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World Gold Price Prediction After United State Election Using Pulse Function Intervention Analysis

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Abstract

The United States (US) election in November 2024 had a significant impact on global economic conditions, especially world gold prices. A key effect was the strengthening of the US dollar, leading to a sharp drop in gold prices to 2,582.1 USD. This study aims to model and forecast gold prices using the pulse function intervention analysis method. The analysis uses weekly data, with the intervention point set in the second week of November 2024 (t = 101). The best pre-intervention model was identified as ARIMA(0,2,1), while the best intervention model had orders b = 1, r = 0, s = 0, based on analysis of the Cross Correlation Function (CCF). The resulting model shows significant parameters and strong performance, with a MAPE of 1.51%, AIC of -530.394, SBC of -525.030, and MSE of 0.0002037. Forecasts indicate gold prices are likely to increase again through the end of July 2025. These findings show that the pulse intervention model effectively captures external shocks, such as post-election dollar appreciation. The study improves our understanding of the dynamics of global gold prices and offers insights that can help policymakers develop strategies to mitigate the risks caused by fluctuations in the external market.

Keywords: Gold Price, Pulse Function Intervention Analysis, ARIMA

1 Introduction

The United States (US) election that took place in November 2024 had a significant impact on global economic conditions, one of which was the strengthening of the US dollar (USD). According to the Gold Return Attribution Model (GRAM), these factors created a delayed effect in market movements that ultimately led to sudden changes in investor sentiment[1]. This condition led to a decline in gold prices after previously reaching a record high in early October 2024, reflecting the sensitivity of gold prices to external changes in the short term. Gold is a precious metal that serves as a strategic commodity and safe haven asset in the global financial system. Gold is considered an asset capable of maintaining or increasing its value during periods of economic uncertainty or market volatility [1]. The price of gold is inversely correlated with the strength of the USD currency, every 1 unit increase in the US dollar exchange rate tends to decrease the price of gold by 2.374 units due to increased acquisition costs for investors based on non-USD currency [2]. In this context, it is important to consider how gold prices interact with the Sustainable Development Goals (SDGs), namely point 8 on inclusive economic growth and

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[1] https://www.gold.org

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point 10 on reducing inequality [3]. However, the volatility of gold prices due to fluctuations in the US dollar has the potential to disrupt the achievement of the SDGs if not balanced with effective hedging policies [4].

Gold price fluctuations in November 2024 were triggered by the strengthening of the US dollar in the aftermath of the US election and the Federal Reserve's policies, indicating the urgency of accurate modeling to understand external intervention patterns [5]. The 2024 US election created monetary and geopolitical policy uncertainty, leading to sudden volatility in gold prices that declined by 13% in 1 week due to a shift in investment flows to dollar-denominated assets and a decrease in global gold demand[2]. The election of the President of the United States was chosen as a major factor because of its significant impact on global financial markets, particularly in influencing investor sentiment, the strength of the US dollar, and the direction of monetary policy, all of which are closely related to the dynamics of gold WGC 2023 prices. Although other global variables such as oil prices, geopolitical conflicts, and interest rate decisions by major central banks (e.g. the ECB or PBOC) also affect the price of gold[3], this study focuses on the US election as a major form of external intervention due to its clear and immediate shock effect as seen in historical data [6].

This phenomenon requires time series analysis that is able to accommodate external intervention factors, such as policy or political events to predict short- and long-term impacts [7]. ARIMA models with intervention analysis are relevant because they are able to separate the effects of natural trends from external shocks such as the strengthening of the US dollar. Intervention analysis is a method in time series models used to evaluate the influence of both internal and external factors based on the duration of the effect [8]. There are two types of intervention analysis, namely step and pulse function intervention analysis [6]. The difference between the two lies in the time period of the intervention.

There are several studies that have been conducted related to the analysis of pulse function intervention. One of the studies conducted by Sediono and Syahzaqi (2023) provides results that the intervention model obtained is ARIMA (0,2,1) with intervention order b = 0, r = 2, s = 0, and an RMSE value of 790.33 which can be used to predict the number of cases of COVID-19 patients in Jakarta [9]. Another study was conducted by Saputra et al. (2021), obtained an intervention model is SARIMA (0,1,1)(0,1,1)12 with intervention order b = 0, r = 0, s = 0 and AIC value of -143.16. Using the model, the prediction results of hotspots were obtained which will increase from July 2019 to its peak in September 2019, then decrease in October 2019 [10].

Therefore, researchers will conduct research to model and predict world gold prices using the pulse function intervention analysis method with the strengthening of the US dollar due to the 2024 election as an intervention. The novelty of this research lies in the use of a pulse function intervention model specifically targeting the post-election period of 2024, which has not been widely explored in previous studies. By focusing on a short-term external shock such as the US presidential election and capturing its immediate effect on global gold prices, this study offers a unique approach that bridges time series modeling with real-world economic events, particularly from the perspective of emerging markets like Indonesia. Hopefully, this research can provide an overview of how an intervention effect can affect world gold prices and its effects on the global economy, as well as a reference for policy makers in regulating and controlling gold prices in Indonesia.

2 Methods

To achieve the objectives of this study, a structured methodological framework was applied, focusing on pulse function intervention analysis. The methodology consists of two main parts:

[2] https://www.gold.org

[3] https://gjepc.org/solitaire/world-gold-council-study-us-elections-drive-gold-demand-and-price-fluctuations/

research data and data analysis. The analysis includes data description, pre-intervention modeling, intervention analysis, and forecasting. Each part contributes to understanding the effect of the intervention event. The following subsections explain these components in detail.

2.1 Research Data

This research is quantitative in approach by applying the pulse function intervention analysis method. This research was conducted to analyze and assess how the impact of the intervention event, namely the US election on fluctuations in world gold prices. The research data uses secondary data sourced from the investing.com website[4]. This study uses data on world gold commodity prices in the period from week 1 January 2023 to week 2 March 2025 with a total of 118 data. The research data is divided into two, namely training and testing data. Training data is used to build an analysis model, namely data in the period from the 1st week of January 2023 to the 3rd week of January 2025 as much as 101 data. Testing data is used to validate the model that has been formed, namely data in the period from the 4th week of January 2025 to the 2nd week of March 2025 as much as 7 data.

2.2 Analysis Steps

In this research, the analysis stage is divided into three stages in achieving the research objectives, namely as follows.

1. Describe the world gold price data pre and post the intervention due to the strengthening of the US dollar after the US election.
   The first step is to descriptively describe the pre- and post-intervention world gold price data. This stage is carried out by identifying the time series data plot using the overall data, then estimating the point in time that allows an extreme intervention. Furthermore, the data is divided into three parts, namely pre-intervention, post-intervention, and testing data.
2. Modeling world gold price data with a pulse function intervention analysis approach.
   The second stage is modeling world gold price data using pulse function intervention analysis. At this stage, it is divided into two modeling steps namely building an ARIMA model using pre-intervention data and forming an intervention analysis model using post-intervention data.

   a. Build ARIMA model based on pre-intervention data.
      The first step in building the ARIMA model begins with checking the stationarity of the pre-intervention data in mean and variance. Data is said to be stationary if it does not show an increase or decrease pattern and data fluctuations occur around a stable time average value [11]. Mean and variance are said to be constant when they meet as shown in Eq. 1 and Eq. 2 [12].
      Average of Z_t :

$$\mu = \mathbb{E}(Z_t) \tag{1}$$

      Variance of Z_t :

$$\sigma^2 = \mathbb{E}((Z_t - \mu)^2) \tag{2}$$

      In addition, data stationary checks can be carried out through plots of ACF and PACF. ACF as a function that expresses the magnitude of the correlation between the observed values at a given time Z_t with previous time observations $(Z_{t-1}, Z_{t-2}, \ldots, Z_{t-k})$. When the ACF plot drops slowing down linearly towards zero, then the data is said to be

[4] https://id.investing.com/commodities/gold-historical-data

non-stationary in the mean. In a stationary state $\gamma_0 = Var(Z_t) = Var(Z_{t-k})$, the autocorrelation equation is obtained as follows in Eq. 3 [12].

$$\rho_k = \frac{\gamma_k}{\gamma_0} \tag{3}$$

Where, ρ_k is the autocorrelation of lag k, γ_k is the autocovariance of lag k, and γ_0 is the variety values of Z_t. Meanwhile, PACF as a function expresses the partial correlation between the observed value at one time Z_t and the previous observation at time $(Z_{t-1}, Z_{t-2}, \ldots, Z_{t-k})$ assuming that there is no effect of all lag times k. The function of PACF in lag k samples is expressed in Eq. 4 [12].

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_j} \tag{4}$$

With, $\phi_k k$ is the partial autocorrelation coefficient for lag k, ρ_k is the partial autocorrelation coefficient for lag k with the estimator ρ_k, and ρ_j is the partial autocorrelation coefficient for lag j with the estimator ρ_j. Furthermore, Box-Cox transformation and differencing are carried out if the data does not meet the assumption of stationarity. The use of Box-Cox transformations is when the data shows an instationarity in variance. The value of the parameter λ and its transformation form are presented in Table 1 as follows [12].

Table 1: Box-Cox Transformation

λ	Transformation
-1	$\frac{1}{Z_t}$
-0.5	$\frac{1}{\sqrt{Z_t}}$
0	$\ln Z_t$
0.5	$\sqrt{Z_t}$
1	Z_t

Differencing is required when there is data not stationary in the mean. Differencing is done by calculating the difference between the observation value of time t and time $t-1$ [11]. Systematically, differencing with orde d can be written as Eq. 5.

$$W_t = (1 - B)^d Z_t \tag{5}$$

Where, $B^d Z_t = Z_{t-d}$, B is the backshift operator, d is the orde of differencing, Z_t is the value of observation at the time of t, and $(1 - B)^d$ is the difference for orde d. After the data stationary, both in mean and variance, then the formulation of the ARIMA model is carried out through ACF and PACF plots. Furthermore, diagnostic tests were carried out to determine the best ARIMA model using the concept of parsimony which consisted of parameter significance tests, residual white noise, and residual normality. The significance test of model parameters is carried out with the aim of determining whether the parameter components that make up the model are significant or not. The parameter significance test was performed with the following hypothesis as follows.

$H_0 : \beta = 0$ (Model parameters are insignificant)
$H_1 : \beta \neq 0$ (Model parameters significant)

The test statistic used for the stationarity test is presented in Eq. 6 below.

$$t = \frac{\hat{\beta}}{se(\beta)} \tag{6}$$

The critical area is to reject H_0 when $|t| > t_{a/2}, d_f = n - n_p$ or $p - value < \alpha = 0.05$. With n are a number of observations, n_p is the consisting of the parameters, and β is an estimate of the parameters of the ARIMA model which includes ϕ (AR) and θ (MA). The residual white noise test is a process in which the residual a_t is said to meet the white noise test when there is no correlation between the residuals, it has a constant mean value, namely $E(a_t) = \mu_0$ which is assumed to be zero, has a constant variance value $Var(a_t) = \sigma_a^2$ and $\gamma_k = Cov(a_t, a_{t-k}) = 0$ for $k \neq 0$ [12]. The test statistic used in the white noise test is the Ljung-Box test with the following test hypothesis Eq. 7.

$H_0 : \rho_1 = \rho_2 = \ldots = \rho_k = 0$ (Residual model white noise)
H_1: There is at least one $\rho_k \neq 0$, for $k = 1, 2, 3, \ldots, K$ (Residual models are not white noise).

The test statistic used for the white noise test is presented in Eq. 7 below.

$$Q = n(n+2) \sum_{k=1}^{K} \frac{\rho_k^2}{n-k} \tag{7}$$

With, n is the number of observations, ρ_k is the autocorrelation coefficient in the lag k, k is the time lag k, K is the seasonal time lag, In critical areas, H_0 is rejected when $Q > X_{(\alpha;k-p-q)^2}$ or $p - value < \alpha = 0.05$.
A residual normality test is required to analyze whether the residual model follows a normal distribution [13]. In the statistical approach, the Kolmogorov-Smirnov test is used with the following test hypothesis, with the statistic test as follows in Eq. 8.

H_0 : Residual models are normally distributed
H_1 : Residual models are not normally distributed.

The test statistic used for the normality test is presented in Eq. 8 below.

$$D = \sup |S(X) - F_0(X)| \tag{8}$$

With, Sup is the total supreme value X of the difference $S(X)$ and $F_0(X)$, $S(X)$ is the cumulative distribution function of the origin data and $F_0(X)$ is the distribution function of the data that are suspected to be normally distributed. With a critical area, reject H_0 when $D > D_{1-\alpha;}$ or $p - value < \alpha = 0.05$. There are several measures of model goodness in this study, namely mean square error (MSE), Akaike's information criteria (AIC), Schwartz's Bayesian criterion (SBC), and mean absolute percentage error (MAPE). The equations for MSE, AIC, SBC, and MAPE can be mathematically formulated as shown in Equations (9)–(12) [12], [14].

i. **Mean Square Error (MSE)**

$$\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} (Z_t - \hat{Z}_t)^2 \tag{9}$$

Where:

- Z_t is the observation value at time t
- $\hat{Z}_t$ is the predicted value at time t
- n is the number of observations

ii. **Akaike's Information Criterion (AIC)**

$$\text{AIC} = n \ln \hat{\sigma}^2 + 2M \tag{10}$$

Where:

- n is the number of observations
- $\hat{\sigma}^2$ is the estimated residual variance
- M is the number of parameters in the model

iii. **Schwartz's Bayesian Criterion (SBC)**

$$\mathrm{SBC}(M) = n \ln \hat{\sigma}^2 + M \ln(n) \tag{11}$$

Where:

- n is the number of observations
- $\hat{\sigma}^2$ is the estimated residual variance
- M is the number of parameters in the model

iv. **Mean Absolute Percentage Error (MAPE)**

$$\mathrm{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \times 100\% \tag{12}$$

Where:

- Z_t is the observation value at time t
- $\hat{Z}_t$ is the predicted value at time t
- n is the number of observations

The model is said to be good and meets the goodness test if it has the minimum MSE, AIC, SBC, and MAPE values. After obtaining the best ARIMA model, the model was formulated. The ARIMA (p,d,q) equation using the backshift operator can be written as Eq. 13 [12].

$$\phi_p(B)(1-B)^d Z_t = \phi_0 + \theta_q(B) a_t \tag{13}$$

With, $\phi_p(B) = (1-\phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$, and $\theta_q(B) = (1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$. Where, Z_t is the observation value at time t, Z_{t-i} is the observation values in the period before t, a_t is the errors at time t, a_{t-i} is the errors in the period before t, ϕ_i is the parameter AR at lag i for $i = 1, 2, \ldots, p$,θ_i is the parameter MA at lag i for $i = 1, 2, \ldots, q$, and $(1-B)^d Z_t$ is the operator differencing (d).

b. Building an intervention model based on post-intervention data.
Furthermore, modeling was carried out using intervention analysis which began with determining the order of intervention (b,r,s) through a Cross Correlation Function (CCF) plot formed from the value of post-intervention data and the value of the prediction results of pre-intervention data. Then, parameter estimation was carried out using the Ordinal Least Square (OLS) method and diagnostic tests were carried out again on the ARIMA model with intervention orders (b,r,s) using the parsimony concept. The general form of the intervention model can be formulated as follow as Eq. 14 [6].

$$Z_t = \frac{\omega_\delta(B)\, B^b}{\delta_r(B)}\, I_t^T + N_t \tag{14}$$

Where, $\omega_s = \omega_0 - \omega_1 B - \cdots - \omega_s B^s$ with s is the duration of the effect of the intervention after b period and $\delta_r = 1 - \delta_1 B - \cdots - \delta_r B^b$, r is a pattern of intervention effects after b period from the intervention at the time t, Z_t is the observation value at time t, I_t is the intervention variables for $t = 1, 2, \cdots, k$, b is the delay time begins to affect intervention I_t against Z, N_t is the ARIMA model without the influence of intervention.

3. Predicting world gold prices with pulse function intervention analysis approach.
   The third stage is to predict world gold prices based on the intervention ARIMA model that has been obtained. In addition, an examination of the accuracy of the prediction model was also carried out using data testing with measures of the goodness of the model used, namely MSE, AIC, SBC, and MAPE values. When all measures of model goodness are met, it is possible to predict the world gold price in the next few weeks using the intervention ARIMA model that has been obtained.

3 Results and Discussion

The statistical description is used to provide an overview of the extreme changes in each week in the world gold price. An overview of the world gold price from week 1 January 2023 to week 2 March 2025 is outlined in Table 2 below.

Table 2: Descriptive Statistic of Pre and Post Intervention

Variable	N	Mean	StDev	Min	Max
Pre-Intervention	101	2161.7	255.9	1833.9	2749.2
Post-Intervantion	17	2778.4	120.3	2618.4	3001.1

In Table 2, it can be identified that the world gold price for pre-intervention data in the first week of January 2023 to the 2nd week of November 2024 has an average of 2162.7 USD while post-intervention data in the 3rd week of November 2024 to the 2nd week of March 2025 has an average of 2778.4 USD. Then, to see the trend data pattern of the world gold price is presented in Figure 1 below.

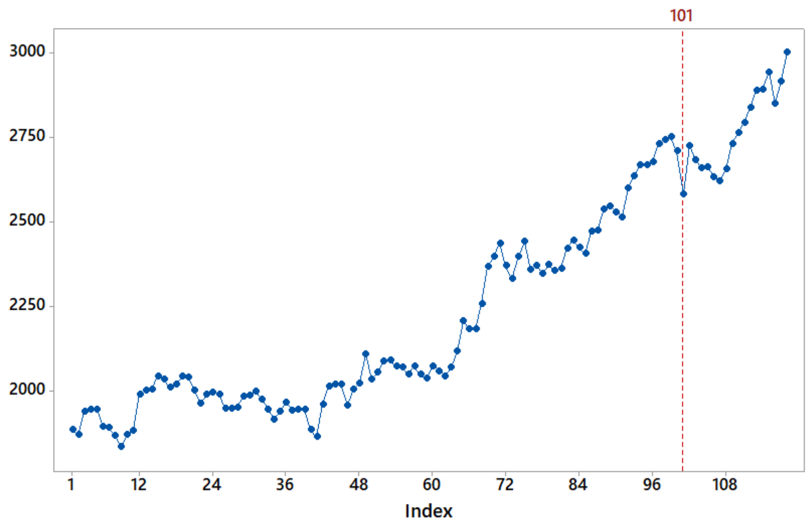


Figure 1: Time Series Plot of World Gold Prices

As shown in Figure 1, the pattern of world gold price data fluctuates with increasing value over the week. However, there was a significant decline in the second week of November 2024, namely at t = 101. The extreme decline that occurred in the 2nd week of November 2024 was due to an uncontrollable event, namely the strengthening of the USD currency after the results of the US election in 2024.

3.1 Modeling Pre-Intervention with ARIMA

To model the pre-intervention data with ARIMA, stationarity requirements in variance and average must be met, a Box-cox plot is used to check whether the data is are stationary in variance. The Box-Cox plot of the world gold price data before intervention can be seen in Figure 2 below.

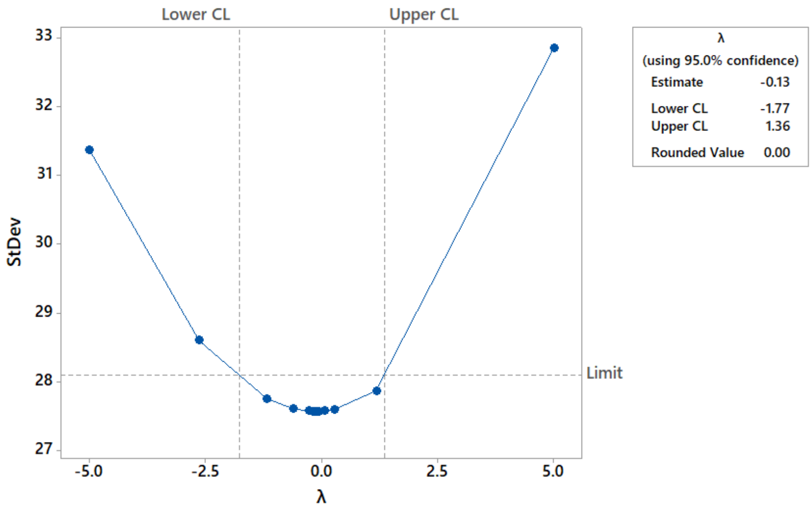
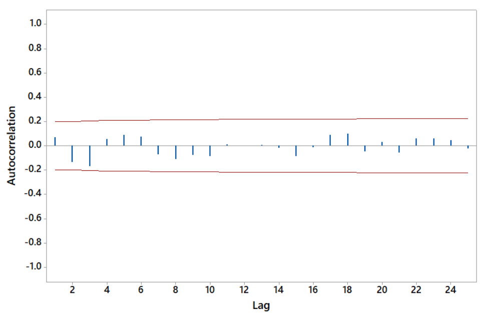
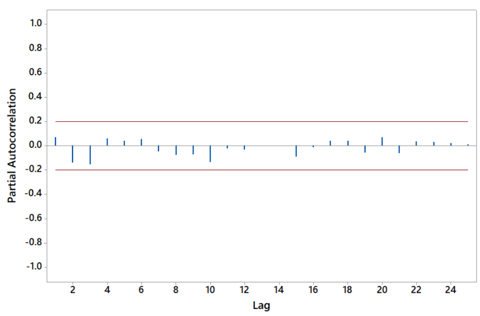


Figure 2: Pre-Intervention Box-Cox Plot

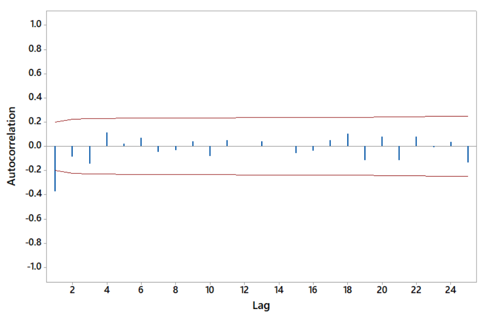
Based on Figure 2, the result of Box-Cox transformation is rounded value $\lambda = 0.00$. This shows that the preintervention world gold price data are not stationary in variance. So, it is necessary to do a transformation process with $\lambda = 0.00$ namely $\ln(Z_t)$ so that the data can be said to be stationary in variance. After the transformation is done, then identify stationarity in the mean using the ACF and PACF plots presented in Figure 3.



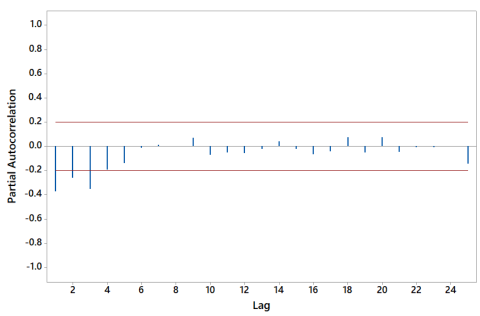
(a) ACF differencing 1



(b) PACF differencing 1



(c) ACF differencing 2



(d) PACF differencing 2

Figure 3: ACF and PACF Plot of Differencing 1 and 2

The stationary process of pre-intervention world gold price data is carried out with 2 times differencing. Figure 3, shows that the ACF plot results that there is a line that goes beyond, namely at lag 1, while the PACF plot result goes out past the limit, namely at lags 1, 2, and 3. Thus, the estimation of the ARIMA model for pre-intervention world gold price data can be formulated. Some ARIMA models that can be formulated 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). The following are the results of the parameter significance test, residual white noise test, and residual normality test.

Table 3: Diagnostic Test Results of Pre-Intervention ARIMA Model

ARIMA Models	Parameter Significance	White Noise	Normality Test
ARIMA (0,2,1)	significant	significant	significant
ARIMA (1,2,1)	not significant	significant	not significant
ARIMA (2,2,1)	significant	not significant	significant
ARIMA (3,2,1)	not significant	significant	not significant
ARIMA (1,2,0)	significant	not significant	not significant
ARIMA (2,2,0)	significant	not significant	not significant
ARIMA (3,2,0)	significant	significant	not significant

Based on Table 3, taking into account the parameter significance test, residual white noise, and residual normality, the models that fulfill the diagnostic test are ARIMA (0,2,1) and ARIMA (3,2,0). Then the AIC, MSE, SBC, and MAPE values are used to determine the best model.

Table 4: Comparison of MSE, AIC, SBC, and MAPE Values of ARIMA Models

Model	MSE	AIC	SBC	MAPE
ARIMA (0,2,1)	0.0003713	-563.1874255	-560.5723050	1.51%
ARIMA (3,2,0)	0.0004445	-773.5746108	-765.7292493	17.51%

Based on Table 4, the minimum values of MSE, AIC, SBC and MAPE are ARIMA (0,2,1). Thus, the model is said to be the best model in modeling pre-intervention data. The ARIMA (0,2,1) model can be written in Eq. 15 and Eq. 16.

$$(1-B)^2 Z_t^* = \theta_1(B)a_t \tag{15}$$

$$(1-2B+B^2)Z_t^* = (1-\theta_1 B)a_t$$

$$Z_t^* = 2Z_{t-1}^* - Z_{t-2}^* + a_t - \theta_1 a_{t-1} \tag{16}$$

3.2 Intervention Analysis

After the ARIMA model of the pre-intervention has been obtained, the next step is to determine the intervention order, namely b, r, and s, by analyzing the cross-correlation function (CCF) plot of the predicted post-intervention data using the best model with the actual post-intervention data of world gold prices. The CCF plot that has been obtained is presented in Figure 4 as follows.

Based on the CCF plot, the intervention starts to have an impact at lag 1, which indicates a delay of one period so that the intervention order is b = 1. There is no visible wave pattern, so the value of r = 0 indicates that the impact of the intervention is temporary. The value of s = 0 is because the effect of the intervention immediately decreases after the first lag. Next, the parameter estimation for the pulse function intervention model is presented in Table 5 below.

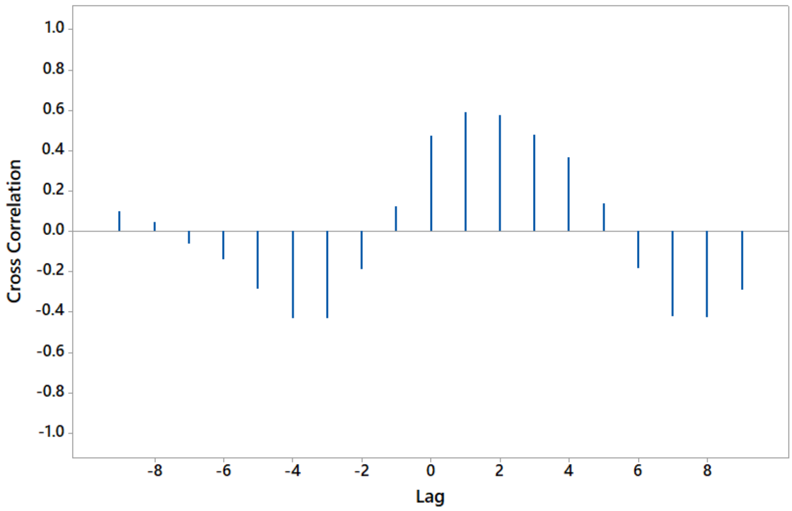


Figure 4: CCF Plot of Post-Intervention Data and Predicted Data of the Best ARIMA Model

Table 5: Intervention Model Parameter Significance Test Results

Intervention Model		Estimate	P-Value	White Noise	Normality
ARIMA (0,2,1) dengan $b = 1$, $r = 0$, dan $s = 0$	θ_1	0.84558	< 0.0001	Significant	Significant
	ω_0	0.03528	0.0102		

Table 5, shows that all parameters have a p-value $< \alpha = 0.05$. Therefore, the parameters of the ARIMA (0,2,1) intervention model with intervention order b = 1, r = 0 and s = 0 are significant. In addition, the residual white noise and normality tests have also been met. The general form of the equation of the intervention model is mathematically written as Eq. 17.

$$\dot{Z}_t = \frac{\omega_0(B)B^1}{\delta_0(B)} P_t^{(101)} + N_t$$

$$\dot{Z}_t = \frac{\omega_0 B^1}{1} P_t^{(101)} + N_t$$

$$\dot{Z}_t = \omega_0 P_{t-1}^{(101)} + N_t$$

Substituting $N_t = (1 + (2 - \theta_1)B + (2(2 - \theta_1) - 1)B^2 + \ldots)\alpha_t$, we get:

$$\dot{Z}_t = \omega_0 P_{t-1}^{(101)} + (1 + (2 - \theta_1)B + (2(2 - \theta_1) - 1)B^2 + \ldots)\alpha_t$$

Substitute the estimation $\omega_0 = 0.0352$ and $\theta_1 = 0.84558$:

$$\dot{Z}_t = 0.0352\, P_{t-1}^{(101)} + \Big(1 + (2 - 0.84558)B + (2(2 - 0.84558) - 1)B^2 + \ldots\Big)\, \alpha_t$$

$$\dot{Z}_t = 0.0352\, P_{t-1}^{(101)} + \Big(1 + 1.15442B + 1.30884B^2 + \ldots\Big)\, \alpha_t \tag{17}$$

with $\dot{Z}_t = \ln(Z_t)$.

3.3 Prediction of the World Gold Prices

After the intervention analysis model is formulated, model validation can then be carried out using test data totaling 7 data. With the calculation of MAPE in Table 6 below.

Table 6: Calculation of MAPE Value Based on Post-Intervention Data

Period	Date	Prediction	Actual	APE (%)
112	W4 January 2025	2811.574709	2835	0.8262889269
113	W1 February 2025	2830.758568	2887.6	1.968466265
114	W2 February 2025	2850.073322	2888.9	1.343995218
115	W3 February 2025	2869.519864	2940.5	2.413879815
116	W4 February 2025	2889.099093	2848.5	1.425279728
117	W1 March 2025	2908.811915	2914.1	0.1814654776
118	W2 March 2025	2928.366389	3001.1	2.423565507
MAPE (%)				**1.511848643**

Table 6 shows that the prediction results have a MAPE value of 1.512%, which means that the model has excellent predictive ability. In addition, there is a measure of the goodness of the intervention analysis model used, namely the MSE, AIC, and SBC values. The MSE, AIC and SBC values obtained from the ARIMA (0,2,1) model with intervention order b = 1, r = 0 and s = 0 are presented in Table 7 below.

Table 7: MSE, AIC, and SBC Value of Intervention Analysis Model

Intervention Model	MSE	AIC	SBC
ARIMA (0,2,1) dengan $b = 1$, $r = 0$, dan $s = 0$	0.0002037	-530.394	-525.030

Based on Table 6 and Table 7, the pulse function intervention model obtained resulted in a MAPE value of 1.51% and an MSE of 0.0002037, showing a very high prediction accuracy. Compared to a similar study, Aliffia et al. (2023) modeled world crude oil prices using a pulse intervention model and obtained an MAPE of 2.8982% and an MSE of 10.2687 [15]. Furthermore, Wasani and Projo (2022) used a pulse intervention model to analyze the impact of fuel price increases on inflation in South Sulawesi and obtained an AIC value of 104.09 [16]. This comparison shows that the model in this study not only results in lower prediction errors but also better information criterion values, thus strengthening its reliability and competitive performance in capturing the impact of external shocks on time series data. The comparison graph between the predicted data and the actual data is presented in the Figure 5 as follows.

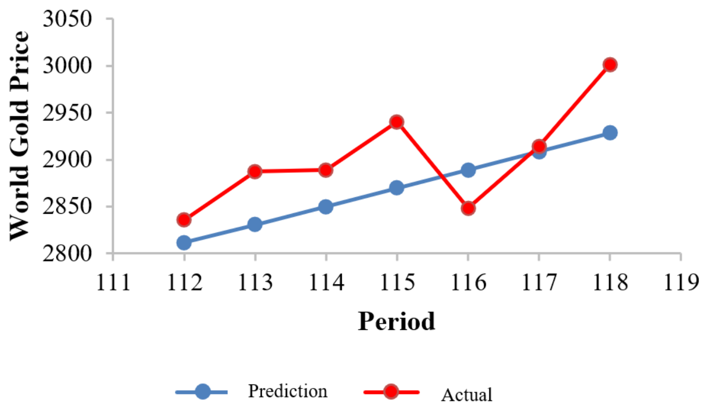


Figure 5: Comparison Plot of Actual Data and Predicted World Gold Price Results

Then predictions were made for the next 18 weeks, namely in the period from the 3rd week of March 2025 to the 4th week of July 2025, which are presented in Table 8 below.

Table 8: World Gold Price Prediction Results

Period	Date	Prediction	Period	Date	Prediction
119	W3 March 2025	2948.347138	128	W4 May 2025	3134.108366
120	W4 March 2025	2968.464219	129	W1 June 2025	3155.177395
121	W1 April 2025	2988.718562	130	W2 June 2025	3176.705715
122	W2 April 2025	3009.111104	131	W3 June 2025	3198.380926
123	W3 April 2025	3029.642789	132	W4 June 2025	3220.204030
124	W4 April 2025	3050.009548	133	W1 July 2025	3242.176038
125	W1 May 2025	3070.820289	134	W2 July 2025	3264.297964
126	W2 May 2025	3091.773026	135	W3 July 2025	3286.242192
127	W3 May 2025	3112.868726	136	W4 July 2025	3308.664789

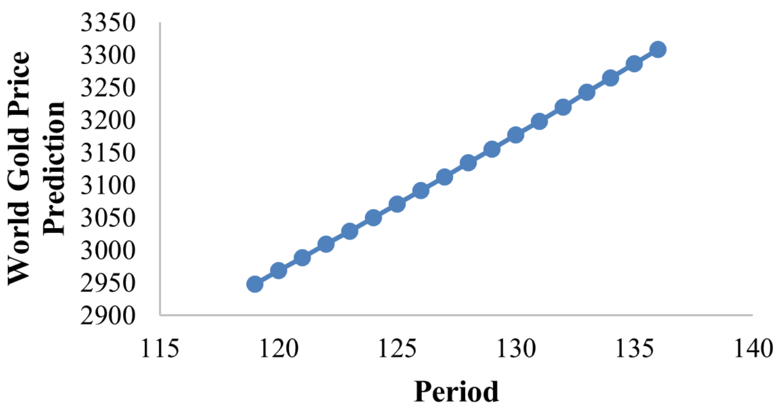


Figure 6: World Gold Price Prediction Plot

Based on the prediction results shown in Figure 6, it is known that the world gold price in the period from the 2nd week of March 2025 to the 4th week of July 2025 has an upward trend. This prediction model is built on data until the second week of March 2025, and the prediction results are carried out until the fourth week of July 2025. Therefore, the validity of the model is limited to these short-term periods. After July 2025, the model will need to be re-evaluated or retrained using the latest data, given the possibility of external or structural changes that could affect its accuracy. From a practical perspective, the use of historical gold price data for at least the past one to two years, such as the one used in this study since January 2023 provides enough information to capture market trends and recent structural changes. Shorter periods may miss long-term patterns, while data that are too long may reflect conditions that are no longer relevant. Therefore, a historical window of one to two years is recommended for investors who want to make short-term predictions or respond to recent global events.

4 Conclusion

The 2024 US presidential election triggered significant external shocks to world gold prices, marked by a sharp decline in the second week of November 2024. This study successfully applied the ARIMA model (0,2,1) with the intervention orde b = 1, r = 0, s = 0 to capture the direct and temporary impact of the strengthening of the US dollar. All parameters in the model were shown to be statistically significant and the model showed excellent prediction performance with a MAPE value of 1.51%, as well as low MSE, AIC, and SBC values. The predicted results show an upward trend in gold prices until the end of July 2025. These findings confirm the effectiveness of pulse intervention analysis in modeling sudden political economic events and provide important information for investors and policy makers on managing financial risk amid market volatility.

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. **Anggi Triya Vionita**: Data Curation, Formal Analysis, Writing-Review and Editing. **Fayza Shafira Renianti**: 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 (version 4, OpenAI) was 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.

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Data Availability

Data supporting the findings of this study were obtained from a publicly accessible source. Specifically, the historical gold price data used for the analysis can be found on the Investing.com website[5]. This ensures transparency and facilitates the reproducibility of the study results.

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