CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 11 (1) (2026), Pages 75-90
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Nasdaq Inc. Stock Price (NDAQ) Prediction Due to Trump's Tariff Policy Using Pulse Function Intervention Analysis

Sediono*, Kimberly Maserati Siagian, and Josephin Viona Aditya

Statistics Study Program, Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia

Abstract

Nasdaq Inc. (NDAQ) is one of the leading stock exchanges in the United States, ranking second globally after the New York Stock Exchange (NYSE) based on market capitalization. As a highly dynamic and information-sensitive market, Nasdaq Inc. stock prices respond quickly to internal corporate conditions and external macroeconomic or policy changes. One notable event affecting market stability was President Donald Trump's import tariff policy, aimed at protecting U.S. industries from foreign competition, particularly Chinese imports. The implementation of this policy triggered significant volatility, including a sharp decline in Nasdaq Inc. stock prices on March 2, 2025. This study examines the impact of this policy on Nasdaq Inc. stock movements using the ARIMA(0,2,1) model with an intervention of order $b = 0$, $r = 1$, and $s = 0$. The results show that all model parameters are statistically significant and produce accurate forecasts, with a MAPE of 2.19%, an RMSE of 5.98766, and an MAE of 2.05232. These findings indicate that intervention analysis effectively captures the impact of import tariff policies on stock market dynamics and provides valuable insights for investors and policymakers in anticipating market fluctuations driven by global economic policy changes.

Keywords: ARIMA; Nasdaq Inc. Stock Price; Pulse Function Intervention Analysis; Trump's Tariff Policy.

1. Introduction

The stock exchange plays an important role as a regulator in securities trading activities in the capital market. From a macroeconomic perspective, the performance of the stock exchange affects the economic development of a country, where positive trading activities can drive economic growth, while market weakness can lead to economic slowdown [1]. One of the largest stock exchanges in the world is Nasdaq (National Association of Securities Dealers Automated Quotations). Nasdaq is a US-based stock exchange that ranks second in the world in terms of market capitalization, after the New York Stock Exchange (NYSE). Stock exchanges are dynamic because they are highly responsive to changes in information, both internal to the company and external, such as government policy [2]. This is reflected in the period when President Donald Trump's tariff policy triggered market volatility. Boer et al. (2022) showed that restrictive policy shocks can suppress the US stock index [3]. These findings prove that tariff policies have a direct effect on market dynamics, including Nasdaq stock movements.

*Corresponding author. E-mail: sediono101@gmail.com

Submitted: October 28, 2025 Reviewed: November 07, 2025 Accepted: November 27, 2025
DOI: https://doi.org/10.18860/cauchy.v11i1.37168

The protectionist tariff policy issued by President Trump in early 2025 had a widespread impact on the global economy. On March 4, 2025, import tariffs from China were raised from 10% to 20% in an effort to curb trade practices deemed detrimental to the United States [4]. This policy was reinforced on March 12, 2025, with a 25% tariff on global steel and aluminum [5], and through Executive Order 14245 on March 24, 2025, President Trump expanded sanctions by targeting other countries that still import Venezuelan oil by imposing a 25% tariff [6]. This series of policies has increased trade policy uncertainty and triggered negative market reactions [7].

The tariff policy issued by President Trump also had a significant impact on the macroeconomic conditions of the United States. J.P. Morgan, as one of the largest financial institutions and investment banks in the world, lowered its projection for US Gross Domestic Product (GDP) growth in 2025 from 1.9% to 1.6% due to increased trade uncertainty and the impact of the tariff policy [8] . This downward revision in GDP projections reflects a weakening of the macroeconomy, which then has a direct impact on the stock market [9].

This shows that tariff policies not only create volatility in the stock market, but also have a direct impact on macroeconomic growth. Therefore, analyzing the movement of Nasdaq Inc. stock prices is relevant as an approach to understanding macroeconomics and future market responses. This research can serve as a leading indicator that provides early signals about the direction of the macroeconomy in the United States. Thus, research on Nasdaq Inc. stock prices is not only important for assessing the impact of Trump's tariff policy, but also as a means of reading the potential direction of future global economic development, given that the United States is the main engine of the global economy. For this reason, the intervention analysis method is used as an initial approach in forecasting Nasdaq Inc. stock price movements.

Intervention analysis is a type of time series analysis that is influenced by events beyond control that can cause changes in time series patterns, thereby affecting the stationarity of time series data [10]. Intervention methods are divided into two types, namely step functions and pulse functions. Step function intervention analysis is used for long-term and continuous interventions after the intervention, while pulse functions capture temporary changes that occur at a specific point in time [11]. In the Nasdaq Inc. stock price data, before conducting a more in-depth time series analysis, the data was first examined in the form of a time series plot. Based on the results, the plot shows a significant spike in data at a specific point in time. Therefore, the appropriate model to apply is the pulse function. This is because the effect of the intervention only lasts for a limited period of time.

Several studies have been conducted related to the analysis of pulse function intervention. One of the studies conducted by Ermawati & Nurhadi (2025) provides results that the intervention model obtained is ARIMA (0,1,0) with intervention order b=36, r=0, s=[5,7,8,10,14,15,19] and MAPE value of 0.87%, which can be used to predict stock price indices during the pandemic [12]. Another study was conducted by Miranda et al., (2025), obtained an intervention model is ARIMA (0,2,1) with intervention order b = 0, r = 2, s = 0 and MAPE value of 1.289%. This shows that the model is very good at predicting the Russia- Ukraine war on gold prices [13].

Therefore, based on the previous description, the researcher will analyze Nasdaq Inc. stock price using the pulse function intervention approach. The novelty of this research is its focus on a new asset–event setting: assessing the effect of Trump's 2025 tariff announcement on Nasdaq Inc. stock prices using intervention analysis. The research data is sourced from investing.com from April 24th, 2022, to August 31st, 2025. This study is expected to provide new insights into how protectionist trade policies affect not only the overall stock market index but also the shares of companies that manage the exchange.

2. Methods

To achieve the objective of this study, a rigorous methodological framework was adopted, with a primary focus on pulse function intervention analysis. The methodology is structured into two major components, which are research data and data analysis. The analytical procedures comprise data description, pre-intervention model development, intervention analysis, and forecasting. Each component serves a distinct role in elucidating the influence of the intervention event. The subsequent subsections provide a comprehensive explanation of these methodological elements.

2.1. Research Data

This study adopts a quantitative approach that uses the pulse intervention function method. The research employs secondary data obtained from the website investing.com[1]. The dataset consists of weekly stock price data for Nasdaq Inc. from April 24$^{\text{th}}$, 2022, to August 31$^{\text{st}}$, 2025, yielding a total of 176 observations. The dataset is divided into two subsets, namely training data and testing data, which are used for model development and validation purposes.

2.2. Analysis Step

In this study, the analysis stages are divided into four stages to achieve the research objectives. The following are the analysis stages.

1. Describing the pre- and post-intervention data of Nasdaq Inc. stock prices to provide an overview of the observed patterns.
   Group the data into pre-intervention and post-intervention data by looking at the time series plot. The time series plot is also needed as a basis for selecting the appropriate intervention model. After that, describe the pre- and post-intervention data for Nasdaq Inc. stock price shares as a result of Trump's tariff policy.
2. Form an appropriate ARIMA model using pre-intervention data.
   a. Testing stationarity in the mean and variance. The first step in forming the ARIMA model is to ensure that the data are stationary in terms of mean and variance. According to Wei (2006), a time series is stationary when its mean and variance remain constant over time, as presented in the following equations [14]:

   $$E(Z_t) = E(Z_{t-k}) = \mu$$

   $$\text{Var}(Z_t) = E[(Z_t - \mu)^2] = E[(Z_{t-k} - \mu)^2] = \gamma_0$$

   Stationarity in the mean can be examined using the Autocorrelation Function (ACF) plot. ACF describes the correlation between observation Z_t and Z_{t-k} separated by a lag k [14]. Under stationarity, $\gamma_0 = \text{Var}(Z_t) = \text{Var}(Z_{t-k})$, so the correlation between Z_t and Z_{t-k} can be written as:

   $$\rho_k = \frac{\gamma_k}{\gamma_0}$$

   Meanwhile, the Partial Autocorrelation Function (PACF) is used to measure the direct relationship between Z_t and Z_{t-k} after removing the effects of intermediate lags [15]. Mathematically, the PACF estimator can be written as:

   $$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_j}$$

   where ϕ_{kk} is the partial autocorrelation at lag-k, ρ_k is the autocorrelation at lag k, and ρ_j is the autocorrelation at lag j.
   If the data are not stationary in variance, a transformation is required. The Tukey transformation method is applied to modify the values of Z_t so that the variance becomes more stable. The Tukey transformation is defined as [16]:

[1] https://www.investing.com

$$T(Z_t^{(\lambda)}) = \begin{cases} Z_t^{(\lambda)}, & \lambda \neq 0 \\ \ln(Z_t), & \lambda = 0 \end{cases}$$

The parameter λ ranges from $-1 \leq \lambda \leq 1$ and is estimated from the data to make the distribution closer to normality. This method was later developed into the Box–Cox transformation. Variance stationarity can be visually assessed using a Box–Cox transformation plot. If the Box–Cox output yields a rounded value of $\lambda = 1$, then the data are considered stationary in variance [17].

Table 1: Box-Cox Transformation

λ	Transformation
-1	$1/Z_t$
-0.5	$1/\sqrt{Z_t}$
0	$\ln(Z_t)$
0.5	$\sqrt{Z_t}$
1	Z_t

Source: [14]

Differencing is a method used to overcome non-stationarity in the mean [18]. The differencing process involves subtracting the data value at a given period from the value in the previous period. According to Cryer and Chan (2008), differencing can be expressed using the backshift operator [19]. The general form of differencing of order d is written as follows:

$$W_t = (1 - B)^d Z_t$$

where $(1 - B)^d$ denotes differencing of order d, and Z_t represents the observation at time t.

b. Identifying the model with ACF and PACF plots
To determine the order of the ARIMA model, initial identification is performed using the ACF and PACF plots. The ACF plot is used to identify the order of the Moving Average (MA) component (q), while the PACF plot plays an important role in determining the appropriate number of lags for the Autoregressive (AR) component (p).

c. Identifying the model by estimating parameters using the Ordinary Least Squares (OLS) method
Parameter estimation is performed to obtain the values of unknown parameters in the population. One estimation method that can be used is the Ordinary Least Squares (OLS) method. The ARMA(p, q) model is assumed to be stationary, with a_t representing white noise that follows an independent and identically distributed $N(0, \sigma^2)$ process. One example of an ARMA model is the moving average model MA(1), expressed as:

$$Z_t = (1 - \theta_1 B)\, a_t, \quad t = 1, 2, \ldots, n \tag{1}$$

From Eq. (1), the form of a_t can be written as:

$$a_t = Z_t + \theta_1 a_{t-1}$$

Thus, the Sum of Squared Errors (SSE) for the MA(1) model can be formulated as:

$$S(\theta, \mu) = \sum_{t=2}^{n} a_t^2 = \sum_{t=2}^{n} (Z_t - \theta_1 a_{t-1})^2$$

Based on the principle of the OLS method, the parameter estimator θ_1 is obtained by minimizing $S(\theta, \mu)$. The estimator is given as follows:

$$\hat{\theta}_1 = \frac{\sum_{t=2}^{n} Z_t \, a_{t-1}}{\sum_{t=2}^{n} a_{t-1}^2}$$

d. Performing parameter significance tests and residual assumption tests
Next, a parameter significance test is conducted to determine whether there are any insignificant parameters in the model. A model is considered good if the estimated parameters are statistically significant [20]. The parameter significance test hypothesis is formulated as follows:

$$H_0 : \beta = 0 \quad \text{(Parameter is not significant)}$$
$$H_1 : \beta \neq 0 \quad \text{(Significant parameter)}$$

With the test statistic:

$$t_{\text{hit}} = \frac{\hat{\beta}}{SE(\hat{\beta})}$$

With the rejection region, H_0 is rejected if $|t_{\text{hit}}| > t_{\alpha/2;v=n-n_p}$ or p-value $< \alpha$ (significant level). Where n is the number of observations and n_p is the number of parameters. Meanwhile, β is a model parameter and $SE(\hat{\beta})$ is the standard error of the estimated value $\hat{\beta}$.
The residual assumption test is an important step that must be carried out. In this step, there are two assumption tests that must be met by the residual, namely white noise and normally distributed residual. The white noise test can be carried out using the Ljung–Box test. The hypothesis used can be formulated as follows:

$$H_0 : \rho_1 = \rho_2 = \cdots = \rho_k = 0 \quad \text{(White noise residual)}$$
$$H_1 : \text{at least one } \rho_k \neq 0 \quad \text{(Residual not white noise)}$$

With the test statistic:

$$Q_k = n(n+2) \sum_{k=1}^{K} \frac{\hat{p}_k^2}{n-k} \tag{12}$$

In this case, n denotes the amount of data, k is the k-th lag, and $\hat{p}_k^2$ is the autocorrelation coefficient at the k-th lag. The decision criteria are to reject H_0 if $Q_k > \chi^2_{(\alpha;\, k-p-q)}$ or p-value $< \alpha$.
Next, the residual assumption test that must be met is the residual normality test using the Kolmogorov–Smirnov test. This test is necessary because a model can be considered good if the residuals are normally distributed [21]. The hypothesis used in the residual normality test can be formulated as follows:

$$H_0 : \text{residual data is normally distributed}$$
$$H_1 : \text{residual data is not normally distributed}$$

$$D = \sup_x |S(X) - F_0(X)| \tag{13}$$

Where $S(X)$ is the cumulative distribution function of the original data and $F_0(X)$ is the distribution function of the data hypothesized to be normally distributed. With the critical region, reject H_0 if $D > D_{1-\alpha,n}$ or p-value $< \alpha$ (significance level).

e. Determining the best ARIMA model According to Wei (2006), Akaike's Information Criterion (AIC) is a model selection criterion that considers the number of model parameters. The model with the lowest AIC value is selected as the best model. Systematically, the AIC is formulated as follows:

$$\text{AIC} = n\ln(\hat{\sigma}_a^2) + 2M$$

On the other hand, Schwartz's Bayesian Criterion (SBC) is a metric for assessing model fit quality based on Bayesian principles, introduced by Schwartz (1978). The SBC is formulated as follows:

$$\text{SBC}(M) = n\ln(\hat{\sigma}_a^2) + M\ln(n)$$

with:

- M : number of parameters in the model, where $M = p + q$
- n : number of observations
- $\hat{\sigma}_a^2$: residual variance, $\hat{\sigma}_a^2 = \frac{\text{SSE}}{\text{df}}$

In addition, Mean Square Error (MSE) is also used as a model selection criterion. MSE measures the overall estimation error of a forecasting model. The MSE formula is as follows:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2$$

Model accuracy can also be measured using Mean Absolute Percentage Error (MAPE), which is based on percentage error. The MAPE value is computed as follows [22]:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\%$$

with:

- n : number of observations
- Z_t : actual value
- $\hat{Z}_t$: predicted value

MAPE categories are shown in Table 2 [23].

Table 2: MAPE Value Categories (Lewis, 1982)

MAPE	**Interpretation**
MAPE $\leq$ 10%	Very good performance
10% $\leq$ MAPE < 20%	Good performance
20% $\leq$ MAPE < 50%	Acceptable performance
MAPE $\geq$ 50%	Poor performance

To assess stability and error magnitude, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) will be used with the following formulas:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Z_t - \hat{Z}_t\right|$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2}$$

MAE and RMSE are used together because each has its own advantages. MAE shows the average error without considering the direction of the error, while RMSE is more sensitive to large errors because it squares the difference. Therefore, comparing MAE and RMSE provides information about the variation of errors in the model.

3. Forming an intervention model based on post-intervention data
The next step is the modeling process using intervention analysis, which begins with determining the intervention sequence (b, r, s) through the cross-correlation function (CCF) plot. This plot is constructed using actual post-intervention data and post-intervention prediction values. Parameter estimation is then carried out using the Ordinary Least Squares (OLS) method, followed by diagnostic testing of the ARIMA model with the selected intervention sequence (b, r, s) based on the principle of parsimony. The general formulation of the intervention model is shown in Eq. (2) [24].

$$Z_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^{(T)} + N_t \tag{2}$$

where N_t is the pre-intervention ARIMA model, defined as:

$$N_t = \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t$$

Thus, the intervention model can be written as:

$$Z_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^{(T)} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t$$

with:

- $\omega_s(B)$: Operator of order s.
- $\delta_r(B)$: Operator of order r.
- I_t : Intervention variable.
- b : Indicates when the intervention occurs.
- s : Duration until the effect stabilizes after lag b.
- r : Pattern of residual correlation after intervention.

According to Wei (2006), short-term intervention effects are modeled using a pulse function. The pulse function is defined as:

$$I_t = P_t^{(T)}$$

where:

$$I_t = 0 \quad \text{for } t \neq T,$$
$$I_t = 1 \quad \text{for } t = T.$$

Here, T represents the time at which the intervention occurs.

4. Forecasting Nasdaq Inc. Stock Price using the pulse intervention model
The final stage of this research involves forecasting the weekly stock price of Nasdaq Inc. using the previously obtained ARIMA intervention model. In addition, the accuracy of the predictions was evaluated using several model goodness measures, such as MSE, AIC, SBC, MAPE, MAE, and RMSE. Once all model evaluation criteria were met, the ARIMA intervention model was then used to forecast the Nasdaq Inc. stock prices for the upcoming weeks.

3. Results and Discussion

Descriptive statistics are used to provide an overview of weekly changes in Nasdaq Inc. stock price data. A summary of weekly Nasdaq Inc. stock price data for the period from April 24, 2022 to June 8, 2025 is presented in Table 3 as follows:

Table 3: Descriptive Statistics of Pre and Post Intervention

Variable	N	Mean	StDev	Min	Max
Pre-Intervention	149	60.774	9.416	47.590	82.990
Post-Intervention	15	77.430	5.340	68.250	85.610

Table 3 shows that the average weekly Nasdaq Inc. stock price during the pre-intervention period, from April 24, 2022, to February 23, 2025, was recorded at USD 60,866. Meanwhile, in the post-intervention period, from March 2, 2025, to June 8, 2025, the average share price increased to USD 77.63. To visually illustrate the trend in Nasdaq Inc. weekly share price changes, the trend plot during the study period is presented in Fig. 1 below.

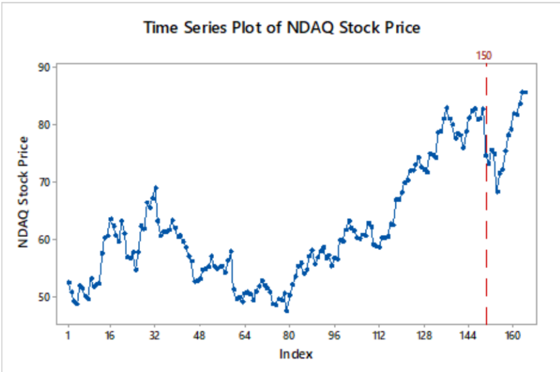


Fig. 1: Time Series Plot of Nasdaq Inc. Stock Price

As shown in Fig. 1, weekly Nasdaq Inc. stock price data shows a fluctuating pattern throughout the research period. However, there was a significant price decline on March 2, 2025, namely at $t = 150$. This significant decline was associated with the announcement of a new tariff policy issued by the President of the United States, Donald Trump. Because the impact appears as a sharp, one-time drop rather than a sustained shift, it is appropriately modeled using a pulse intervention.

3.1. Modeling Pre-Intervention with ARIMA

The ARIMA model is fitted exclusively to the pre-intervention data to establish the baseline pattern of the series prior to the policy event. Before estimating the model, stationarity in both variance and mean must be verified. To check the stationarity of the variance, a Box-Cox plot is used. The Box-Cox plot for the weekly Nasdaq Inc stock price data in the pre-intervention period is presented in Fig. 2 below.

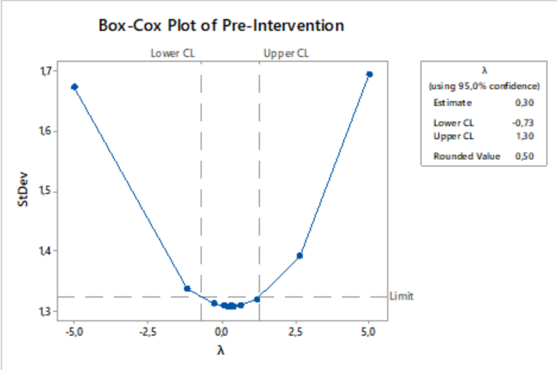
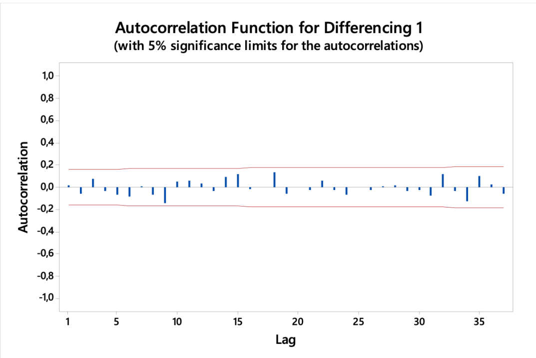
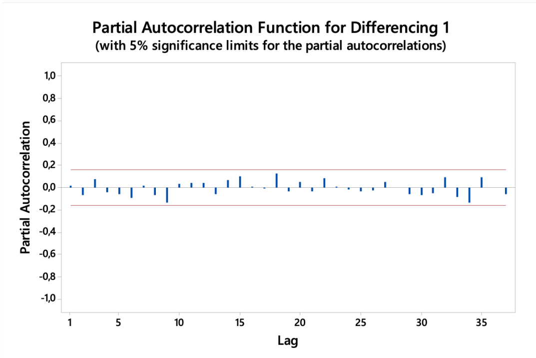


Fig. 2: Pre-Intervention Box-Cox Plot

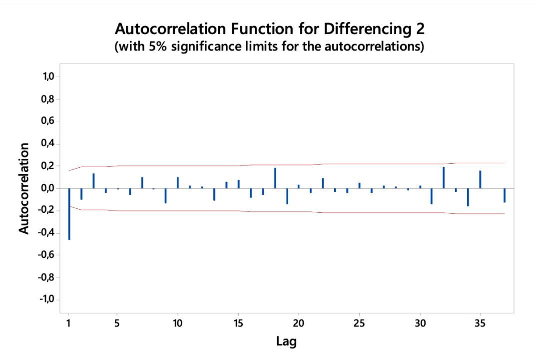
Based on Fig. 2, the Box-Cox transformation results show a value of $\lambda = 0.50$. This indicates that the weekly Nasdaq Inc. stock price data in the pre-intervention period is not stationary in variance. Therefore, a transformation process with $\lambda = 0.50$ is required, namely using $\sqrt{Z_t}$ so that the data becomes stationary in variance. After the transformation is performed, stationarity in the mean can be evaluated by looking at the ACF and PACF graphs presented in Fig. 3 below.



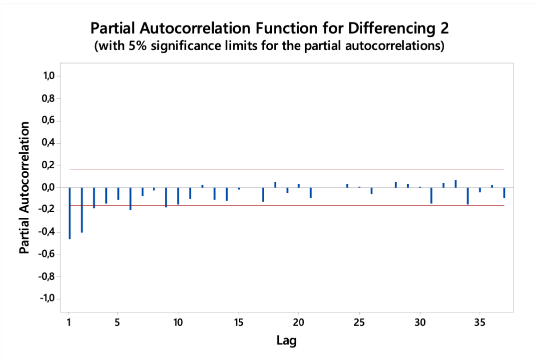
(a) ACF Differencing 1



(b) PACF Differencing 1



(c) ACF Differencing 2



(d) PACF Differencing 2

Fig. 3: ACF and PACF Plots for Differencing 1 and 2

The process of achieving stationarity of weekly Nasdaq Inc. stock price data in the pre-intervention period was carried out through two rounds of differencing. As shown in Fig. 3, the ACF plot shows one lag that crosses the significance threshold, namely lag 1. Meanwhile, the PACF plot shows two lags that cross the significance threshold, namely lags 1 and 2. Based on this pattern, several ARIMA model candidates for Nasdaq Inc. weekly stock price data in the pre-intervention period that can be considered are ARIMA (0,2,1), ARIMA (1,2,1), ARIMA (2,2,1), ARIMA (3,2,1), ARIMA (1,2,0), ARIMA (2,2,0), and ARIMA (3,2,0). Furthermore, the results of testing the significance of parameters, white noise residuals, and residual normality tests for each ARIMA model are presented in Table 4 below.

Table 4: Parameter Significance of Pre-Intervention ARIMA Models

ARIMA Models	Parameter Significance
ARIMA (0, 2, 1)	Sig.
ARIMA (1, 2, 1)	Not Sig.
ARIMA (2, 2, 1)	Not Sig.
ARIMA (3, 2, 1)	Not Sig.
ARIMA (1, 2, 0)	Sig.
ARIMA (2, 2, 0)	Sig.
ARIMA (3, 2, 0)	Sig.

Based on Table 4, the ARIMA (0,2,1), ARIMA (1,2,0), ARIMA (2,2,0), and ARIMA (3,2,0) models show that all estimated parameters are statistically significant. Therefore, this model selected for further evaluation, including diagnostic checking or the residuals to assess whether they exhibit white-noise behavior and the assumption of normality

Table 5: Diagnostic Test Results of Pre-Intervention ARIMA Models

ARIMA Models	White Noise	Normality Test
ARIMA (0, 2, 1)	Sig.	Normal
ARIMA (1, 2, 1)	Sig.	Normal
ARIMA (2, 2, 1)	Sig.	Normal
ARIMA (3, 2, 1)	Sig.	Normal
ARIMA (1, 2, 0)	Not Sig.	Normal
ARIMA (2, 2, 0)	Sig.	Normal
ARIMA (3, 2, 0)	Sig.	Normal

Based on Table 5, the ARIMA models that meet the criteria of white noise residuals and residual normality are ARIMA (0,2,1),ARIMA (2,2,0), and ARIMA (3,2,0). Next, to determine the best model among the two models, evaluation indicators such as AIC, MSE, SBC, and MAPE values are used, as presented in Table 5 below.

Table 6: Comparison of MSE, AIC, and SBC Values of ARIMA Models

Model	MSE	AIC	SBC
ARIMA (0, 2, 1)	0.01734	-599.143	-596.146
ARIMA (2, 2, 0)	0.02080	-573.233	-570.236
ARIMA (3, 2, 0)	0.01888	-578.841	-575.844

Based on Table 6, the minimum values for MSE, AIC, SBC, and MAPE are ARIMA (0,2,1). Therefore, it can be said that ARIMA (0,2,1) is the best model for modeling pre-intervention data. The ARIMA (0,2,1) model can be expressed in Eq. (3) as follows.

$$
\begin{aligned}
(1-B)^2 Z_t &= \theta_1(B)a_t \\
\left(1-2B+B^2\right) Z_t &= (1-\theta_1 B)\, a_t \\
Z_t = N_t &= \frac{(1-\theta_1 B)\, a_t}{(1-2B+B^2)} \\
Z_t &= \left(1+(2-\theta_1)\, B+(2\,(2-\theta_1)-1)\, B^2+\cdots\right) a_t \\
Z_t &= \left(1+(2-0.995112)B+(2(2-0.995112)-1)B^2+\cdots\right) a_t \\
Z_t &= \left(1+1.004888B+1.009776B^2+\cdots\right) a_t
\end{aligned}
\tag{3}
$$

3.2. Intervention Analysis

After identifying the optimal ARIMA model for the pre-intervention data, the next stage involves determining the intervention order, represented by the parameters b, r, and s. This is accomplished by examining the Cross Correlation Function (CCF) plot between the predicted post-intervention values generated by the ARIMA (0,2,1) model and the actual weekly Nasdaq Inc. stock price data during the post-intervention period as an illustrative short-term forecast. The resulting CCF plot is presented in Fig. 4 below.

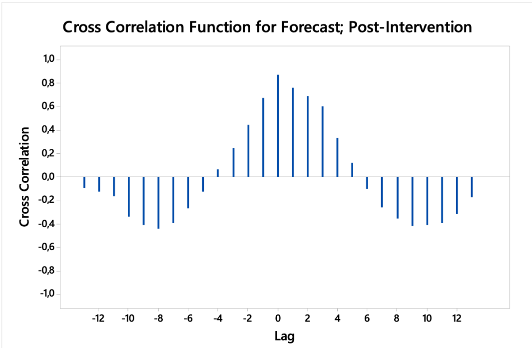


Fig. 4: CCF Plot of Post-Intervention Data and Predicted Data of the Best ARIMA Model

Based on the results of the CCF plot analysis, it can be seen that the impact of the intervention began to appear at lag 0, indicating that the intervention effect occurred immediately without any time delay. Therefore, the intervention order was set as $b = 0$. The pattern that formed resembled a wave, indicating a value of $r = 2$. Meanwhile, the value of $s = 0$ decreased because the direct intervention effect declined after the first lag. Furthermore, the parameter estimates for the pulse function intervention model are presented in Table 7 below.

Table 7: Intervention Model Parameter Significance Test Result

Parameter	Estimate	P-Value
MA(1)	0.58432	< 0.0001
ω_0	-0.23941	0.1000
δ_1	0.69577	0.3373
δ_2	0.30423	0.6046

Model: ARIMA $(0, 2, 1)$ dengan $b = 0$, $r = 2$, dan $s = 0$.

It can be seen in Table 7 that there are several insignificant parameters. Referring to Wei (2006), if insignificant parameters are found, the values of b, r, and s can be adjusted or modified to obtain a more accurate and parsimonious model. This adjustment aims to simplify the model without reducing its ability to describe the actual data pattern. In this way, the resulting model is expected to contain only parameters that are truly influential and capable of providing more accurate and efficient forecasting results.

Table 8: Modified Intervention Model Parameter Significance Test Result

Intervention Model	Parameter	Estimate	P-Value
ARIMA$(0, 2, 1)$	MA(1)	0.74837	< 0.0001
dengan $b = 0, r = 1$,	ω_0	-0.32447	0.0189
dan $s = 0$	δ_1	1.00000	0.0010

Table 9: White Noise Residual and Normality Test Result

Lag 6	Lag 12	Lag 18	Lag 24	Normality
0.1523	0.2569	0.3749	0.3843	> 0.1500

$P - Value < \alpha = 0.05$, Table 8 shows that all parameters have a p-value less than 0.05, which means that all of them are statistically significant. Thus, both the parameters in the ARIMA (0,2,1) model and in the intervention model with orders $b = 0$, $r = 1$, and $s = 0$ have passed the significance test. In addition, the test results also show that the assumptions of white noise residuals and normality have also been met. Therefore, the resulting intervention model can be considered valid. The mathematical equation of the intervention model can be written as follows.

$$
\begin{aligned}
\dot{Z}_t &= \frac{\omega_s(B)B^b}{\delta_r(B)} l_t^{(T)} + N_t, \qquad N_t = (1 + 1.004888B + 1.009776B^2 + \cdots)a_t \\
&= \frac{\omega_0(B)}{\delta_1(B)} P_t^{(150)} + N_t \\
&= \frac{\omega_0}{\delta_1(B)} P_t^{(150)} + N_t \\
&= \frac{\omega_0}{1 - \delta_1 B} P_t^{(150)} + N_t \\
&= (\omega_0 + \omega_0\delta_1 B + \omega_0\delta_1^2 B^2 + \cdots) P_t^{(150)} + N_t \\
&= (-0.32447 - 0.32447B - 0.32447B^2 + \cdots) P_t^{(150)} + N_t \\
&= (-0.32447 - 0.32447B - 0.32447B^2 + \cdots) P_t^{(150)} \\
&\qquad + (1 + 1.004888B + 1.009776B^2 + \cdots)a_t \\
&= -0.32447P_t^{(150)} - 0.32447P_{t-1}^{(150)} - 0.32447P_{t-2}^{(150)} + \cdots \\
&\qquad + (1 + 1.004888B + 1.009776B^2 + \cdots)a_t
\end{aligned}
$$

3.3. Prediction of the Nasdaq Inc. Stock Prices

Based on the results of the modeling, predictions were made for the next 12 weeks. Before evaluating the model's accuracy, the predicted values were transformed back to the original scale by applying the inverse of the $\sqrt{Z_t}$. The prediction results are shown in the following table.

Table 10: Calculation of MAPE Value Based on Post-Intervention Data

Period	Date	Prediction	Actual	APE (%)
165	15/06/2025	86.73011	86.10	0.731831
166	22/06/2025	87.87938	89.08	1.347805
167	29/06/2025	89.03432	90.07	1.149859
168	06/07/2025	90.19871	89.41	0.882124
169	13/07/2025	91.36875	89.37	2.236484
170	20/07/2025	92.54825	94.84	2.416440
171	27/07/2025	93.73338	95.17	1.509532
172	03/08/2025	94.92800	96.85	1.984515
173	10/08/2025	96.12822	94.68	1.529595
174	17/08/2025	97.33598	94.75	2.729269
175	24/08/2025	98.55327	94.74	4.024985
176	31/08/2025	99.77613	94.30	5.807132
MAPE (%)				**2.195798**

Table 10 shows that the MAPE value is 2.19%, indicating that the model has excellent predictive capabilities. In addition to MAPE, the accuracy of the model was also evaluated using four additional metrics, namely MAE (Mean Absolute Error), RMSE (Root Mean Square Error), AIC (Akaike's Information Criterion), and SBC (Shwarz Information Criterion). MAE value were obtained at 2.05232, RMSE value were obtained at 5.987662, AIC value were obtained at -180.783, and SBC value were obtained at -171.539. To provide a visual overview of the model's performance, a comparison between the actual values and the predicted values in the testing data is presented in the graph in Fig. 5 below.

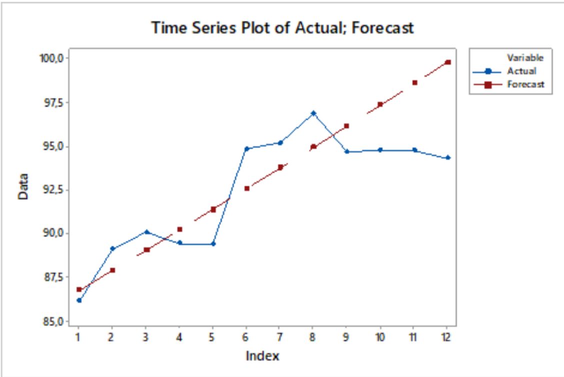


Fig. 5: Comparison Plot of Actual Data and Predicted Nasdaq Inc. Stock Price Results

Next, predictions were made for the next 8 weeks, from September 7, 2025 to October 26, 2025. The prediction results can be seen in the following table.

Table 11: Nasdaq Inc. Stock Price Prediction Results

Period	Date	Prediction
177	07/09/2025	101.0085
178	14/09/2025	102.2465
179	21/09/2025	103.4940
180	28/09/2025	104.7470
181	05/10/2025	106.0097
182	12/10/2025	107.2778
183	19/10/2025	108.5556
184	26/10/2025	109.8388

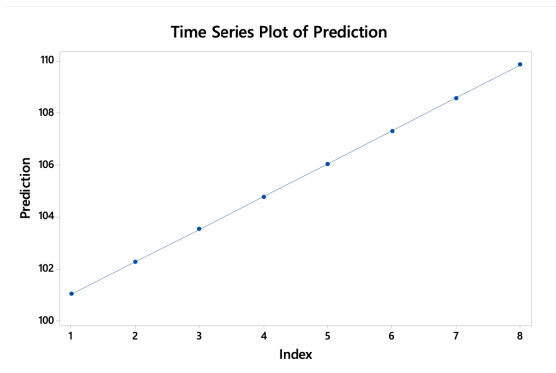


Fig. 6: Nasdaq Inc. Stock Price Prediction Plot

Based on the prediction results shown in Fig. 6, it can be seen that the weekly Nasdaq Inc. stock price for the period from September 7, 2025 to October 26, 2025 shows an upward trend. However, the validity of this prediction model is limited to the short term. Therefore, after

October 26, 2025, this model needs to be reevaluated or reanalyzed using the latest data. This is important considering the possibility of data changes caused by external factors that can affect the accuracy of predictions.

4. Conclusion

The tariff policy implemented by President Donald Trump caused a sharp decline in Nasdaq Inc. stock prices on March 2, 2025. This study successfully applied the ARIMA (0,2,1) model with order b=0,r=1,s=0. All parameters in the model were statistically significant, and the model showed excellent predictive performance with a MAPE value of 2.20%. In addition, it also has an RMSE value of 5.98766 and MAE value of 2.05232. These findings indicate that intervention analysis is able to capture the impact of Donald Trump's import tariff policy on the movement of the Nasdaq Inc. stock price.

CRediT Authorship Contribution Statement

The contributions of each author are detailed based on the Contributor Roles Taxonomy (CRediT) as follows: **Sediono**: Review of the supervision, Guidance, and Final Manuscript. As the corresponding author and final contributor. **Kimberly Maserati Siagian**: Data Curation, Formal Analysis, Writing - Review, Methodology, and Editing. **Josephin Viona Aditya**: Methodology, Formal Analysis, Data Collection, and Investigation.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools were used during the preparation of this manuscript. Specifically, ChatGPT and DeepL are utilized to assist in language refinement, paraphrasing, and improving the clarity of certain sections. The final content was reviewed and approved by the authors to ensure accuracy and integrity.

Declaration of Competing Interest

The authors declare no conflict of interest

Funding and Acknowledgments

We sincerely thank the Research Internship Program at the Department of Statistics, Faculty of Science and Technology, Universitas Airlangga, for their generous support and the facilities provided, which played a significant role in the successful completion of this research. This study was conducted without any external funding.

Data and Code Availability

supporting the findings of this study were obtained from a publicly accessible source. Specifically, the historical Nasdaq Inc. Stock Price used for the analysis can be found on the Investing.com website[2]. This ensures transparency and facilitates the reproducibility of the study results.

References

[1] G. J. T. Hartarto, "Status yuridis bursa efek sebagai pengatur kegiatan perdagangan pasar modal," *Masalah-Masalah Hukum*, vol. 50, no. 2, pp. 143–150, Apr. 2021. DOI: 10.14710/mmh.50.2.2021.143-150.

[2] urlhttps://www.investing.com/equities/nasdaq-omx-group

[2] C. Chikwira and J. I. Mohammed, "The impact of the stock market on liquidity and economic growth: Evidence of volatile market," *Economies*, vol. 11, no. 6, p. 155, Apr. 2023. DOI: 10.14710/mmh.50.2.2021.143-150.

[3] L. M. L. Boer and M. Rieth, "The multifaceted impact of us trade policy on financial markets," *Journal of Applied Econometrics*, vol. 38, no. 3, pp. 388–406, Dec. 2022. DOI: 10.1002/jae.2952.

[4] L. S. Rabinowitz, R. Mangas, D. S. Stein, and M. Orlando, *Tariffs update: Imposed, paused, changed, and reciprocal tariffs involving the us, canada, china, and mexico (as of march 7)*, https://www.gtlaw.com/en/insights/2025/3/tariffs-update-imposed-paused-changed-and-reciprocal-tariffs-involving-the-us-canada-china-and-mexico-as-of-march-7, Accessed: 2025-09-15, 2025.

[5] T. H. T. Barrabi and L. Fickenscher. "The early winners and losers of trump's tariff battle with canada, mexico, china and europe." New York Post, Accessed: Sep. 15, 2025. https://nypost.com/2025/03/14/business/trump-tariff-battle-with-canada-mexico-china-and-europe-points-to-early-winners-losers/.

[6] T. W. House. "Imposing tariffs on countries importing venezuelan oil." The White House, Accessed: Sep. 15, 2025. https://www.whitehouse.gov/presidential-%20actions/2025/03/imposing-tariffs-on-countries-importing-venezuelan-oil/.

[7] E. Haslett and N. Sherman. "Wild market swings as tariffs rattle us economy." BBC News, Accessed: Sep. 15, 2025. https://www.bbc.com/news/articles/czrvngj03jlo.

[8] J. Morgan. "Us tariffs: What's the impact on global trade and the economy?" J.P. Morgan, Accessed: Sep. 15, 2025. https://www.jpmorgan.com/insights/global-%20research/current-events/us-tariffs.

[9] S. B. C. Baek and M. Glambosky, "Macroeconomic impact and stock returns' vulnerability by size, solvency, and financial distress," *Journal of Applied Econometrics*, vol. 59, no. 1, p. 104 718, 2023. DOI: 10.1016/j.frl.2023.104718.

[10] S. W. A. Ramadhani and M. Siringoringo, "Forecasting the number of foreign tourist visits to indonesia used intervention analysis with step function," *Jurnal Matematika, Statistika, dan Komputasi*, vol. 19, no. 1, pp. 146–162, 2022. DOI: 10.20956/j.v19i1.21607.

[11] A. T. R. Dani and F. B. Putra, "Time series modeling with intervention analysis to evaluate covid-19 impact on the stock markets in indonesia and global," *Euler: Jurnal Ilmiah Matematika, Sains, dan Teknologi*, vol. 13, no. 1, pp. 113–126, 2025. DOI: 10.37905/euler.v13i1.31081.

[12] S. Ermawati and B. Nurhadi, "Analisis indeks pasar saham global terhadap issi : Studi pada djia , nikkei 225 , dan ssec dengan pendekatan error correction model," *Journal of Economics Research and Policy Studies*, vol. 5, no. 2, pp. 385–400, 2025. DOI: 10.53088/jerps.v5i2.1808.

[13] A. S. Miranda, P. E. Andriani, S. Sediono, and I. Syahzaqi, "Forecasting futures gold prices using pulse function intervention analysis approach," *Inferensi*, vol. 8, no. 1, p. 53, 2025. DOI: 10.20956/j.v19i1.21607.

[14] W. W. S. Wei, *Time Series Analysis: Univariate and Multivariate Methods*. New York: Pearson Education, 2006.

[15] T. R. R. V. Suryani and I. Ruslianto, "Penerapan metode arima untuk memprediksi pemakaian bandwidth di universitas tanjungpura," *Coding : Jurnal Komputer dan Aplikasi*, vol. 10, no. 3, pp. 421–432, 2022. DOI: 10.26418/coding.v10i03.56016.

[16] J.W.Tukey, "On the comparative anatomy of transformations," *Coding : Jurnal Komputer dan Aplikasi*, vol. 28, no. 3, pp. 602–832, 1957. DOI: 10.1214/aoms/1177706875.

[17] C. E. M. M. Pangalila and D. Hatidja, "Analisis peramalan harga minyak goreng di provinsi sulawesi utara dengan menggunakan metode analisis autoregresive integrated moving average," *D'Cartesian*, vol. 13, no. 1, pp. 23–29, 2024. DOI: 10.35799/dc.13.1.2024.53818.

[18] M. N. M. R. Ekayanti and E. Sulistianingsih, "Analisis model intervensi fungsi step untuk peramalan kenaikan tarif dasar listrik (tdl) terhadap besarnya pemakaian listrik," *Buletin Ilmiah Matematika, Statistika. dan Terapannya (Bimaster)*, vol. 3, no. 3, pp. 174–184, 2014.

[19] J. D. Cryer and K. S. Chan, *Time Series Analysis: with application in R*, 2nd ed. New York: Springer, 2008.

[20] S. W. A. F. Syawal and M. Siringoringo, "Peramalan curah hujan di kota samarinda menggunakan autoregressive integrated moving average (arima)," *Eksponensial*, vol. 13, no. 2, pp. 153–160, 2024. DOI: 10.30872/eksponensial.v13i2.1058.

[21] M. Maswar, "Analisis time series model arma untuk memprediksi jumlah santri pp salafiyah syafi'iyah sukorejo 2017-2021," *Jurnal Lisan Al-Hal*, vol. 11, no. 1, pp. 59–86, 2017. DOI: 10.35316/lisanalhal.v11i1.177.

[22] C. L. J. D. C. Montgomery and M. Kulahci, *Introduction Time Series Analysis and Forecasting*, 1st ed. New Jersey: John Wiley & Sons, Inc, 2008.

[23] C. D. Lewis, *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*. New York: Butterworth-Heinemann, 1982. https://onlinelibrary.wiley.com/doi/10.1002/for.3980020210.

[24] E. D. Rosilawati, T. Tarno, and T. Wuryandari, "Peramalan indeks harga saham gabungan (ihsg) menggunakan model intervensi fungsi pulse," *Jurnal Gaussian*, vol. 12, no. 3, pp. 382–391, 2024. DOI: 10.14710/j.gauss.12.3.382-391.