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# The Effect of Rise of Federal Funds Rate on US Stock Market: From the Perspective of US Dollar Appreciation

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***Abstract:*** The study examines the impact of the rise of the Federal Funds Rate (FFR) on the stock price returns and volatility of the United States of America. The study extracted the stock price from January 3, 2022, to June 16, 2023, from the Investing finance terminal, including the Standard and Poor's (S&P 500), US Dollar Index, and the National Association of Securities Dealers Automated Quotations (NASDAQ) Index. This study uses the Vector Autoregression (VAR) model and the ARMA-GARCH model to evaluate the stock returns and daily return volatility, respectively. The two models inspect the effect of the US Dollar index on both the NASDAQ and S&P 500. The result of this study suggests that the rise in the Federal Funds Rate would cause the stock market price to decline for a relatively long period. However, the volatility of the daily return remains stable. By studying the effect of the rise in the Federal Funds Rate, policymakers can change the stock prices by adjusting the Federal Funds Rate based on the market's needs.

***Keywords:*** stock return, volatility, US dollar index, federal funds rate

## 1. Introduction

The change in financial policies has a profound impact on the US stock market. For instance, factors such as the unemployment rate, inflation, and outputs of firms would cause stock price fluctuations in both positive and negative ways. Monetary policy is considered one of the most important factors affecting the FFR. Determined by the Federal Open Market Committee (FOMC), the FFR is the designated interest rate at which commercial banks lend money to other banks using funds in the federal funds reserve [1]. To measure the FFR, studying the change in monetary policies is necessary. So far, some researchers have found a close association between the change in the US Dollar exchange rate and the US economy by measuring factors affecting the real Gross Domestic Product (GDP), such as fuel consumption [2], net imports and exports [2], and unemployment rate [3]. According to Lee and Yue, the change in the US dollar exchange rate has a great influence on fuel consumption and the US's net imports of industrial products from other countries [2]. The rise in the US dollar exchange rate promotes fuel consumption and net imports, which eventually leads to a gradual growth in real GDP [2]. Furthermore, as Prakken and Varvares suggested, the decrease in net exports would cause a decrease in the GDP and eventually increase the unemployment rate [3].

Additionally, many studies focused on monetary policies' effect on the US stock market. For example, Ioannidis and Kontonikas discovered that stock prices are very sensitive the change in interest rates [4]. According to Ioadnnisids and Kontonikas, the increase in the interest rate would result in a lower stock price and thus decreases the expected stock returns [4]. Li, Isçan, and Xu constructed a Vector Autoregression (VAR) model and closely evaluated the impulse response of the stock prices. As Li, Isçan, and Xu suggest, the response of the US stock market to the surprise increase in the interest rate is eventually negative [5]. In addition, Bjornland and Leitemo also discovered that the increase in stock prices is closely related to the increase in stock prices by constructing a VAR model [6]. Furthermore, Bordo, Dueker, and Wheelock not only studied the influence of monetary shocks on stock prices but also measured the stock market condition as a whole, revealing that interest rate fluctuations negatively influence the US stock market [6]. Galí and Gambetti also get similar results by discovering the tightening of monetary policies could result in a long-term stock price decline [6]. These all show that the change in monetary policies could strongly affect the US stock market.

These previous studies highlight how monetary policies change the US economy or the US stock market. However, only a few studies discussed the effect of change in the US Dollar index, which is commonly recognized as the primary medium through which the United States implements its national financial strategy [7]. Since US Dollar Index is closely related to the US economy [7], a close evaluation of its fluctuations is crucial to generate an explanation of the change in the financial market. In addition, only a few studies evaluated how exactly monetary policies change stock returns and stock volatility. As a result, this paper not only uses the US Dollar Index as the main indicator of FFR but also measures the stock market's response by closely evaluating the change in stock returns and volatility. This study uses the NASDAQ and S&P 500 as the main indicator of the change in the stock market. Other than the indicators, this paper uses different financial models, such as the ARMA-GARCH model and VAR model, for the stock returns and volatility analysis.

The remaining parts of this paper are organized as follows: Section 2 includes the data source, an explanation of the VAR model, and the ARMA-GARCH-X model used in Section 3. Section 3 includes the results from the two models and discussions of the stock returns and daily return volatility suggested in the results. Then, this paper includes a discussion on the purpose of this study and provides insights for regulators and investors. Eventually, this paper makes a conclusion.

## 2. Variables and Model

### 2.1. Data Source

Among numerous data indexes, S&P 500, Nasdaq index, and US dollar index could be representative for studying and understanding the influence of the Federal Interest rise on the US stock market. The study captures the daily closing prices of the S&P 500, NASDAQ, and US Dollar Index in the US from January 3, 2022, to June 16, 2023, from the Investing Financial terminal. Further data processing is necessary to analyze the impact of the increased Federal Interest Rate on the US stock market. First, the prices are transformed using the formula ln(1+x) to facilitate analysis in a logarithmic way. Then, the return is calculated by finding the difference between the logarithmic data of a given day and that of its previous day and then dividing the difference by the data of the previous day. With the updated and refined dataset, Stata was employed for data analysis and constructing models to explore the subject further.

### 2.2. Weak Stationarity Test

The ADF test is conducted to figure out whether the data is stationary to build the models. The null hypothesis for the ADF test is that the data is not stationary. According to the results of the ADF test from Stata (please see Table 1), the p-values for the prices of the US Dollar, NASDAQ, and S&P 500

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are 0.8515, 0.7697, and 0.3794, respectively. Since the p-values are all greater than 0.1, which suggests that the assumption for ADF is accepted, the data of prices is not stationary. However, the results for the return seem exactly the opposite. The p-values for the returns of the US Dollar, NASDAQ, and S&P 500 are all equal to 0, which is regarded as statistically significant. Therefore, the assumption for the ADF test is rejected, and the return variable has a unit root. As a result, the return data is stationary, and the model should be based on the return data.

Table 1: Weak stationarity test: ADF test.

| | t | p |
|---|---|---|
| | Price | |
| US Dollar | -1.431 | 0.8515 |
| Nasdaq | -1.656 | 0.7697 |
| SP 500 | -2.400 | 0.3794 |
| | Return | |
| US Dollar | -15.102 | 0.000 |
| Nasdaq | -14.419 | 0.000 |
| SP 500 | -14.260 | 0.000 |

## 2.3. VAR Model Specification

Christopher Sims introduced the VAR model in 1980 in his Macroeconomics and Reality. From Sims' perspective, the VAR model has one main objective – predicting multivariable time series [8]. By generalizing various variables in a vector, the VAR model allows researchers to see and interpret the relationships between variables despite the explicit strong implications of economic theory [8]. Numerous studies have attempted to suggest the change in monetary policies impacted the economy, but few investigate the relationship between the rise in Federal interest and the US stock market. Since Nasdaq and S&P are two representative time series variables that reflect the US stock market, the VAR model is implemented for further exploration.

The study investigates three times series variables: return of US dollar, return of NASDAQ and return of S&P 500, denoted by $USD_t, NASDAQ_t, and\ SP500_t$

$$USD_t = \alpha_1 + \emptyset_{11}USD_{t-1} + \cdots + \emptyset_{1p}USD_{t-p} + \beta_{11}NASDAQ_{t-1} + \cdots + \beta_{1p}NASDAQ_{t-p} + \delta_{11}SP500_{t-1} + \cdots + \delta_{1p}SP500_{t-p} + e_{1t} \tag{1}$$

$$NASDAQ_t = \alpha 2 + \emptyset_{21}USD_{t-1} + \cdots + \emptyset_{2p}USD_{t-p} + \beta_{21}NASDAQ_{t-1} + \cdots + \beta_{2p}NASDAQ_{t-p} + \delta_{21}SP500_{t-1} + \cdots + \delta_{2p}SP500_{t-p} + e_{2t} \tag{2}$$

$$SP500_t = \alpha_3 + \emptyset_{31}USD_{t-1} + \cdots + \emptyset_{3p}USD_{t-p} + \beta_{31}NASDAQ_{t-1} + \cdots + \beta_{3p}NASDAQ_{t-p} + \delta_{31}SP500_{t-1} + \cdots + \delta_{3p}SP500_{t-p} + e_{3t} \tag{3}$$

The general equation for the VAR model is written in same forms. The VAR model uses the past return values to forecast the future return value for each variable. Each equation is composed of three components. Take equation (1) as an example,$\alpha_1 + \emptyset_{11}USD_{t-1} + \cdots + \emptyset_{1p}USD_{t-p}$ represents the past lag orders of the return of US Dollar index return. The terms $\beta_{1p}NASDAQ_{t-p} + \delta_{11}SP500_{t-1} + \cdots + \delta_{1p}SP500_{t-p} + e_{1t}$ represents the return of NASDAQ and S&P 500 respectively. In addition, the term $e1t$ represents the error. In general, US Dollar return is modelled by the past values of US Dollar index return, NASDAQ return, and the S&P 500 return.

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### 2.4. ARMA-GARCH-X Model

The study applies the ARMA-GARCH model to forecast the volatility and return of the NASDAQ and S&P 500 to better forecast the US stock market. The two major components of the ARMA-GARCH model are ARMA and GARCH.

The general equation for the ARMA model is shown in equation (4),

$$R_t = \phi_o + \sum_{i=1}^{p} \phi_i R_{t-i} + \alpha_i - \sum_{i=1}^{q} \phi_i \alpha_{t-i} \tag{4}$$

As the word ARMA suggests, ARMA (p, q) is composed by two main components: AR(p) and MA(q). The equation $\phi_o + \sum_{i=1}^{p} \phi_i R_{t-i}$ indicates the AR(p), which forecasts the future return value of Nasdaq and S&P 500 using the past return values from January 3, 2022, to June 16, 2023. The second part of the equation, $\alpha_i - \sum_{i=1}^{q} \phi_i \alpha_{t-i}$, represents the weighted average of the error terms. The ARMA model introduced the MA(q) model based on AR(p) to restrict the coefficient $\phi_i$ , which allows researchers to generate more accurate forecasted future values of returns.

The second section involves the GARCH model. GARCH model is the generalization of the ARCH model [9]. Both models take variance into consideration and treat it as the volatility of the stock return values. Since ARCH model requires researchers to make additional assumptions before getting the empirical results, GARCH (1,1) model would be the optimal choice for this study [9]. Additionally, in a GARCH model, the conditional variance is modeled as a function of lagged conditional variances itself [10], and thus allows this study to capture the high and low volatility period of the NASDAQ and S&P 500.

The equation for GARCH (1,1) is shown below.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \theta USD_t \tag{5}$$

In equation (6), the $\alpha_0 + \alpha_1 \varepsilon_{t-1}^2$ represents the terms for ARCH, and the $\beta_1 \sigma_{t-1}^2$ represents the terms for GARCH, and $\theta USD_t$ represents an exogenous variable.

## 3. Empirical Results and Analysis

### 3.1. Order of VAR Model

To determine the ideal lag order for the VAR model, it is necessary to evaluate the Likelihood Ratio test and other information criterions. The optimal lag order would be marked by the asterisk sign (*).

Table 2: Likelihood ratio test and information criterion.

| Lag | LL | LR | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|
| 0 | 2061.58 | | | 1.8e-09 | -11.6304 | -11.6174 | -11.5976 |
| 1 | 3759.78 | 3396.4 | 0.000 | 1.3e-13 | -21.1739 | -21.1217* | -21.0427* |
| 2 | 3769.12 | 18.69* | 0.028 | 1.3e-13* | -21.1758* | -21.0845 | -20.9463 |
| 3 | 3775.38 | 12.525 | 0.185 | 1.3e-13 | -21.1604 | -21.0299 | -20.8325 |
| 4 | 3778.52 | 6.2826 | 0.711 | 1.3e-13 | -21.1273 | -20.9577 | -20.701 |
| 5 | 3782.85 | 8.6491 | 0.470 | 1.4e-13 | -21.1008 | -20.8921 | -20.5762 |

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Table xw2:(continued).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 6 | 3786.13 | 6.5635 | 0.682 | 1.4e-13 | -21.0685 | -20.8207 | -20.4455 |
| 7 | 3788.49 | 4.7173 | 0.858 | 1.5e-13 | -21.031 | -20.744 | -20.3096 |
| 8 | 3791.25 | 5.5277 | 0.786 | 1.5e-13 | -20.9958 | -20.6696 | -20.176 |
| 9 | 3795.48 | 8.4607 | 0.488 | 1.6e-13 | -20.9688 | -20.6035 | -20.0507 |
| 10 | 3801.85 | 12.727 | 0.175 | 1.6e-13 | -20.9539 | -20.5495 | -19.9374 |
| 11 | 3805.67 | 7.6381 | 0.571 | 1.6e-13 | -20.9247 | -20.4811 | -19.8098 |
| 12 | 3809.15 | 6.9678 | 0.640 | 1.7e-13 | -20.8935 | -20.4108 | -19.6802 |

In Table 2, both Lags 1 and 2 are signified by the asterisk sign. Based on the AIC method, the minimum value of AIC represents the best lag order of the VAR model. In the AIC column, the smallest value is -21.1758, which falls in lag order 2. Although the HQIC and SBIC are also marked with an asterisk sign, they suggest the optimal lag order for different models. For the VAR model, the optimal choice of lag order would be 2.

After figuring out the optimal order of the VAR model, the study then tests the stability of the VAR model. In the case that the VAR model is not stationary, it is possible that the impulse-response function will not converge to zero, indicating a lasting impact of the increase in the US dollar index on the US stock market. Whether the VAR (2) is stable depends on the results of the unit root test. To visualize the results, the study sketches all the roots in a unit circle. As presented in Figure 1, all roots fall within the unit circle, which suggests that our previous evaluation of the lag order is suitable for the VAR model. In addition, it also suggests that VAR (2) is stable.

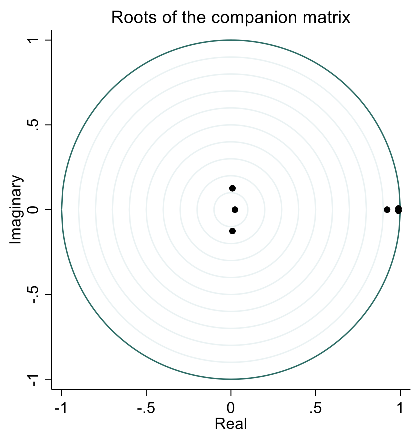


Figure 1: Unit root test (photo credit: original).

## 3.2. Impulse Response

As suggested in the impulse response diagram, when the US dollar increases by 1% at t=0, the NASDAQ is positively impacted from t=0 to t=2 As shown in Figure 2, there exists a peak at around t=3. However, after t=3, the influence of the US dollar on Nasdaq continues to decrease for at least 100 steps. As shown in the figure, the US dollar obviously negatively impacted the Nasdaq index. The greatest negative influence on NASDAQ occurs at t=47, at around -0.5% as the left figure shows. Similar to NASDAQ, the influence on S&P 500 also increases at first and reaches a peak at t=2 and continues to decrease for 100 steps. However, the S&P 500 experiences the most significant negative impact at around t=37 with a level of -0.4. In both situations, the US dollar exerts a continuing negative influence on both NASDAQ and S&P 500 for a certain time period, but Nasdaq is more significantly influenced than S&P 500 since -0.5%>-0.4%.

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Respond variable: Nasdaq Respond variable: SP500

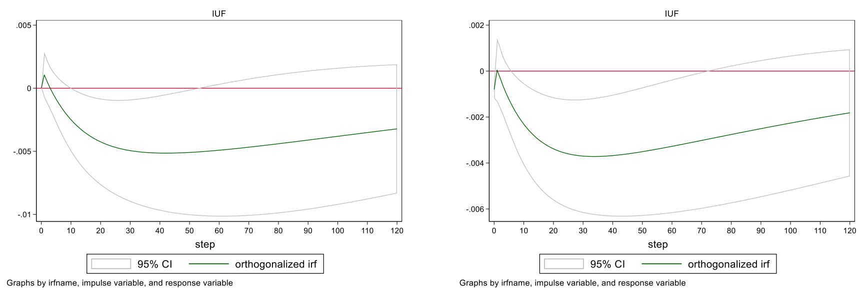



Figure 2: Impulse and response (impulse variable: US dollar).

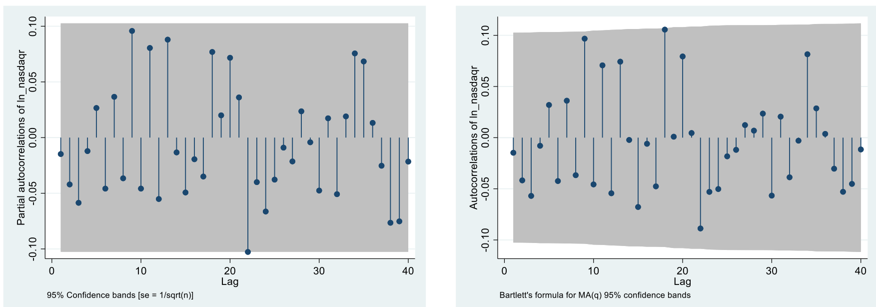
Photo credit: Original

## 3.3. ARMA

To determine the lag orders of ARMA (p, q) model, this study generates the graph for PACF and ACF for NASDAQ and S&P 500 respectively. As shown in the Figure 3, the plots for both NASDAQ and S&P 500 have similar trends. In the PACF column, the first value that goes off the critical region appears at lag order 22 for NASDAQ and Similarly, in the ACF plots, the lag order appears to be 18. This is the same for the PACF and ACF plots for S&P 500. Therefore, the value of p is 22, and the value of q is 18, forming a ARMA (22,18) model for both NASDAQ and S&P 500.

PACF ACF

Nasdaq




SP500

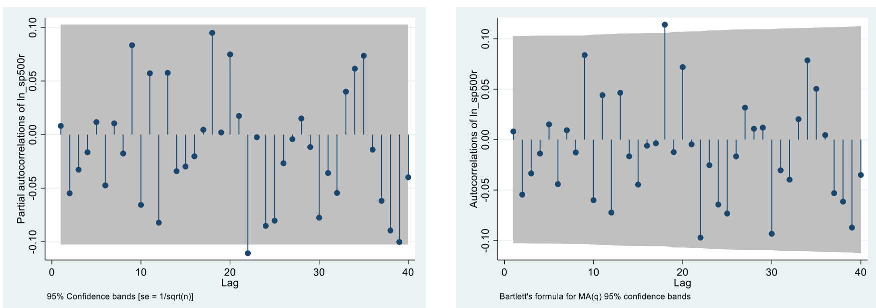



Figure 3: ARMA (p, q) identification.

Photo credit: Original

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### 3.4. Variance Equation

To measure the daily volatility of the NASDAQ and S&P 500, the ARMA-GARCHX model is introduced. The ARMA-GARCH model estimates the results for the variance equation, as shown in Table 3. The p values for the ARCH and GARCH models are both smaller than 0.05, which suggests that they are statistically significant. The estimated results of the variance equation of the ARMA-GARCH model are shown in Table 3. In both (1) and (2), the p-values for the ARCH and GARCH models are both smaller than 0.05, which is considered statistically significant. Therefore, there exists conditional heteroskedasticity in both NASDAQ and S&P 500 returns, which suggests that the stock volatility is clustered, and thus the GARCH model can be employed. However, since the p values corresponding to the US dollar index are all greater than 0.05, the US Dollar returns are considered statistically insignificant. As a result, the p-value fails to provide enough evidence to reject the assumption that the coefficient is zero. Therefore, the increase in the US Dollar index would not impose a significant impact on the volatility of the NASDAQ and S&P 500.

Table 3:ARMA-GARCHX regression: variance equation.

| | (1) Nasdaq | | (2) SP500 | |
|---|---|---|---|---|
| | Coef. | p | Coef. | p |
| US dollar | 61.1663 | 0.675 | 55.7692 | 0.708 |
| ARCH | 0.0339 | 0.047 | 0.0397 | 0.022 |
| GARCH | 0.9618 | 0.000 | 0.9568 | 0.000 |
| Constant | -301.3174 | 0.662 | -276.5007 | 0.6941 |

Table 3:(continued).

## 4. Discussion

Similar to other studies, this paper investigates how the change in monetary policies, especially the rise in FFR, affect the US stock market as a whole. However, rather than examining factors related to the real GDP and the stock prices, this paper pays more attention to the behavior of the stock returns and its volatility with respect to the change in the US Dollar Index, the indicator of the FFR. In other words, rather than studying the change in US economy and the stock market in the general setting, this paper focuses on specific indexes that is highly corresponded to the stock returns and volatility. In addition, this paper utilizes different research methods and financial models, such as ADF Unit Root Test, VAR model, and ARMA-GARCH model.

The relationship between the rise in FFR and the stock returns and its volatility can provide valuable information to financial institution regulators. By regulating the FFR, the stock returns can be in both positive and negative ways, while its daily volatility stays the same. The regulators should be concerned about the balance of the market and policy goals before adjusting the monetary policies. It is also important for the investors to be able focus on the change in the monetary policies and its future directions to adjust asset allocations. As a result, the investors should pay attention to the news of the financial investments.

## 5. Conclusion

The main purpose of this study is to investigate the effect rise in Federal Funds Rate on the US stock market. Since the rise of the FFR can cause an increase in the US Dollar index, this study uses the data of the US Dollar index as the main indicator for FFR. Additionally, this study uses NASDAQ

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and S&P 500 as the two main indicators of the US stock market's response. The stock market is measured in two dimensions: 1. stock returns and 2. stock volatility. During this process, the VAR and ARMA-GARCH models are introduced. The VAR model is used to investigate the impulse response, with the impulse variable being US Dollar indexwhile the response variables being NASDAQ and S&P500, and a strong negative correlation is suggested. To further explore the stock volatility and the conditional variance, the ARMA-GARCHX model is introduced. The empirical results of the VAR model suggest that the rise in FFR causes the stock market to decline. Rather than observing a rapid decline, this study discovers this downward movement is gradually reflected, and it could last for a relatively long period. However, although the stock market continues to move downward, the daily stock volatility does not increase but remains at a stationary level. As a result, the rise in FFR would cause the US stock market to decline in the long-term, but its daily volatility will stay at a normal level without a significant increase.

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