Analysis of International Gold Prices Using ARIMA, SVR with Linear Regression

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***Abstract*—As an important hedge asset and investment variety, gold has relatively stable value and wide market influence. The decisions made by people, businesses, and nations regarding their investments will be significantly impacted by the fluctuations in gold prices. Therefore, the analysis of international gold price is of great significance. The goal of this paper is to improve the existing gold price forecast models and analyze the daily gold price of US Dollar in the particular period by a hybrid model. This paper uses Root of Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to estimate the error of different models. Through a brief review of current research techniques on global gold price prediction, we may incorporate their benefits and reduce the errors that may exist in the single model and create a new hybrid model to enlarge the presicion of forecasting the gold price. The improvement of the hybrid model will relatively impact the modeling accuracy of gold price forecasting.**

***Keywords*—forecast, gold price, Autoregressive Integrated Moving Average model (ARIMA), Support Vector Regression (SVR), linear regression, hybrid model**

I. INTRODUCTION

The world economy is developing quickly and dynamically, which gives investors several new ways to deposit their available funds. One of these opportunities can be represented, for example, by investing in precious metals. Nowadays, there are many applications for precious metals, including cell phones, catalytic converters, spacecraft and jet plane engines, and electronics and communication gadgets. According to (Canda, Heput, & Ardelean, 2016), the most prevalent metals are and gold from jewelry and electronics, platinum from catalytic converters used for oil refinement, and silver from electronics, radiography, film, jewelry, and industrial applications. Therefore, the knowledge of forecast on gold price is essential for not only institutes but also individuals. Gold is a rare metal with great financial and storage value in addition to its value as a collectible. The majority of researchers have been drawn to actively predict gold price as it is an investment target due to its stability in the face of an increasingly volatile financial environment. Numerous variables, including inflation, monetary policy, and exchange rates, have an impact on gold prices. This paper will mainly focus on the time series model building of the global gold price, and combine the predicted Autoregressive Integrated Moving Average model (ARIMA), Support Vector Regression (SVR) value with linear regression model to generate a hybrid algorithm to forecast the international gold price more precisely.

II. LITERATURE REVIEW

There are now a large number of studies analyzing international gold prices. Guha & Bandyopadhyay (2016) applied ARIMA to forecast the gold prices, they use the data from from November 2003 to January 2014, Multi Commodity Exchange of India Ltd (MCX) to construct the data sourse, evaluate and plot the graph of the data. They use Durbin-Watson Test (DW) to detect the presence of autocorrelation for its suitability for regression analysis. Durbin-Watson (DW) ≈ 2[1−ρ(1)], where ρ(1) is the 1st order auto-correlation.They found out the autocorrelation and partial auto-correlation between the values of the data, and then construct the evaluation system which contains RMSE, MAPE, MAE, Bayesian Information Criterion (BIC), and Q-value. The result shows that when choosing ARIMA (1, 1, 1), and it satisfies all the criteria of fit statistics However, ARIMA is limited to short runs and is used to identify minute variations in the data. Furthermore, because this method of forecasting is predicated on the assumption of linear historical data—as there is no evidence to support the linear nature of the gold price—it becomes difficult to capture precise changes in the event of sudden changes in the data set (when the variation is large), changes in government policies, economic instability (structural break), etc.

In addition, researchers also compared polynomial regression and Double Exponential Smoothing (DES) to predict the gold price (Fahrudin, Riyantoko, Hindrayani, & Gede, 2021). They apply the formula of polynomial regression defined as:

$$y = a_0 + a_1 \times x_1 + a_2 \times x_1^2 + .. + a_n \times x_n^n \tag{1}$$

And the DES model defined as:

$$S'_t = \alpha X_t + (1-\alpha)(S'_{t-1} + T_{t-1}) \tag{2}$$

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Both S'_{t-1} and T_{t-1} need to be computed beforehand. When t = 1, these values are not accessible. As a result, it needs to be ascertained at the start of the time interval where S'_{t-1} and T_{t-1} equal X_1.

They use these two models to forecast the gold bullin price by using the MAPE as the assessment criterion. According to the experiment, Holt's double exponential smoothing outperformed polynomial regression in terms of performance. In the training set, Holt's double exponential smoothing reached MAPE of 0.056%; in one-step testing, it reached 0.047%; and in multi-step testing, it reached 0.898%.

Despite using traditional time series method to predict the gold price, some methods combine time series modeling with maching learning. Dubey (2016) used the Support Vector Regression (SVR) and the Adaptive Neural Fuzzy Inference System (ANFIS) to forecast the daily gold price for Perth Mint, official bullion of Australia. The dependencies between the input and destination datasets are determined using SVR, which blends regression with a support vector machine. A training set for epsilon support vector regression is defined as{(x1,y1)... (xt,yt)} ⊂ R， where where *yi* is the set of goal values and *xi* is the set of input features. Hence, the function is defined as:

$$f(x) = w \times \Phi(x) + b \quad (3)$$

The primary goal of this function is to determine the values of w and b that will allow for the least amount of regression risk while evaluating the value of x. The regression function is defined as:

$$R_{reg}(f) = C\sum_{i=0}^{l} \tau(f(x_i) - y_i) + \frac{1}{2} \parallel w \parallel^2 \quad (4)$$

where $\tau(f(x_i) - y_i)$ is the cost function (ε-insensitive loss function), we consider the absolute difference between predicted value and real value,

$$\tau(f(xi) - yi) = 0\,, if\ |f(xi) - yi| \leq \ \varepsilon \quad (5)$$

$$\tau(f(xi) - yi) = \ |f(xi) - yi| - \ \varepsilon, if\ |f(xi) - yi| > \ \varepsilon \quad (6)$$

Here, C is the constant that establishes how to change the flatness of the function and deviations from the target that are greater than ε.

ANFIS model is a sugeno fuzzy model which can be described as:

$$\text{If } x_1 \text{ is } A \text{ and } x_2 \text{ is } B\text{, then:} \\ y = f(x_1, x_2) = f(A, B) \quad (7)$$

where A and B define the fuzzy sets and f is the function that is connected to the facts of x_1 and x_2, which correspond to A and B. The ANFIS model's architecture, which is broken down into five layers, is shown in Fig. 1. The following is a description of these five layers:

Finally, they evaluate the accuracy of the model by calculating RMSE (Root Mean Square Error), MAE (Mean Absolute Value) and MAPE (Mean Absolute Percentage Error). From the results obtained they made a conclusion that the support vector regression has a better prediction ability for gold price than ANFIS.

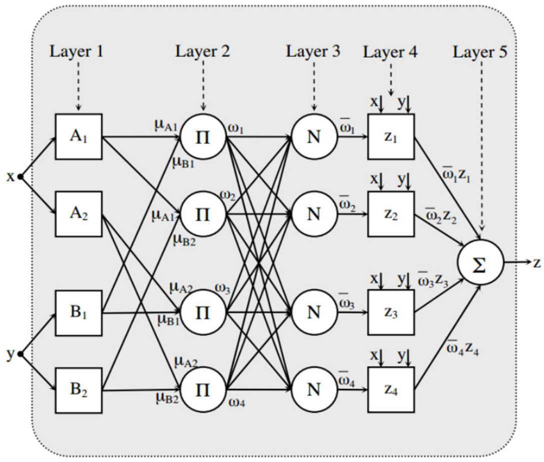

Fig. 1. Basic architecture of ANFIS.

Hybrid method is also considered in gold price forecast in the study. According to another research (Hassani, Silva, Gupta, & Segnon, 2015), Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) was combined with ARIMA model. Consequently, hybrid ARIMA-GARCH modeling is used in predicting the gold price. The researchers used 40 daily gold price data series and build the hybridization of ARIMA(1,1,1)-GARCH(0,2), which met all diagnostic requirements, including the heteroskedasticity test, and displayed a 1% significance level, and the transformed data are given by:

$$y_t^* = 0.274y_{t-1}^* + 0.726y_{t-2}^* + \varepsilon_t - 0.992\varepsilon_{t-1} \quad , \\ \varepsilon_t \sim \text{ iid } N(0,1) \quad (8)$$

$$\sigma_t^2 = 1.16 \times 10^{-5} + 1.992\sigma_{t-1}^2 - 1.025\sigma_{t-2}^2 \quad (9)$$

The researchers also used the similar evaluation system as above, and eventually the result was that of ARIMA(1,1,1) - GARCH(0,2) demonstrates the hybrid model's promising performance in predicting the daily gold price series, where the predicted price trend closely resembles the real data, even for the five-day out-of-sample simulation portion.

The combination of ARIMA-GARCH is a new potential method for analyzing and forecasting the daily gold price because it combines the power and flexibility of ARIMA with the strength of GARCH models in handling volatility and risk in the data series as well as overcoming the linear and data limitation in the ARIMA models, which implies that hybrid method may have better precision than the single method.

Although each of these methods works well in the given data in the sample, they may not work as well as they are expected when they are singly applied to forecast recent international gold price data provided by World Gold Council. Therefore, we are supposed to generate a better method based on these previous researches and let the new method better approach the data in recent days that we have.

III. Materials and Methods

A. Data Sources

This paper uses the data that are collected from the World Gold Council, consisting observations from 2023, January 1st to 2024 Augest 9th, totally 420 data. The sample will be divided into two parts: training set and testing set. In particular, we will choose recent data that have strong correlation and close time periods to classify them into two parts. In the training set, we choose data in 2023, totally 260 data, to build the model, in terms of the test set, we will choose 2024 gold prices data, totally 160 data as observations.

B. Data Description

We depict the series plot of the gold price in the given periods. And we will use these data as the training set and build a model for the test set.

Fig. 2. Daily gold price from 20230101 to 20231229.

Fig. 2 displays the daily gold price from January 1st, 2023 to December 29th, 2023. It shows that gold price fluctuates during this period between 1,850 USD and 2,050 USD. It shows that the international gold price is oscillating in a relatively fixed range in 2023.

C. Methodology

1) ARIMA (Auto Regressive Integrated Moving Average Model)

ARIMA model seems to be one of the models that is used most frequently to forecast the price of gold (George & Jenkins, 1970). When the data is collected, ARIMA shows good performance in analyzing the trend and fluctuations in the immediate future. Generally, ARIMA model can be recognized as:

$$\text{ARIMA}\ (p,d,q) : y'_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y'_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}$$

$$\text{With } y'_t = \Delta^d y_t = (1-L)^d y_t \tag{10}$$

2) SVR (Support Vector Regression)

SVR is an extended model from the Support Vector Machine (SVM), SVM is a supervised learning technique that classifies data using an ideal hyperplane in N-dimensional space (Wang, 2005). SVR combines the property of regression and that of SVM. It allows more flexibility to define the maximum acceptable error rate in the model. The model's epsilon, ϵ, can be changed to provide the required precision. The $L2$ loss, which is the least squares error between the actual and predicted values, is the loss function that we used in the SVR. Finding a function $f(x)$ whose variation is as flat as possible and at the maximum ϵ from all target values is the aim of SVR (Yang, Montigny, & Treleaven, 2021)

3) Linear regression (Hoffmann, 2021)

Since we just consider the First-Order case, we could construct a multi-variable linear regression model, which is depicted as:

$$y = X\beta + \alpha \tag{11}$$

Traditionally, we could fit the data from different factors by considering it as a matrix and the parameter vector is found by the formula.

$$X^{\top} X \vec{\beta} = X^{\top} Y \tag{12}$$

D. Performance Measurement Tools

1) RMSE

Root Mean Square Error (RMSE) is a common estimator to evaluate the average difference between statistical model's predicted values and the actual values. Mathematically, It is the residuals' standard deviation. The distance between the data points and the regression line is represented by residuals. Its formula is defined by:

$$RMSE = \sqrt{\frac{\Sigma\left(y_i - \hat{y}_i\right)^2}{N-P}} \tag{13}$$

where y_i is the actual value for the ith observation, $\hat{y}_i$ is the predicted value for the ith observation, N is the number of observations, P is the number of parameter estimates, including the constant. When comparing different models, we usually look at the relative difference of RMSEs for different prediction model, the relative RMSE comparison formula is:

$$Relative\ RMSE = \left|\frac{(RMSE1 - RMSE2)}{RMSE1}\right| \tag{14}$$

Small relative changes (e.g., within 2%) may frequently be regarded as modest when assessing the relevance of RMSE value differences, however differences of above 3% may suggest a relatively significant variation in model accuracy, particularly in smaller datasets (e.g., with less than 500 data points) (Chai and Draxler, 2014).

2) MAE

Mean Absolute Error (MAE) is a simple but powerful metric used to evaluate the accuracy of regression models. It evaluates the average aboslute difference between the predicted values and the real values. MAE assigns equal weight to all errors, regardless of their direction, in contrast to other metrics that square the errors. Because of this characteristic, MAE is especially helpful for determining the size of errors without taking into account whether they are overestimations or underestimations. The formula is described as:

$$\text{MAE} = \frac{\sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|}{n} \tag{15}$$

where n is the number of data points. y_i represents the actual target value for data point i. $\hat{y}_i$ represents the predicted value for data point i.

3) MAPE

Mean Absolute Percentage Error is known as MAPE. One of the most widely used metrics for comparing and evaluating forecasting performance is this one. By dividing the average absolute percentage error minus the actual value by the actual value, it determines the performance accuracy. So the formula is defined as:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\text{Actual} - \text{Forecast}}{\text{Actual}} \right| \tag{16}$$

We will use these three indicators mentioned above to determine the performance and accuracy among different models.

IV. RESULT AND DISCUSSION

By fitting the data with those three models, we get the formulas for three prediction models. For the best ARIMA we use auto_arima to find the best parameters including (p, d, q), which are (0,1,0). Therefore the ARIMA model is ARIMA (0,1,0). For SVR model, we use Radial Basis Function (RBF) kernel to find out the best parameters that minimize.

$$R_{reg}(f) = C \sum_{i=0}^{l} \tau(f(x_i) - y_i) + \frac{1}{2} \parallel w \parallel^2 \tag{17}$$

The RBF kernal is defined as:

$$\kappa(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{18}$$

Finally, we combine the predicted value of two models and use least square method to find out the parameters of the hybrid linear model and establish its formula as:

$$\hat{y} = -5.2717 + 1.1208 \cdot \text{ARIMA} - 0.1173 \cdot \text{SVR} \tag{19}$$

After doing those steps, we plotted the curve to observe the trends among three models. The result is plotted in Fig. 3.

When we plot all three models to the time diagram in Fig. 3, we observe that three models seem to be relatively acceptable, they all fit the trend of the real values. Therefore, we should consider the three evaluation factors mentioned above to demonstrate that the hybrid ARIMA-SVR linear model is better than the two single models.

In Fig. 4, we compare the RMSE of three models. we find that the linear-mix model performs better than ARIMA Which has the second lowest RMSE. Particularly, the relative RMSE between hybrid model and ARIMA is 4%, which could be considered as a relative significant impact on the data prediction.

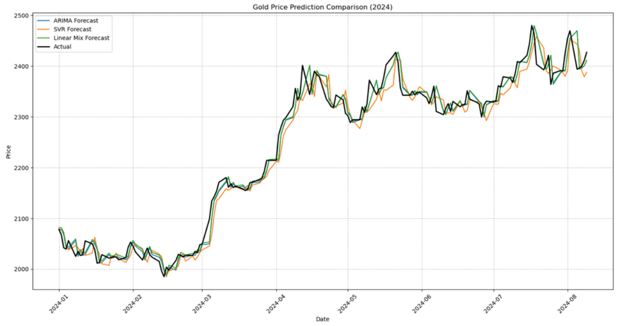

Fig. 3. Time plot of 3 models.

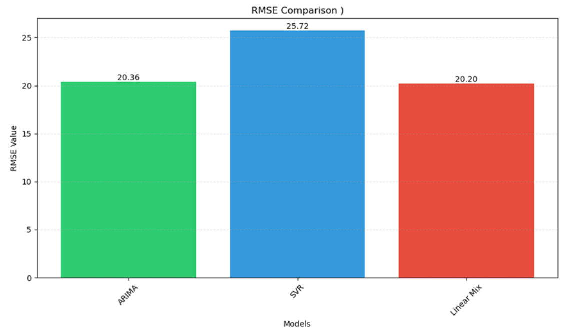

Fig. 4. RMSE comparison among 3 models.

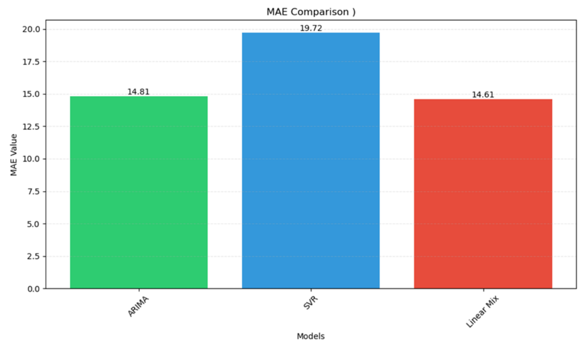

Fig. 5. MAE comparison among 3 models.

Meanwhile, we also compare the MAE in Fig. 5. It implies that the hybrid model has the lowest MAE, which also implies the hybrid model has relatively better performance and accuracy on the prediction on gold price.

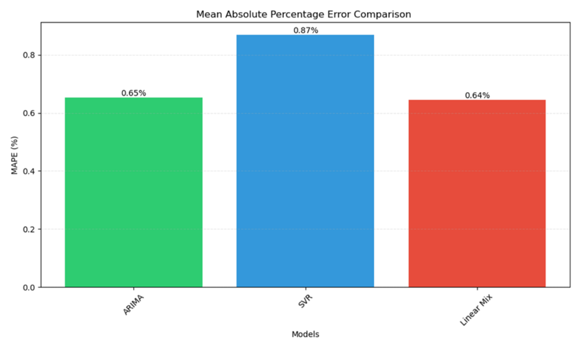

Fig. 6. MAPE comparison among 3 models.

Similarly, if we calculate the MAPE,which is shown in Fig. 6, we also find that the linear-mix hybrid model has the lowest factor among three models. Hence, the data clearly support and demonstrate the better performance and error control on the hybrid model. we can also see the evaluation factors on the table below:

TABLE I. THE SUMMARY OF ALL COMPARED DATA

Model	RMSE	MAE	MAPE (%)
ARIMA	20.36	14.81	0.65
SVR	25.72	19.72	0.87
LinearMix	**20.20**	**14.61**	**0.64**

By observation, we can easily find that the hybrid linear-mix model has the lowest value in all there indicators, which can be conclued to have the best prediction accuracy among these three models.

V. APPLICATIONS

A. *Prediction Simulations*

After building this hybrid model, we use it to predict the near future's data of international gold price, the test set is given by the international gold price data starting from 2024. 01.01.to 2024. 08.07. We fix the parameters of our model and to see the accuracy of our predicted information and the real data. The accuracy trend of the estimators are given in Fig. 7, dividing quarterly.

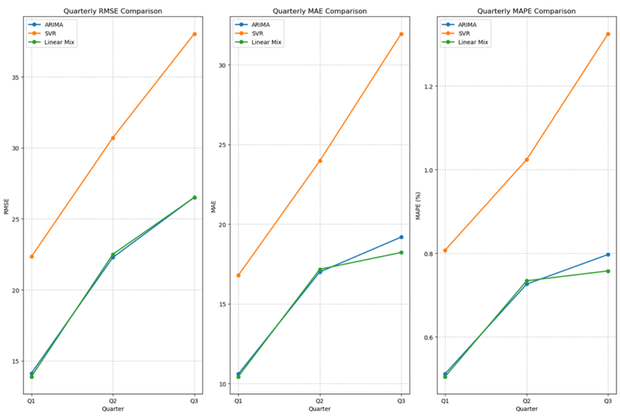

Fig. 7. Accuracy trend (quarterly).

We can easily observe that the linear mixed model has smaller absolute error and error fluctuations over longer forecast periods than the traditional ones. We also make an appendix table to list the predicted value among those three models to numerically see the differences. Hence, if we use this hybrid model to do the investment, it will be more accurate and with less risk.

B. *Connections with Management Theory*

Accurate gold price forecast plays an essential role in management analysis. For a financial management perspective, companies can hedge against potential losses due to investment volatility by leveraging accurate international gold price forecast. By the Portfolio Theory (Constantinides & Malliaris, 1995), as a save-haven asset, the accurate prediction of the price volatility of international gold price enables corporates and investors to provide protections on the asset when encountering market instability or economic uncertainty. Therefore, gold price prediction can be used to improve the risk-adjusted return of the portfolio. For instance, the equity and stock risks can be reduced by adding gold assets to the portfolio in the appropriate time period to hedge the exposure. In summary, gold price prediction is an important part in the application of Portfolio Theory, which can help companies and investors better deal with market dynamics, optimize asset allocations and and manage risks.

VI. CONCLUSIONS

In this paper, we creatively found a hybrid linear-mixed model that combines ARIMA and SVR, and it performs relatively better compared to the existing single ARIMA model and SVR model. However, we still cannot find the specific principle to form a theory of these discovery. It is currently becoming more and more popular to forecast international gold price using hybrid model and machine learning. This paper may give a hint for scholars to find out a much better hybrid models among different single models and also to discover the principles and theorems to support the hybrid methods.

APPENDIX A

TABLE I. LINEAR MIXED MODEL PREDICTION SUMMARY (2024)

Date	Actual Price (Troy ounce)	Linear-mix Prediction	Linear-mix Error
01–01	2078.40	2080.38	1.98
01–02	2067.55	2080.33	12.78
01–03	2042.10	2069.11	27.01
01–04	2039.55	2043.13	3.58
01–05	2056.35	2041.10	−15.25
01–08	2025.10	2058.50	33.40
01–09	2034.90	2025.90	−9.00
01–10	2026.80	2036.76	9.96
01–11	2029.15	2028.07	−1.08
01–12	2055.65	2030.77	−24.88
01–15	2049.90	2058.05	8.15
01–16	2038.15	2051.47	13.32
01–17	2011.75	2039.51	27.76
01–18	2013.20	2012.47	−0.73
01–19	2028.55	2014.61	−13.94
01–22	2021.60	2030.44	8.84
01–23	2022.95	2022.95	0.00
01–24	2024.65	2024.50	−0.15
01–25	2023.75	2026.16	2.41
01–26	2018.45	2025.21	6.76
01–29	2022.50	2019.78	−2.72
01–30	2043.05	2024.07	−18.98
01–31	2053.25	2045.18	−8.07
02–01	2045.85	2055.24	9.39

02–02	2034.15	2047.37	13.22
02–05	2018.00	2035.43	17.43
02–06	2030.80	2019.02	−11.78
02–07	2041.60	2032.64	−8.96
02–08	2028.65	2043.50	14.85
02–09	2023.50	2029.92	6.42
02–12	2015.20	2024.88	9.68
02–13	1996.10	2016.39	20.29
02–14	1985.10	1996.91	11.81
02–15	2004.05	1986.02	−18.03
02–16	1997.90	2005.82	7.92
02–19	2017.05	1999.05	−18.00
02–20	2029.10	2018.99	−10.11
02–21	2026.75	2030.90	4.15
02–22	2024.00	2028.22	4.22
02–23	2027.45	2025.43	−2.02
02–26	2027.20	2029.02	1.82
02–27	2035.05	2028.70	−6.35
02–28	2032.45	2036.83	4.38
02–29	2048.05	2033.95	−14.10
03–01	2049.80	2050.12	0.32
03–04	2098.05	2051.54	−46.51
03–05	2134.40	2101.32	−33.08
03–06	2142.85	2137.67	−5.18
03–07	2153.45	2145.57	−7.88
03–08	2171.20	2156.26	−14.94
03–11	2180.45	2174.27	−6.18
03–12	2161.25	2183.44	22.19
03–13	2168.40	2163.43	−4.97
03–14	2160.80	2171.25	10.45
03–15	2163.45	2163.21	−0.24
03–18	2158.15	2166.19	8.04
03–19	2154.90	2160.64	5.74
03–20	2157.45	2157.41	−0.04
03–21	2170.50	2160.11	−10.39
03–22	2171.60	2173.52	1.92
03–25	2176.70	2174.36	−2.34
03–26	2179.80	2179.60	−0.20
03–27	2192.70	2182.64	−10.06
03–28	2214.35	2195.89	−18.46
03–29	2214.35	2217.93	3.58
04–01	2214.35	2217.42	3.07
04–02	2264.50	2217.42	−47.08
04–03	2280.15	2269.14	−11.01
04–04	2293.50	2284.12	−9.38
04–05	2298.55	2297.60	−0.95
04–08	2320.25	2302.40	−17.85
04–09	2356.10	2324.66	−31.44
04–10	2333.00	2361.17	28.17

04–11	2345.65	2336.50	−9.15
04–12	2401.50	2350.11	−51.39
04–15	2344.20	2407.36	63.16
04–16	2369.15	2346.98	−22.17
04–17	2390.35	2374.16	−16.19
04–18	2382.70	2395.24	12.54
04–19	2379.70	2387.01	7.31
04–22	2334.95	2384.11	49.16
04–23	2328.45	2337.89	9.44
04–24	2320.25	2332.28	12.03
04–25	2318.70	2323.95	5.25
04–26	2343.10	2322.63	−20.47
04–29	2333.55	2347.84	14.29
04–30	2307.00	2337.37	30.37
05–01	2302.35	2310.22	7.87
05–02	2288.85	2305.98	17.13
05–03	2294.45	2292.15	−2.30
05–06	2294.45	2298.32	3.87
05–07	2319.60	2298.17	−21.43
05–08	2309.05	2324.14	15.09
05–09	2325.70	2312.63	−13.07
05–10	2372.45	2330.08	−42.37
05–13	2343.80	2377.87	34.07
05–14	2354.85	2347.23	−7.62
05–15	2357.50	2359.36	1.86
05–16	2377.40	2361.69	−15.71
05–17	2402.60	2382.27	−20.33
05–20	2420.30	2407.82	−12.48
05–21	2427.30	2425.48	−1.82
05–22	2407.90	2432.27	24.37
05–23	2357.35	2412.05	54.70
05–24	2342.70	2360.34	17.64
05–27	2342.70	2346.41	3.71
05–28	2350.65	2346.77	−3.88
05–29	2343.35	2355.07	11.72
05–30	2348.55	2347.35	−1.20
05–31	2348.25	2352.85	4.60
06–03	2337.70	2352.37	14.67
06–04	2326.00	2341.51	15.51
06–05	2340.05	2329.68	−10.37
06–06	2360.60	2344.45	−16.15
06–07	2310.80	2365.34	54.54
06–10	2304.40	2313.49	9.09
06–11	2316.50	2308.05	−8.45
06–12	2326.25	2320.58	−5.67
06–13	2310.80	2330.48	19.68
06–14	2330.45	2314.33	−16.12
06–17	2319.90	2334.92	15.02
06–18	2324.35	2323.52	−0.83

06–19	2324.25	2328.43	4.18
06–20	2351.60	2328.17	−23.43
06–21	2335.05	2356.42	21.37
06–24	2328.75	2338.70	9.95
06–25	2325.05	2332.61	7.56
06–26	2299.65	2328.87	29.22
06–27	2323.60	2302.77	−20.83
06–28	2330.90	2328.13	−2.77
07–01	2329.10	2335.06	5.96
07–02	2331.75	2333.10	1.35
07–03	2361.35	2335.83	−25.52
07–04	2358.65	2366.28	7.63
07–05	2379.05	2362.82	−16.23
07–08	2376.65	2383.97	7.32
07–09	2367.90	2380.94	13.04
07–10	2384.35	2372.00	−12.35
07–11	2409.20	2389.17	−20.03
07–12	2406.85	2414.42	7.57
07–15	2421.25	2411.46	−9.79
07–16	2443.20	2426.37	−16.83
07–17	2480.25	2448.62	−31.63
07–18	2463.80	2486.38	22.58
07–19	2403.50	2468.53	65.03
07–22	2392.70	2406.67	13.97
07–23	2403.10	2396.88	−6.22
07–24	2421.45	2407.88	−13.57
07–25	2364.20	2426.72	62.52
07–26	2386.10	2367.20	−18.90
07–29	2391.10	2391.10	0.00
07–30	2390.25	2395.63	5.38
07–31	2426.30	2394.79	−31.51
08–01	2454.55	2431.99	−22.56
08–02	2469.85	2460.22	−9.63
08–05	2393.85	2475.40	81.55
08–06	2396.55	2396.55	0.00
08–07	2400.45	2401.11	0.66

CONFLICT OF INTEREST

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

Hang Zheng conducted the research and analyzed the data and wrote the paper. The author had approved the final version of the paper.

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