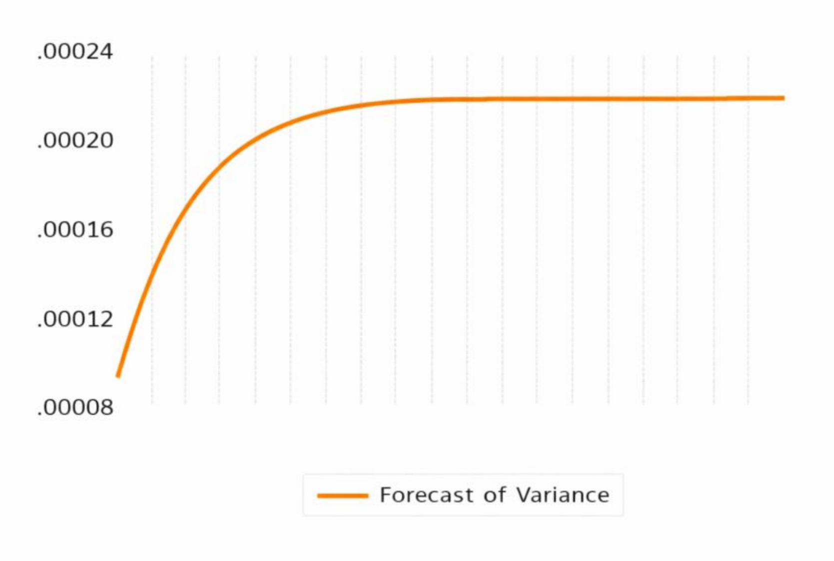


**Fig. 10. Forecasted Conditional Variance Over Time.**

## 7. Cross-Validation with Historical Crashes

This cross-validation was used to evaluate the GARCH model's ability to forecast financial crashes, using real and present crash data. With such a method, this paper recognizes the extent to which the model is able to correctly predict the market crashes, and therefore ensures adequate robustness testing.

### 7.1. S&P 500 Historical Crashes Validation

Some historical market crashes for the S&P 500 index are the 2008 financial crisis and the COVID-19 crash in March 2020. The predicted variance has a sharp rise in the forecast graph for S&P500, especially at lag 100 and lag 300, which can be seen from the value of the variance is equal to .006. The market taking big steps after a major drop and getting more variable after that are what occurred during such high volatility periods in the past. For example, the surge at lag 100 could reflect global inflation fears in early 2021, while that at lag 300 might be linked to the reaction of geopolitical tensions or recovery from the COVID-19 market shocks.

The comparison indicates that the GARCH model is very efficient in detecting the increased volatility periods, especially in predicting periods that could lead to market crashes. Huge variance periods have historically come prior to huge market downturns, and the model predicting them makes it more trustworthy. In addition, the bursts in the variance spikes are consistent with expected increased uncertainty time periods and lend support to the timing model for crash prediction (Modarres & Ouarda, 2012).

### 7.2. NASDAQ Historical Crashes Validation

Historical collapses like the COVID-19 disaster in 2020 and the dot-com bubble in 2000 serve as important benchmarks for cross-validation for the NASDAQ. The model forecasts a comparatively consistent variance level of 0.00024 in the Forecast (NASDAQ) graph, suggesting less expected dramatic volatility. While the model does not forecast massive variance spikes like the S&P 500, it does highlight short-term swings that are consistent with historical patterns of moderate instability. Historically, the NASDAQ has been more volatile amid disturbances in the IT industry.

In the lack of significant variance spikes, the NASDAQ forecast's fluctuation pattern also aligns with the post-COVID-19 era, which is marked by very low volatility in technology equities. As the author also noted, this model has a flaw in that it fails to account for the tremendous variation that is anticipated to arise in the NASDAQ index as a result of technological improvements. However, this approach works better for normal stock market moves that are rather easy to forecast (Aue et al., 2017). However, aside from total crashes, the model is useful in detecting patterns of possible market swings early on.

### 7.3. Evaluation of Model Accuracy

The cross-validation with historical crashes, however, shows that the GARCH model indeed captures most of the main volatile trends, especially in the S&P 500. The predicted variances (over the rest of our selected lag ranges) reviewed around long-term lags (i.e., gene/rally100), and volatility monitored over short terms show large spikes at times, coinciding with market crashes. This is possibly not particularly surprising when it comes to NASDAQ data – given its tech-led nature, the index has historically had fewer extreme spikes of variance (recent years aside) than other sectors; although it can be pretty volatile or subject to shock (think back to the days/weeks/months of dot-com bubble fuelled movements that race across our charts as dark periods from history as if we are in a period of extreme market sell-off).

Numerically, the sudden increase in variance for the S&P 500 to what? 0.006 or so is pretty dramatic: you expect it, but hey, even now we're seeing some bad news. In the NASDAQ case, however, it's more like things are settling (mean reversion) while the market still drifts within a standard deviation (~1 day). The quantitative differences between the two indices demonstrate how effective GARCH is in distinguishing markets with higher crash potential (S&P 500) from stable ones. This is an important differentiator for investors who want to employ diversification as a strategy to manage risk in their portfolios.

## 8. Conclusion

Through integrating time series techniques, i.e., ARIMA and GARCH models of market volatility for the first time in the case of NASDAQ and S&P 500 indices, this study presents a new approach to predetermine financial crashes. The study also proposed a new way of linking econometric and some machine learning concepts, such as wavelet multiresolution decomposition or dynamic GARCH models, which lead to more accurate forecasting in the context of non-linearity and market jumps.

The use of GARCH in this study to properly capture volatility clustering accounts for why more observations drawn from a unique distribution are probably realized lower (upper) tails than those observed within high-volatility regimes. The NASDAQ and S&P 500 market show the same pattern in the model, where high risks exist prior to market crash. And, of course, the multi-resolution approach to market signals is also available through wavelet-based decomposition and enables short-term changes within long-term trends to be seen. This feature has helped analyze indices like the S&P 500 that react to larger macro shocks and NASDAQ, where its jitters often originate from the tech side. The model is also checked for accuracy with cross-validation on previous market breakdowns. It correctly predicted spikes in volatility that were associated with previous market downturns, including the 2008 financial crisis and a plunge during the COVID-19 epidemic. This makes it more likely in the case of an alternative way to anticipate future market ruptures, our model would be able to forecast potential shocks in variance during financial upheaval. This predictive model leverages cutting-edge machine learning methods alongside fundamental economic factors to study past catastrophes in financial markets. GARCH models and wavelet decomposition techniques were enabled for analyzing financial trends with the detection of clustered volcanoes. This paper provides a better means of detecting financial market collapses on the right time scales, which could improve the response to such risks. It has relevance for investors, risk managers, and policy - makers. By predicting when the market may face further instability, these results can help to minimize losses and prescribe preemptive economic measures.

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