

# U.S. Imports Price of Goods Forecasting by Customs Basis from China using SARIMA Model

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**Abstract.** Changes in the import price of goods will have an influence on the global economy and trade, corporate decision-making, and many other aspects. Therefore, the aim of this research is to forecast the future customs prices of US imports from China. The data comes from the Bureau of Economic Analysis. It can provide an important reference for enterprises, government, and academia to make better decisions. In this paper, due to the strong seasonality, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a common technique that is generally used in analyzing and predicting seasonality and stationary time series data. Using the Sarima model to predict U.S. imports of goods from January 1986 to December 2016 and to compare the predicted data with original data. To identify the best model and find out the highest accuracy of the model, this paper utilizes the Grid Search method and calculates Akaike's Information Criterion (AIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and adapted MAPE (AMAPE) value as the criterion for selection. The result shows that in the next six months, the amount will still be seasonal, but the overall trend will show small fluctuations and will not change much.

**Keywords:** SARIMA; AIC; RMSE; MAPE; Grid search.

## 1. Introduction

The rapid ascent of China to significance in the global economy in recent times is an important feature of the contemporary global economy [1]. America's imports of goods from China, Mainland, and Customs Basis were 36,099.50 as of 2023-07-01, according to the Bureau of Economic Analysis [2]. Exports of Chinese goods to developed countries are quite substantial. There are several studies that have demonstrated the impact of China's increasing import competition on American society, including negative effects on the employment prospects of manufacturing workers [3], health and mortality [4], and the marriage market and fertility rates [5]. The U.S. House declared that China's economic growth plays an important role in America. As a result, Congress has deemed it a matter of major interest to the country [6].

In recent years, there has been a trade war between America and China. Imposing tariffs has been the most prevalent tactic used by both sides in this "war" between the U.S. and China, and as a result, the two countries' tariff levels have increased dramatically [7]. The United States and China struck a first-phase deal in January 2020, but the tariffs remain in place. Therefore, there is still a great deal of uncertain situations concerning the two nations' commercial and economic connections [8]. Predicting customs prices can help businesses and governments better manage risk. If they know that the United States is about to impose higher tariffs on Chinese imports, Chinese companies can take steps to reduce costs or find other markets to mitigate the impact of tariffs. The U.S. government can also use this information to assess the risks of tariff policies and take steps to address potential negative impacts.

In similar directions, Christian Grimme et al. believe that domestic import demand should be reflected in the expected export development of its major trading partners, therefore they choose to use the Import Climate as an indicator to predict imports [9]. In order to improve the accuracy of import predictions, Wang et al. established a Non-linear autoregressive neural network ARIMA [10]. This approach enhances the readability of non-linear time series and minimizes the impact of non-linear components on the forecast. Furthermore, Dave et al. predicted imports by using the ARIMA-

long short-term memory (ARIMA-LSTM) model [11]. By combining ARIMA and LSTM models, the hybrid model was able to leverage the strengths of both. LSTM was applied on the non-linear component of the data, while ARIMA was used on the linear component, resulting in a highly accurate forecast.

The ARIMA model is widely used in forecasting for various applications. The prediction of financial time series has multiple applications in predicting capital flow across various industries. For example, Fan used the ARIMA model to predict the overall trend of total purchases and redemptions in the future [12]. Assistance is provided to the inflow and outflow of managed funds. Additionally, Lai proposed a novel application of the Prophet model to forecast consumption tax for passenger cars. This approach represents a unique perspective on tax prediction for industry categories [13].

ARIMA is indeed one of the most widely used time series models for statistical forecasting. It is known for its significant forecasting accuracy and efficiency, making it a popular choice among data analysts and researchers. Box et al. proposed an ARIMA model that could analyze and predict future data and the SARIMA model is more suitable for seasonal time series prediction [14]. In addition, The ARIMA model is a combination of autoregressive polynomials (AR) and moving average polynomials (MA) with complex polynomials. Instead, the SARIMA model is employed when the data exhibits seasonal cyclical fluctuations that repeat throughout the year. Therefore, the SARIMA method is the most effective for analyzing data with seasonal cyclical variations, such as monthly mean temperature data [15].

The SARIMA model is known to be a popular method for prediction in a lot of fields, including solar PV power generation forecast [16], prediction and analysis of aircraft failure rate [17], power load data prediction [18], etc. The model stands out in its ability to predict trends in data series regardless of whether they are seasonal or not.

In summary, after consideration and optimization, forecasting the U.S. Imports price of Goods by Customs Basis from China can help businesses and governments make more informed decisions, understand market needs and trends, manage risks, assess policy effects and impacts, and provide a valuable reference for academic study.

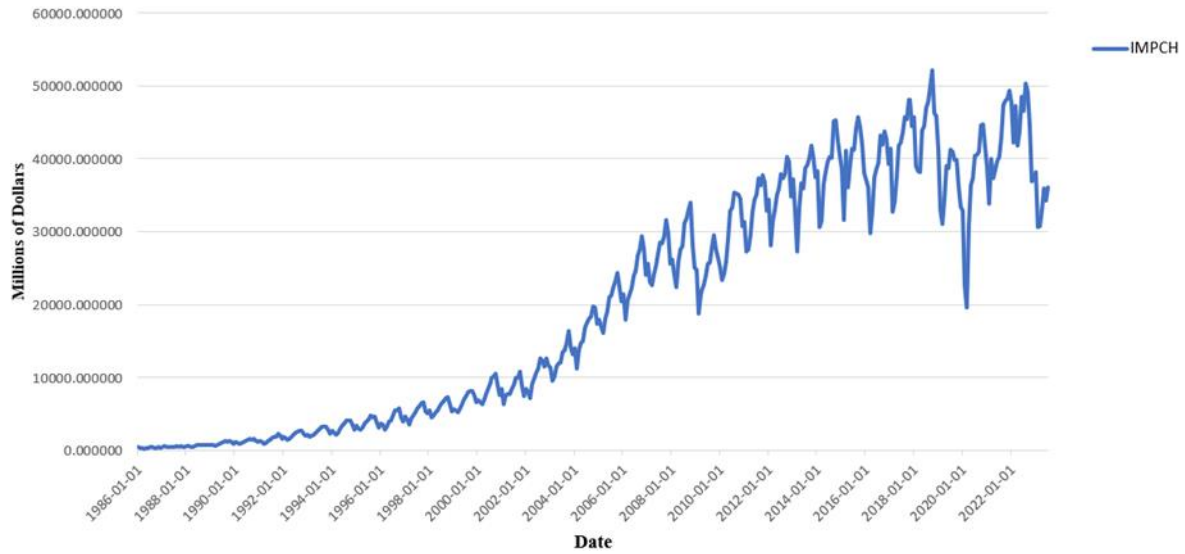
## 2. Methodology

### 2.1. Data Source

Data for the literature were obtained from the U.S. Census Bureau and the U.S. Bureau of Economic Analysis, retrieved from FRED. The site's data is updated monthly, most recently to July 2023. There are 451 historical data from January 1986 to July 2023.

### 2.2. Data Preparation

The data used in this paper count a total of 451 days, displaying the Times Series Graph below to examine the overall pattern. The fig.1 presents that the overall trend of the broken line showed a clear upward trend. However, the growth rate was relatively fast before 2014, and the growth rate was slower after 2010. It is also easy to observe that the data has seasonality, with the trend changing from year to year the same as the previous year.



**Fig. 1** The total amount of IMPCH from January 1986 to July 2023

### 2.3. SARIMA Model

The SARIMA model is a time series that Box and Jenkins proposed to predict future data in the 1970s [19]. The SARIMA model is composed of two parts:  $(p, d, q)(P, D, Q)_S$ . Mathematically it is represented in the next Equation [20]:

$$\phi(B)\Phi(B^S)(1 - B^S)^D(1 - B)^dZ_t = \theta(B)\Theta(B^S)\varepsilon_t \quad (1)$$

Where for non-seasonal AR:  $\phi(B) = 1 - \phi_1B - \phi_2B^2 - \phi_3B^3 - \dots - \phi_pB^p$ . For non-seasonal MA:  $\theta(B) = 1 - \theta_1B - \theta_2B^2 - \theta_3B^3 - \dots - \theta_qB^q$ . For seasonal AR:  $\Phi(B^S) = 1 - \Phi_1B^S - \Phi_2B^{2S} - \Phi_3B^{3S} - \dots - \Phi_pB^{pS}$ . For seasonal MA:  $\Theta(B^S) = 1 - \Theta_1B^S - \Theta_2B^{2S} - \Theta_3B^{3S} - \dots - \Theta_qB^{qS}$ .  $Z_t$  ( $t = 1, 2, \dots, k$ ) represents observed value,  $\varepsilon_t$  is the residual error,  $B$  is the backward shift operator.

The process of this model involves four steps: data preprocessing, identification and estimation, diagnostic checking, and prediction. Stationarity, white noise, and seasonality are the prerequisites for the establishment of the SARIMA model. The augmented Dickey-Fuller (ADF) test is the most used unit root test method that could test whether the time series is stationary.

The determination of the order of the SARIMA model is based on the analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs. These graphs provide information on the correlation between observations at different lags. The method commonly used to select a suitable model is AIC.

RMSE and MAPE and AMAPE are commonly used metrics to evaluate the performance of forecasting models. If the values of RMSE, MAPE, and AMAPE are smaller, it means the model fits better. If the fitting effect is accurate well, it is used to predict future data.

Before forecasting the future data, the availability of the model needs to be verified by parameter and white noise testing. The residual should follow an independent normal distribution, and the Ljung-box test is usually used to diagnose the white noise of the residual.

## 3. Results and Discussion

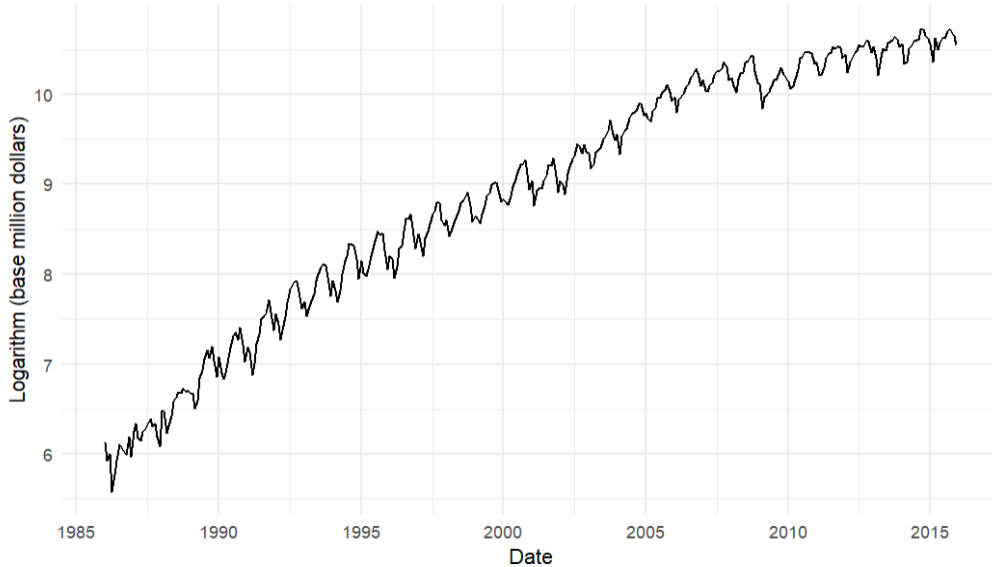
### 3.1. Preliminary Work

The data set can be divided into two parts, with the first 80 percent of the data used as the training set and the last 20 percent as the test set. This approach is commonly used in time series analysis to assess the model's ability to generalize to new data. The training set is used to estimate the model

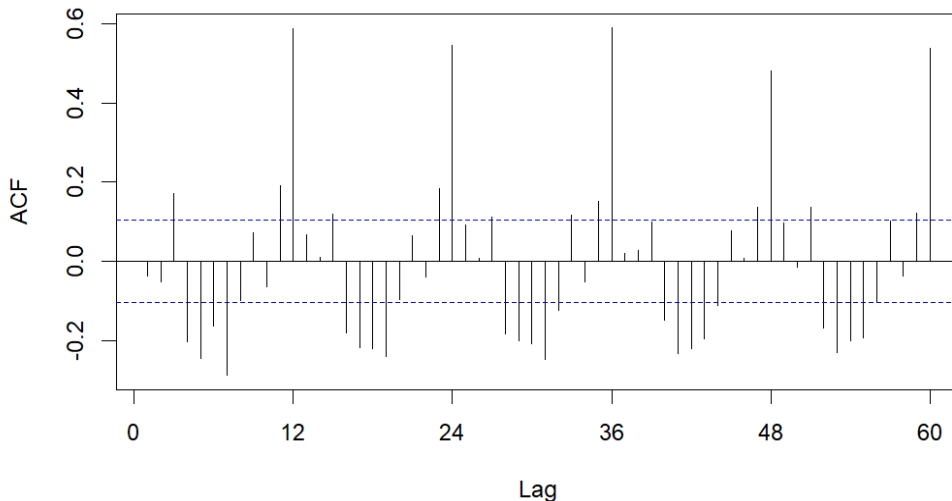
parameters and the test set is used to evaluate the model's performance on unseen data. And January 1986 to December 2015 was used as a training set to test the next 20 percent.

To eliminate heterogeneity, taking logarithms of time series can help stabilize the variance. Fig. 2 shows the plot of logarithmic time series from January 1986 to December 2015. This time series obviously shows trend, seasonality and it is also non-stationary by using the ADF test( $p=0.9112$ ). It is suggested to use SARIMA model to fit the data. To get the stationary time series, it needs to do a difference ( $\text{lag}=1$ ).

From fig. 3, there is a clear pattern for every 12 spikes, which clearly shows that this time series has seasonality, so series also need to do a seasonal difference. Therefore, the model is SARIMA( $p, 1, q$ )( $P, 1, Q$ )<sub>12</sub>. Then testing ADF test( $p<0.01$ ), the time series shows stationary.

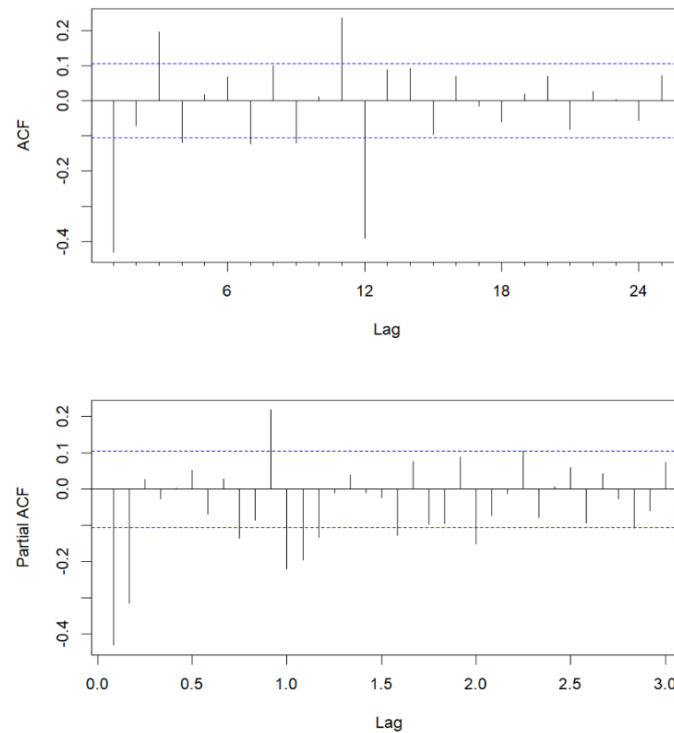


**Fig. 2** Logarithmic time series from January 1986 to September 2016



**Fig. 3** The ACF plot after applying a regular difference

After doing one regular and one seasonal difference to the data. Fig. 4 shows that autocorrelations with lags of 1 and 12 are significant in the PACF of residuals and autocorrelations with lags of 12 are significant in the ACF of residuals. It seems that spikes of 4 cut off in ACF and Spikes of 2 cut off in PACF respectively. However, it could not determine the best model (Fig 4).



**Fig. 4** The plot of ACF and PACF after doing a regular and seasonal difference

The Grid Search method can search all possible parameter combinations exhaustively, train and evaluate each set of parameters, and finally select the parameter combination with the best performance as the final model. Therefore, after applying one conventional and one seasonal difference, the range of the p, q, P, and Q values is specified. The range of p is 0 to 2 and the range of p is 0 to 1. For P and Q, both have a range of 0 to 2. Use the following precision measurements to select which is the best fitted model: RMSE, MAPE, AMAPE, and AIC. It could observe how accurately the model is trained and tested (Table 1).

Taking these factors into account, the conclusion is that Sarima (2,1,1) (2,1,1)<sub>12</sub> model is the best choice. The AIC value of this model (AIC= -843.1196) is close to the minimum AIC and it also has the lowest values in the two degrees of MAPE and AMAPE. The low values of MAPE and AMAPE show that the SARIMA model has less prediction error and is very helpful for future prediction. Furthermore, according to the results of the Box-Ljung test (p=0.08044>0.5), which is greater than the common significance level of 0.05. Therefore, the residual is white noise, which means that the prediction errors are random, independent, and do not have any predictable patterns. This is generally considered a good model fit because it shows that the model has captured all the meaningful patterns and relationships in the data.

The parameters of the best model are estimated by using a maximum likelihood function in the Table 2.

**Table 1.** Four models with minimal AIC, RMSE, MAPE, AMAPE

	p	q	P	Q	AIC	RMSE	MAPE	AMAPE
Models with minimal AIC	4	1	2	2	-845.393	0.188	1.310	1.294
Models with minimal RMSE	3	0	2	0	-841.078	0.129	0.903	0.899
Models with minimal MAPE	2	1	2	1	-843.120	0.129	0.895	0.894
Models with minimal AMAPE	2	1	2	1	-843.120	0.129	0.895	0.894

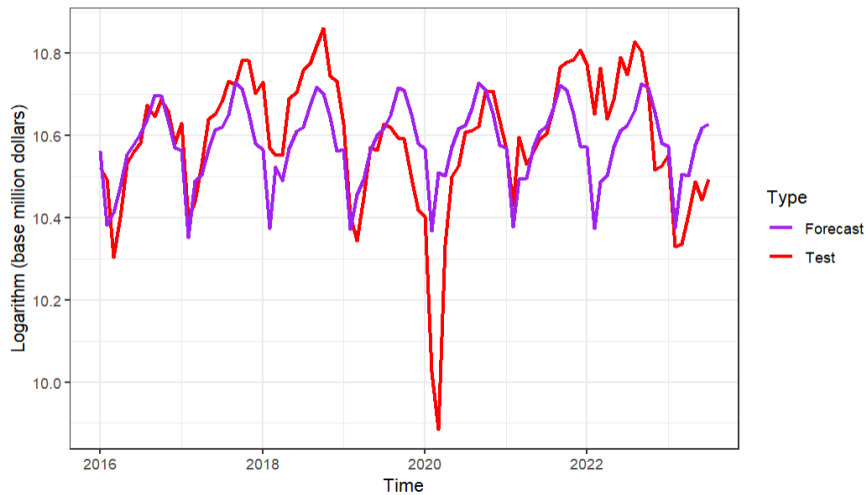
**Table 2.** Coefficients of Sarima (2,1,1) (2,1,1)<sub>12</sub>

Coefficients	AR 1	AR2	MA1	SAR1	SAR2	SMA1
	-0.812	-0.402	0.310	-0.988	-0.501	0.403
s.e.	0.138	0.069	0.149	0.124	0.068	0.140

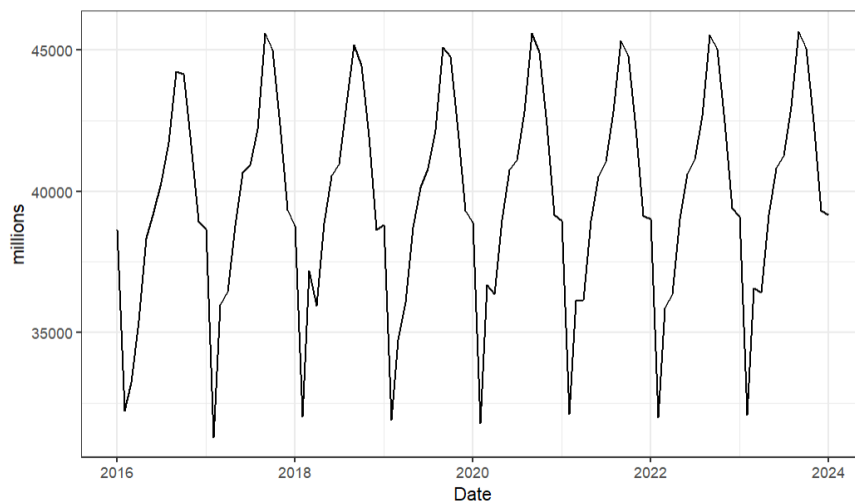
### 3.2. Model Results

The final model is used to predict the last 20 percent of the data (January 2016 to July 2023), and Fig. 5 compares the true and predicted values. The RMSE value was 0.1290904, the MAPE value was 0.8953377 the AMAPE value was 0.8943666 (Fig 5).

Fig. 6 shows the prediction value from January 2016 to January 2024. And Table 3 shows more specific data.



**Fig. 5** Forecast value and true value from January 2016 to July 2023



**Fig. 6** The plot of forecast value from January 2016 to January 2024

**Table 3.** Forecast value from January 2016 to January 2024

Date	million
2023-08-01	43008.10
2023-09-01	45656.16
2023-10-01	45046.82
2023-11-01	42471.08
2023-12-01	39316.52
2024-01-01	39159.82

### 3.3. Discussion

This study revealed that the SARIMA(2,1,1) (2,1,1)<sub>12</sub> was best model for predicting monthly U.S. Imports price of Goods from China based on the data from January 1986 to July 2023. The forecast results show that in the following six months, the U.S. Imports price of Goods still has seasonality,

and the upward trend in recent years has gradually slowed down. It seems like the change in the amount is influenced by a variety of complex factors, and more research is necessary to fully understand this issue. Based on this model and a 12-month seasonality, it can be a useful tool to monitor and predict these changes. This model can serve as the foundation for an early warning system for U.S. and Chinese importers and exporters, enabling them to make better decisions and avoid potential profit losses.

In this study, the amounts were recorded every other month to analyze the seasonal distribution. Overall, the peak is reached in September and October every year, and the trough is reached in February and March. It means that the demand will be relatively large in autumn. In the spring, production and shipments may be delayed due to the Chinese New Year, which affects the price and supply of U.S. imports.

However, this model still has some limitations. First, due to the impact of the Sino-U.S. trade war and the epidemic in 2020, the data changes greatly, so the prediction accuracy of future data may be affected. The second data is also affected by many factors, such as exchange rate fluctuations. Because trade between China and America is typically denominated in dollars, fluctuations in the yuan's exchange rate against the dollar can affect the price of Chinese exports and the cost of U.S. imports. In some seasons, fluctuations in exchange rates may be more pronounced, further affecting seasonal changes in customs prices. There are many other reasons, such as demand and policy et al. Due to the study's focus on data availability and time series, the external factors are not considered. Thirdly, the SARIMA model is suitable for short-term predictions only. It is essential to update the model with latest data dynamically to make the predictions are accurate and stable.

#### 4. Conclusion

In this study, based on the seasonal pattern of U.S. imports price of Goods by Customs Basis from China, this paper proposes the SARIMA model as a useful tool for prediction. This model predicts better results, especially for seasonal models. The results show that in September, the amount of money will peak at 45656.16 million, and then slowly fall back. Although it is affected by the epidemic and trade war from 2020 to 2023 year, there is a clear trend to return to the pattern of seasonality. Research results will be used as part of market research to help understand the demand and trends of Chinese imports in the United States, as well as Chinese exporters to develop more targeted market strategies. Merchants can adjust the price of their goods according to the different prices of each season, which will achieve the maximum profit. By forecasting and studying customs prices, the characteristics and trends of Sino-US trade can be better understood, to promote trade cooperation and development between the two countries.

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