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The comparison of macroeconomic development between the united states and japan in recent in recent years is analyzed from nasdaq and nikkei index

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Abstract. The changes in the Nasdaq and Nikkei over the past in recent years offer valuable insights for evaluating macroeconomic developments in the United States and Japan. Through an analysis of these two indicators, this paper can initially draw conclusions about the state of both countries' economies. Over the past three years, the Nasdaq index has exhibited a relatively stable growth trend, maintaining strong overall growth despite fluctuations caused by global uncertainties. This may reflect advancements in areas such as technological innovation and the Internet sector, as well as investors' optimism regarding future prospects. In contrast, the Nikkei index has displayed a more intricate and volatile pattern during this same period. While there have been some gains, it has experienced an overall decline marked by shocks. This could be attributed to various challenges faced by Japan including an aging population, low growth rate, and declining corporate competitiveness. The objective of this paper is to explore a similar model that explains stock markets in both the US and Japan. Many long-term investors base their stock decisions on the assumption that corporate cash flows should grow alongside economic performance while considering a constant or slow-moving discount rate. Therefore, it is expected that stock returns may exhibit correlation with future economic performance. Another concern worth addressing is how deflation might impact real stock returns.

1 Introduction

The primary motivations of the Federal Reserve for raising interest rates include inflation control, economic stability maintenance, and employment boost. By increasing interest rates, the Fed can effectively curb inflation, prevent overheating of the economy, and maintain a stable value of money [1]. Moreover, higher interest rates can impact consumption and investment behavior, thereby influencing various aspects of the economy such as stock market performance, bond market dynamics, currency exchange rates in global markets as well as affecting enterprises' and individuals' financial situations [2]. This paper aims to explore the potential impact of the Federal Reserve's policy on raising interest rates specifically on the stock market. It does so by constructing an ARIMA model to forecast stock index trends while considering both policy effects on the market and non-white noise components within the forecasting model. Additionally, this paper proposes a method for identifying significant influencing factors and analyzes time characteristics related to policy implementation in financial markets [3].

The subsequent sections are organized as follows: Part 2 introduces data sources and unit root testing; Part 3 employs an ARIMA model to forecast stock index trends; Section 4 discusses findings including analysis of policy implications and non-white noise components; Finally, Section 5 summarizes research findings while providing suggestions for policymakers and investors [4].

2 Research design

2.1 Source of data

According to the demand, the analysis involves downloading and examining the closing price data of the Nasdaq Index and Nikkei Index from investing [1] for the period spanning from March 2021 to March 2023. These two indexes hold significant importance as representative indicators in the global financial market and possess substantial reference value for investors. Being one of the most prominent technology stock indexes in the US stock market, the Nasdaq index encompasses numerous renowned technology companies such as Apple, Microsoft, Amazon, among others.

By analyzing the closing price data of the Nasdaq index, valuable insights can be gained into the trajectory of economic development. The Nikkei index serves as a pivotal and extensively monitored composite average of stock prices in the Japanese stock market, encompassing companies from diverse industries and reflecting the overall performance of Japan's economic system.

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Through acquiring and scrutinizing daily and weekly closing price data, profound understanding can be acquired regarding the challenges and opportunities encountered by companies listed on the Tokyo Stock Exchange, as well as comprehending Japan's economy holistically in recent years. To ensure utmost accuracy and comprehensiveness, it is imperative to exercise caution while selecting reliable sources and employing professional tools for data extraction and processing. Additionally, attention should be paid to whether both daily and weekly closing price information is included since these different frequency types of data offer a more comprehensive and detailed perspective on asset movement. In summary, upon obtaining and analyzing the closing price data of both Nasdaq index and Nikkei index within a specific time frame, more intricate yet precise conclusions pertaining to global financial market dynamics, Tokyo Stock Exchange-listed companies' status quo, as well as Japan's overall economic situation can be drawn; thereby providing robust support and reference for investors [5].

2.2 Unit root test.

The test statistics and corresponding p-values for different conditions are presented in Table 1. Unit root tests are employed to examine the presence of unit root characteristics, indicating non-stationarity, in the time series data. Generally, if the p-value is less than the significance level (usually set at 0.05), he null hypothesis can be rejected, indicating that the time series is stationary. Based on the data presented in the table, this part are able to provide the following explanations:

The provided daily frequency data shows that all p-values of the original series are greater than 0.05, indicating that there is insufficient evidence to reject the null hypothesis of a unit root presence.; thus, confirming non-stationarity of the original series. However, after applying first and second differencing techniques, all resulting p-values fall below 0.05, indicating stationarity of these differenced series.

For weekly frequency data from US and daily frequency data from Japan, similar observations hold true: initial p-values for both original series surpass 0.05 denoting non-stationarity; however, after employing first difference technique on each dataset separately, resulting p-values become lower than 0.05 signifying stationarity.

Regarding weekly frequency data from Japan alone: just like previous cases mentioned above, the initial p-value exceeds 0.05 implying non-stationarity; nevertheless-value drops below 0.05 upon implementing first difference technique which indicates stationarity. Therefore, based on outcomes derived from unit root tests, it can be concluded that in these scenarios, the application of first differences renders stationary time series suitable for subsequent analysis and modeling.

Table 1 Weak stationarity test

	t	p
US, daily		
Ln index	-1.021	0.9412
1st order difference	-12.010	0
2nd order difference	-17.991	0
US, weekly		
Ln index	-1.435	0.8505
1st order difference	-5.433	0
Japan, Daily		
Ln index	-2.330	0.4176
1st order difference	-11.033	0
2nd order difference	-18.092	0
Japan, weekly		
Ln index	-3.162	0.0922
1st order difference	-5.796	0

2.3 Model specification

The autoregressive component in the ARMA model establishes a linear relationship between the current observation and past observations, while the moving average component represents a linear relationship between the current observation and previous error terms. By fitting historical data and incorporating known parameters for prediction, valuable insights can be gained into patterns and characteristics underlying time series data. The fundamental structure of this article utilizing the ARMA model is as follows:

$$X_t = \phi_0 + \sum_{i=1}^{p} \phi_i x_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i} \tag{1}$$

Where $\{a_t\}$ is a white noise sequence, p and q are non-negative integers. Both AR model and MA model are special cases of ARMA(p,q), and using the delay operator, the above model can be written as:

$$(1-\phi_1 B - \cdots - \phi_p B^p)X_t = \phi_0 + (1-\theta_1 B - \cdots - \theta_q B^q)a_t \tag{2}$$

Among them $1-\phi_1 B - \cdots - \phi_p B^p$ is the AR polynomial model, similarly, $1-\theta_1 B - \cdots - \theta_q B^q$ for MA polynomial model. The AR and MA polynomials are required to be different from each other to ensure that the order (p, q) of the model is the same as that of the AR model. The AR polynomial introduces the characteristic equation of the ARMA model, and if the absolute value of all the solutions of the characteristic equation is less than 1, the ARMA model has the weakly stationary property. At this point, the unconditional mean of the model is:

$$E(x_t) = \phi_0/(1-\phi_1 - \cdots - \phi_p) \tag{3}$$

The date data from the four dta documents should be imported separately before importing the STATA software. To facilitate subsequent modeling analysis, March 16, 2022 should be designated. as T_0, representing the first interest rate hike time by the Federal Reserve. Once data import is completed, the next step involves generating a logarithmic series of the stock index and its corresponding logarithmic return series. By applying a log transformation, Enables more accurate observation of the trend in stock price changes and calculation of the logarithmic return rate between consecutive days. Subsequently, a stationarity test is required to verify whether these resulting four log series and log return series exhibit stationarity characteristics. Stationarity serves as one of the prerequisites for establishing various time series models; hence appropriate statistical methods are employed in this step for testing purposes. Upon confirming stationarity, partial autocorrelation function plots (PACF) and autocorrelation function plots (ACF) can be generated for analyzing log return series. These graphs aid in determining suitable order parameters for AR (autoregressive) and MA (moving average) models. Finally, after selecting appropriate AR and MA order parameters, an ARIMA (p, d, q) model can be constructed to predict stock price trends beyond T_0.

3. Empirical results and analysis

3.1. Order of order

The order in the first difference of the daily data cannot be determined, indicating either an excessively large order or indeterminacy. Consequently, a second-order model is employed for the daily data while a first-order model is utilized for the weekly data. This holds true for Japan as well. Although the original series is non-stationary, its difference series exhibits stationarity; hence, modeling should be based on the difference series. Notably, in daily and weekly data analysis, first differences are used in one case while second differences are used in another case. Subsequently, PACF and ACF are employed to determine parameters of the ARIMA model which comprises three components: p, d, q; where p represents the parameter of AR part and q denotes that of MA part; meanwhile d signifies the number of differencing operations applied [6]

The value of d is set to 2 for daily data and 1 for weekly data. Therefore, the parameters p, sf, and sf are utilized to determine the order of p, i.e., its specific value. Let us ascertain the order or specific value of q through sf. The determination of PD has already been made. Now it is necessary to establish the orders or values of both p and q corresponding to the daily data us while generally disregarding cases exceeding a magnitude of 10 [7]. Since the MLE method often fails to converge, an evaluation standard typically selects levels less than or equal to 10. If the significant interval lies outside this range, a level (ranging from 1 to 10) is chosen instead. The temporal correlation is selected based on whether time exhibits significance or not; if it exceeds a certain threshold, then it is considered significant and corresponding values for p and q are chosen (e.g., selecting "1021" for the first model). Similarly, The respective orders for all four models will be determined (US daily, US weekly, Japan daily, Japan weekly) as (10.2,1) (4,1,4) (10,2,1) (4,1,0) (please see Fig. 1).

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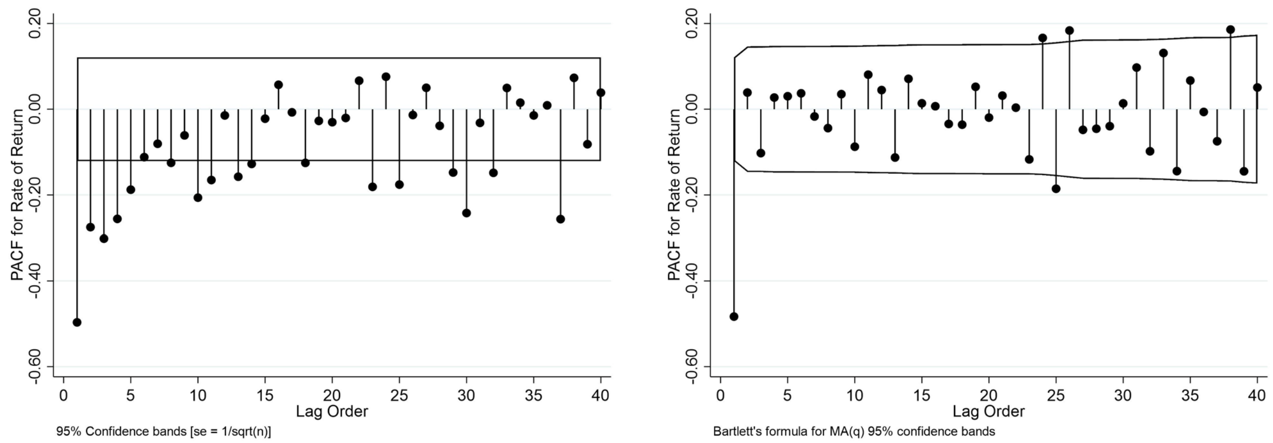
PACF ACF

US, daily



US, weekly

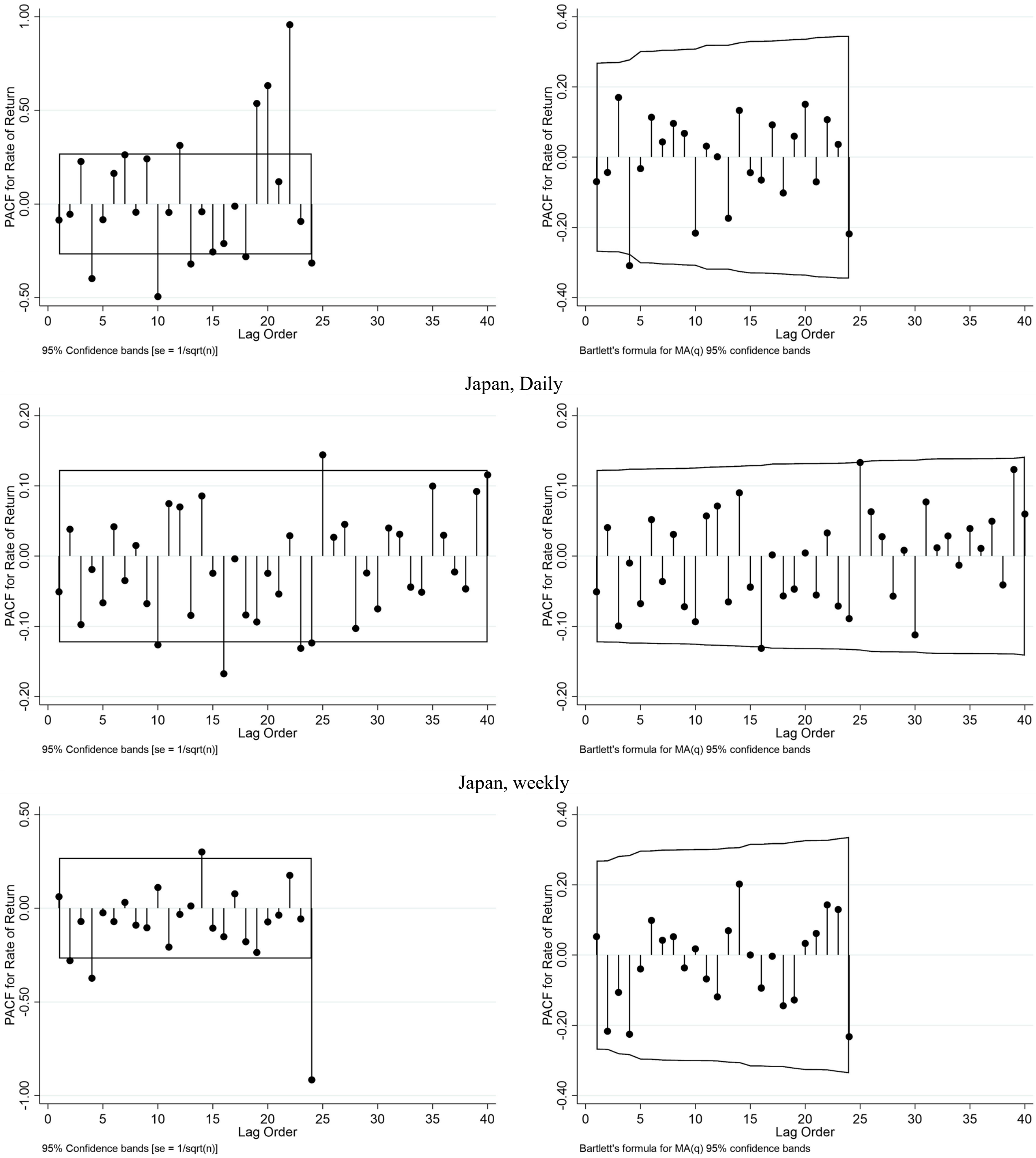


Fig. 1. ARMA (p, q) identification

Photo credit: Original

For the two models with d=2, a residual test is conducted, and Table 2 presents the results indicating that the residuals adhere to the white noise property. However, for the two models with d=1, they fail to meet the condition of white noise. In a model Y=xbeta+epsilon, where epsilon represents the residual and should conform to the characteristics of a white noise distribution. Although there are two non-white noise components present in our current scenario, they do not pose significant concerns for those who are not engaged in quantitative trading and only seek marginal gains of 1% or 2% at most. Hence, even if it deviates from white noise characteristics, it holds no substantial consequences nor leads to model failure. The developed models primarily serve for predicting overall trends of Y; thus minor deviations within a few percentage points do not require excessive attention. Despite some non-white noise components present in these two models, their impact remains acceptable.

Table 2 Residual test

Model	Portmanteau (Q) statistic	Prob > chi2
US, daily - ARIMA(10,2,1)	43.1163	0.3395
US, weekly -	70.6821	0.0020

ARIMA(4,1,4)		
Japan, Daily-ARIMA(10,2,1)	*47.6192*	0.1904
Japan, weekly-ARIMA(4,1,0)	91.3388	0.0000

3.2. Forecast results and interpretation

Making forecasts is akin to our previous objective of utilizing historical data for future prediction. If a certain event had not occurred, what would have been the performance of the index? The predicted values from the orange line and the actual values from the blue line are presented below. In case the Fed had not raised rates, which stock index would you have chosen - Nasdaq 100 or CSI 500? Contrary to expectations, in absence of a rate increase by the Fed, it should have declined but instead showed an upward trend. Reflecting on our earlier narrative, how should the stock market respond following a rate hike by the Fed? Shouldn't there be a decline in stock market indices? According to theory, this should be true as an increase in risk-free rate prompts individuals to prefer holding risk-free assets over risky ones [8]. However, this example contradicts that notion since even though the blue line remains above the orange line, it is crucial to note that this observation is only applicable in short-term scenarios [9]. The interest rates were increased on March 16 and projected backwards for only a period of 10 days, which is the longest time frame considered. Therefore, during this subsequent 10-day period (i.e., from March 16th to March 28th), no significant downward trend can be observed; thus, it cannot be concluded that its impact is absent in short-term durations.

Fig. 2. Actual value and fitted value, US-daily

Photo credit: Original

Figure 2: The graph depicts the correlation between the actual values (blue line) and model-fitted values (orange line) of daily frequency data for the United States. By computing the root mean square error (RMSE), it can be inferred that the model's prediction error is 0.012, indicating high accuracy in its predictions.

As illustrated in the figure, variations may occur in differences between model-fitted and actual values across different time periods; for instance, during early 2019, there was a significant difference between these two values which gradually decreased after mid-2019.

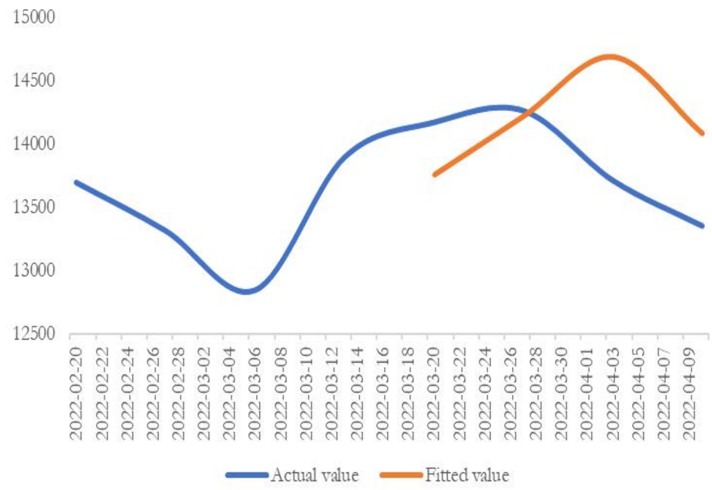


Fig. 3. Actual value and fitted value, US-weekly

Photo credit: Original

Figure 3: The graph illustrates the correlation between the actual weekly frequency data for the United States (blue line) and the model-fitted values (orange line). -By computing the RMSE, it can be inferred that the model's prediction error is 0.008, indicating a high level of accuracy in its predictions. -As depicted in the figure, there are fluctuations in the difference between actual and fitted values over different time periods. For instance, at the beginning of 2022, there was a significant gap between these two values; however, after mid-2022, this difference gradually decreased.

Fig. 4. Actual value and fitted value, Japan-Daily

Photo credit: Original

Figure 4: The graph depicts the correlation between Japan's daily frequency data, represented by the blue line, and the model-fitted values, depicted by the orange line. By calculating the RMSE, The model's prediction error can be determined to be 0.011, indicating a high level of accuracy in its forecasts. As illustrated in the figure, there are temporal variations in the disparity between the model-fitted and observed values. For instance, during early 2019, there was a notable discrepancy between these two sets of values; however, this difference gradually diminished after mid-2019.

Therefore, a weekly data model, 4,1,4, is utilized to conduct an in-depth analysis of short-term movements in financial markets. Through this model, can provide precise predictions for the future state of the financial market in the upcoming month. From this perspective, it becomes evident that financial markets are undergoing a reversal and gradually experiencing the impact of interest rate hike policies. However, it should be noted that policy implementations in financial markets typically do not yield immediate and conspicuous effects; rather they require a certain period of time to manifest fully[10]. This implies that investors and participants need to exercise patience and consider long-term trends comprehensively when making decisions. Furthermore, with regard to the Japanese market specifically, neither daily nor weekly data indicate any discernible impact as evidenced by the consistent positioning of the orange line below the blue line; thus suggesting relative stability at present which may be attributed to unique economic circumstances and policy measures within the country. In summary, through understanding and analyzing various data models meticulously, The future trend of financial markets can be predicted more accurately by adjusting the strategy, taking into account the specific characteristics exhibited by different countries or regions. Simultaneously acknowledging both implementation timelines for policies and variations in economic environments across nations is crucial for maintaining rational thinking throughout investment processes while conducting comprehensive assessments of risks and benefits [7].

4. Discussion

Compared to the existing literature, the conclusions of this paper are partially consistent with other studies [4, 5, 11]. For instance, numerous studies utilize ARIMA models for forecasting stock index trends and focus on policy impacts on the market. However, this paper delves further into examining the influence of non-white noise components on prediction results and proposes a method for establishing acceptable influencing factors. These aspects are relatively scarce in current literature.

The implication of this study is that when constructing forecasting models, various factors should be comprehensively considered, including policy impacts on the market and non-white noise within the model. Simultaneously, attention must also be given to parameter selection and residual testing to ensure model accuracy and reliability. Additionally, the results indicate that policy implementation effects in financial markets typically do not occur immediately but take some time to materialize. This has significant implications for policymakers and investors.

According to the findings of this study, policymakers should recognize that policy implementation usually requires a certain amount of time before producing effects. Therefore, it is necessary to fully predict and analyze market reactions when formulating policies while considering the impact of non-white noise components in forecast models.

Investors can learn from this research that employing an ARIMA model can effectively predict stock index trends while considering policy impacts on the market. Furthermore, investors should also pay attention to how non-white noise components within their models affect prediction results and determine their acceptability level accordingly. When making investment decisions, investors can adjust their strategies based on forecasted outcomes in order to achieve better returns.

5 Conclusion

This study focuses on the issue of stock index forecasting. Through in-depth analysis of daily and weekly data, The ARIMA model for trend forecasting was successfully constructed by employing differencing series and utilizing the PACF and ACF to determine the parameters during the model building process. The results of residual tests indicate that in both models with d=2, the residuals conform to white noise characteristics. However, this white noise condition is not satisfied in the two models with d=1. Although there are some non-white noise components present, their impact is deemed acceptable. In terms of forecasting, By constructing a weekly data model, It is possible to anticipate the potential impact of policy measures, such as a Federal Reserve interest rate hike, on the stock market through forecasting. Our analysis indicates that financial markets have initiated a reversal trend, observed one month in advance, indicating that the effects of interest rate hikes are gradually becoming apparent. This also demonstrates that policy implementation within financial markets typically requires time to yield results. Additionally, neither daily nor weekly data is affected in Japanese markets where consistently throughout observation periods, represented by orange lines always being below blue lines. In summary, this study's findings highlight that ARIMA models can effectively forecast stock index trends while emphasizing consideration for market impacts resulting from policies and attention towards non-white noise components when determining acceptable factors.

References

1. S. Choi. Analysis of stock market efficiency during crisis periods in the US stock market: Differences between the global financial crisis and COVID-19 pandemic. SMIA, 574, 125988 (2021).
2. M. Goldstein, A. Shkilko, B. Van Ness, & R. Van Ness. Competition in the market for NASDAQ securities. JFM, 11(2), 113–143 (2008).
3. Investing. https://cn.investing.com
4. A. Serletis, & A. Rosenberg. Mean reversion in the US stock market. CSF, 40(4), 2007–2015 (2009).
5. Masaryk University. Proceedings of the 14th International Scientific Conference European Financial Systems 2017. In J. Nešleha, K. Urbanovský, & T. Plíhal (Eds.), Proceedings of the 14th International Scientific Conference European Financial Systems 2017 (1st ed.). Brno: Masaryk University. ISBN 978-80-210-8609-8 (2017).
6. P. Pasquariello, & C. Vega. Strategic Cross-Trading in the U.S. stock market. EFR, 19(1), 229–282 (2013).
7. Y. Hsing. (2013). The Stock Market and Macroeconomic Factors in Japan and Policy Implications. ISJFA, 1(1), 20-31 (2013).
8. A. Humpe. Macroeconomic variables and the stock market: An empirical comparison of the US and Japan (Doctoral dissertation, University of St Andrews) (2007).
9. A. Humpe & P. Macmillan. Non-linear predictability of stock market returns: comparative evidence from Japan and the US. IMFI, 11(4): 36-47 (2014).
10. A. Humpe, P. Macmillan. Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. AFE, 19(2): 111–119 (2009).
11. M. Naseem, M. Mohsin, L. Hui, Z. Liyan, & K. Penglai. Investor Psychology and Stock Market Behavior During the Initial Era of COVID-19: A Study of China, Japan, and the United States. FP, 12, 626934 (2021).