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Original Paper

An Analysis of the Trend of China's Export Trade to the USA Based on R Language

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Abstract

After President Trump came to power, in order to change the "imbalance" between China and US trade, he launched a trade war with China, which led to increase uncertainty in China-US trade and increased export volatility. Based on R language environment, this paper compares the advantages and disadvantages of seasonal ARIMA (p, d, q) model and double-index ETS (A, N, A) model in short-term forecast of China's total export value to the United States. Then, the double-index ETS (A, N, A) model is selected to predict the trend of China's export trade to the United States in the months of 2009-2020. The forecast results show that China's export to the United States has seasonal characteristics. The export fluctuation is smaller than that in 2018, but the total value of exports has decreased significantly. Finally, some suggestions are put forward.

Keywords

seasonal ARIMA (p, d, q) model, double-index ETS (A, N, A) model, total export value, forecast

1. Introduction

Against the background of the trade war between China and the United States, some scholars conducted studies on the prediction of the development trend of sino-American trade through CGE model, game model and tv-stvar model, and the results showed that bilateral trade, GDP growth and social welfare would be affected. In recent years, many scholars have used relevant models to predict and analyze social phenomena, industrial structure, economic growth and scientific and technological innovation in R language environment. R language is an open source data analysis solution with powerful statistical calculation and graphic display design capabilities. Maria Brigida Ferraro (2015) used R language to conduct cluster analysis of big data on the main factors affecting obesity. Xue xin (2019) predicted and analyzed the exchange rate based on R language neural network. Wu mingxin (2017) applied R language into the field of auditing and conducted big data processing on auditing finance. Zhang zhe (2013) established a generalized time series model and a regression-time series model under the R language environment to forecast and analyze China's export trade volume and tax revenue. Li ping (2010) used R language statistical analysis software to conduct quantitative analysis of high-tech industry.

The innovation of this paper is that based on R language environment, seasonal ARIMA (p, d, q) model and double index ETS (A, N, A) model are applied in the field of international trade to predict the short-term trend of sino-American trade value, so as to study the impact of sino-American trade war and provide guidance for dealing with trade war.

2. Analysis of the Current Situation of China-US Trade

According to Figure 1, it can be seen that during the period from 2001 to 2018, China's total imports and exports to the United States showed a steady growth every year except for a decrease in 2009 and 2016. China has always maintained a large surplus. Except for a slight decrease in the surplus in 2009, the surplus in the other years has basically become stable.

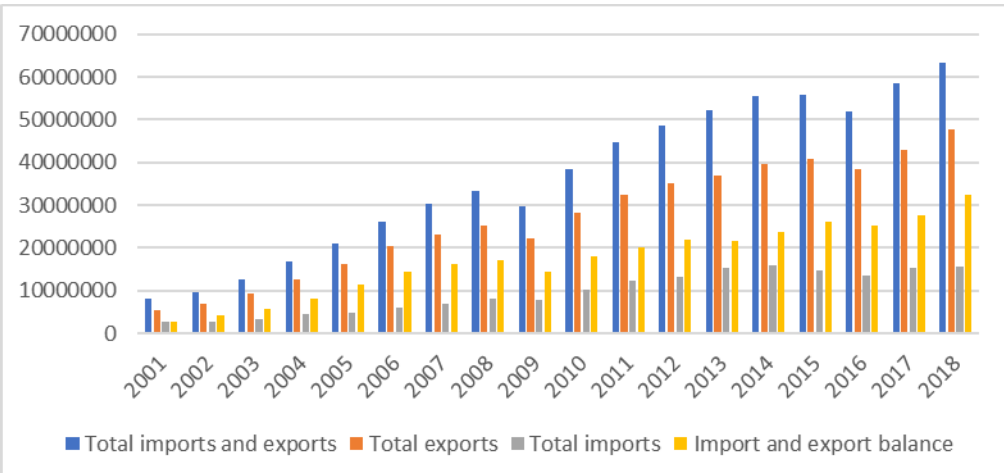

Figure 1. Total Imports and Exports from China to the United States (Unit: thousands of dollars)

Source: "China Statistical Yearbook" & "China Customs Statistics in 2018".

For a long time, the US has been China's largest export market, accounting for about 20% of China's exports. In 2018, the US tariff protection measures against China have affected the proportion of us exports in China to some extent. However, in 2018, the trade value between China and the US reached us $63351,941, an increase of 8.54% year on year. The total value of exports was 47,8423,17 million us dollars, up 11.33% year on year. The total value of imports was us $155,509,623. Year-on-year growth of 0.75%; The surplus reached $323.32694 million, an increase of 17.24%. Judging from the data, the impact of the trade war between China and the United States on China in 2018 is limited.

3. Forecast and Analysis of China's Export to the United States Based on R Language

According to China's general administration of customs issued in June 2014-June 2019, the data of Chinese exports to the United States will be 2018 before and after data is divided into training and testing, and use the double index of ETS (A, N, A) model and seasonal ARIMA (p, d, q) model to predict respectively, and comparing the prediction results of two models, select the best prediction results.

3.1 Model Framework and Principles

3.1.1 ETS (A, N, A) Model

Exponential model is the most common model used to predict the future value of time series. The idea of exponential smoothing method is derived from the improvement of moving average prediction method, which comprehensively uses adjacent values, overall trend and seasonality to conduct prediction analysis, but gives more weight to adjacent values. This kind of model is proved to be good for short-term prediction in practice. ETS function in forecast package in R language can fit the index model. Among them, ETS function can be divided into three index models: ses, holt, and hw, respectively. Ses, holt, and hw functions are convenient packages of ETS function, and the functions have preset parameter values. After data input, the best model is selected as double exponential model.

General ETS function is as follows:

$$ets(ts, \mathrm{mod}\,el = "ZZZ") \tag{1}$$

Where ts is the timing sequence to be analyzed, and there are three letters defining the model. The first letter represents the error term, the second letter represents the trend term, and the third letter represents the seasonal term. Optional letters include: additive model (A), multiply model (M), none (N), automatic selection (Z).

3.1.2 ARIMA Model

ARIMA model (autoregressive integrated moving average moving average mode) is a commonly used stochastic time series model with high accuracy for short-term prediction. It was founded by American statisticians box and Jenkins with the following basic ideas: Some time series are a set of random variables dependent on time t, and the change of the whole series has certain regularity. By establishing a mathematical model and analyzing and studying, the structure and characteristics of time series can be essentially understood, and the most effective prediction results can be obtained.

ARIMA model is made up of autoregressive model AR (P), MA (q) and autocorrelation model poor score (d) of three parts, so that half of the ARIMA model has the characteristics of the autoregressive and moving average characteristics of the process, and through poor score (d) let originally non-stationary time series become stable, improve the accuracy of the subsequent forecast.

The general expression of ARIMA (p, d, q) model is:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} - \theta_1 u_{t-1} - \theta_2 u_{t-2} - \ldots - \theta_q u_{t-q} \tag{2}$$

In general, if the data is a time series with seasonal effects, a product seasonal model is required $ARIMA(p,d,q)\times(P,D,Q)_s$ for simulation, P and Q are the order of seasonal autoregression and moving average, D is the order of seasonal difference, and S is the seasonal cycle.

3.2 Data Basis (Monthly Data) Analysis

Figure 2. Total Value of China's Exports to the United States in R Language Environment (Unit: ten thousand yuan)

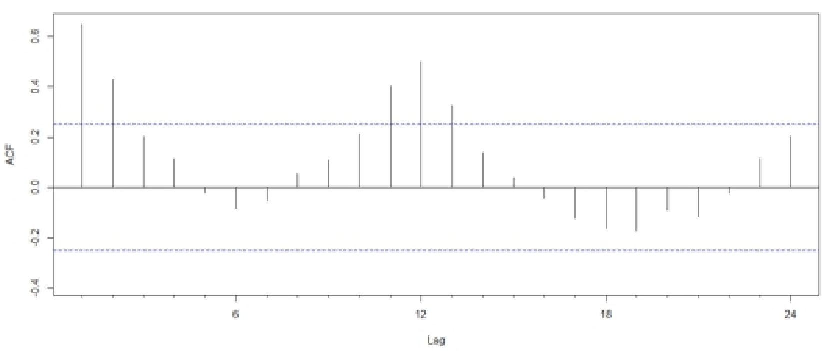

Figure 3. Autocorrelation of Current Values from June 2014 to June 2019.06

The data are mainly from the General Administration of Customs of China, with a total of 61 sample data. Using software is R, make in time for the horizontal axis, exports for the longitudinal axis of the sequence diagram, as shown in Figure 3, March 2015, in February 2016 and February 2017, in March 2018 and February 2019 was the lowest each quarter, in October 2014, in September 2015 and December 2016 and November 2017 and November 2018 were appeared in the annual peak, the whole, China's exports to the United States trade has obvious seasonal characteristic, present the total cost of the export trade fluctuation trend of rising and it peaked in 2018-2019 at a six-year high. At the same time, as shown in Figure 4, the time series of total export trade value shows a certain tardiness in autocorrelation and obvious seasonality, i.e., non-stationary. Therefore, the data belongs to non-stationary time series. In order to eliminate the growth trend, difference is needed. In order to eliminate the seasonal trend, further seasonal difference is needed.

3.3 Model Prediction and Analysis

In order to more directly reflect the impact of us sanctions on China's export trade with the us in the two years from 2018 to 2019, this paper selected China's monthly export trade data from June 2014 to June 2019 for time series analysis, $ARIMA(p,d,q)\times(P,D,Q)_s$ model and $ets(ts, \mathrm{mod}\,el = "ZZZ")$ model mainly uses the short-term prediction of China's export trade value to determine whether the total value of China's export to the United States will decrease significantly or increase after the United States imposes sanctions on China.

3.3.1 Grouping

The data of China's total export to the United States from June 2014 to June 2019 are divided into two groups: the first group is the total export value data before December 2017, named Training; the second group is the total export value data after January 2018, named Testing. In 2018 and January-June 2019, when the trade war between China and the United States was at its peak, a division can improve the accuracy of the model ($ARIMA(p,d,q)\times(P,D,Q)_s$ model and $ets(ts, \mathrm{mod}\,el = "ZZZ")$ model) and the prediction of the total value of China's exports to the United States.

3.3.2 Make Comparative Analysis

The degree of fitting of the model can be determined according to the information criterion. Several information criteria can be used, such as red information criteria, AIC information criteria, AIC revised AICc information criteria, and bayesian information criteria, BIC information criteria. According to Table 4, according to the ARIMA model presented by R and the AIC information criterion, AICc information criterion and BIC information criterion of ETS (A, N, A) model, the fitting degree of ARIMA model is better than ETS (A, N, A) model.

Table 1. Comparison Table of Fitting Degree

	AIC	AICc	BIC
ARIMA（0,1,1）（0,1,0）$_{[12]\mathrm{model}}$	954.15	954.59	954.59
ETS（A,N,A）model	1405.355	1423.132	1431.773

Table 2. ARIMA (0, 1, 1) (0, 1, 0)$_{[12]}$ Model Error Correlation Values

	RMSE	MAE	MAPE	MASE
Training set	1508882	1074948	4.997333	0.5105552
Test set	3829596	3321557	14.615813	1.5775997

Table 3. ETS (A, N, A) Model Error Correlation Values

	RMSE	MAE	MAPE	MASE
Training set	1344986	1021103	4.814283	0.4849811
Test set	2304295	1842249	7.454881	0.8749907

RMSE represents root mean square error, MAE represents mean absolute error, MAPE represents mean absolute percentage error and MASE represents mean absolute scale error. These errors are used to measure the error degree of prediction results of ARIMA (0, 1, 1) (0, 1, 0) $_{[12]}$ model and ETS (A, N, A) model. Through intuitive comparison Tables 5 and 6 error numerical, ETS (A, N, A) model is far less than the error of the model ARIMA (0, 1, 1) (0, 1, 0)$_{[12]}$ model, and the sample data of the average value of 231.0439665 billion yuan, ETS (A, N, A) model RMSE, MAE, and two groups of data under MAPE compared with the average of the sample data is small, at the same time, the MASE is less than 1, so from the Angle of error, ETS (A, N, A) model has better prediction results than ARIMA (0, 1, 1) (0, 1, 0)$_{[12]}$ model.

To sum up, the ARIMA (0, 1, 1) (0, 0)$_{[12]}$ model compared with ETS (A, N, A) model is more complex, the fitting degree of ARIMA (0, 1, 1) (0, 0)$_{[12]}$ model occupy A certain advantage, but in the short-term forecast, in the case of data presents obvious seasonal, ETS (A, N, A) model prediction error rate is lower, so choose the ETS (A, N, A) model in the prediction of the trend for China's exports to the United States.

3.3.3 ETS (A, N, A) Model Testing

Ljung-box test has better sample nature (that is, more effective in statistical sense) than box-pierce test. According to Ljung-box test, under ETS (A, N, A) model, p-value=0.07373>0.05. Therefore, there is no sufficient reason to reject the null hypothesis and the residuals should be considered independent of each other.

3.3.4 Predict Results

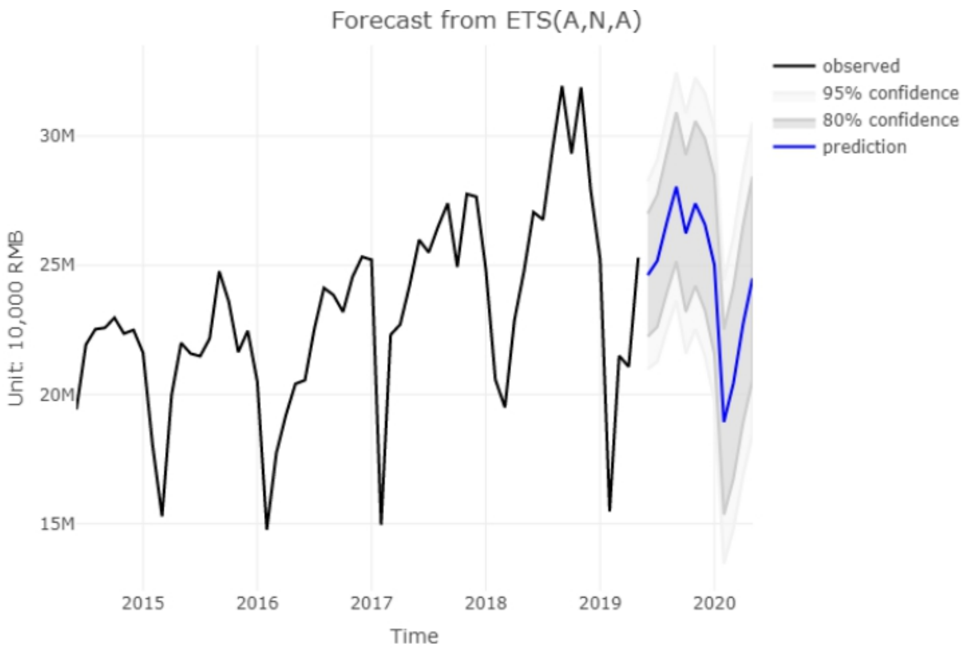

Figure 4. Predicted Value of ETS (A, N, A) Model—Line Graph

Run the monthly data of China's export value to the United States from June 2014 to June 2019 in the forecast package in R, and get the predicted value line chart of ETS (A, N, A) model in Figure 4. The blue line is the point estimate, and the light gray and dark gray areas represent 95% and 80% confidence intervals respectively. As can be seen from the figure, the total value of China's exports to the United States will decline significantly from 2019 to 2020, roughly approaching the level of China's total value of exports to the United States in 2017, because the United States imposes a tariff of up to 25% on imports of Chinese products. The most important thing is that it may change the long-term stable growth trend of China's exports to the United States. The predicted values and actual values are shown in Table 7 and Table 8 (the influence of holiday factors in February 2019 is obvious, so it is removed from the error estimation).

Table 4. Error between Fitting Value and Actual Value from July 2018 to June 2019

Time	The actual value	The fitting values	Error rate（%）
2018.07	26766530	26025160	-2.77%
2018.08	29481821	27034012	-8.30%
2018.09	31931363	28011028	-12.28%
2018.10	29319143	26483546	-9.67%
2018.11	31885204	27145170	-14.87%

2018.12	27942025	27339536	-2.16%
2019.01	25211055	25973371	3.02%
2019.02	15481382	19555027	26.31%
2019.03	21498523	21749741	1.17%
2019.04	21074682	23838726	13.12%
2019.05	25296472	25320438	0.09%
2019.06	26826670	25468902	-5.06%
Mean absolute error rate (except 2019.02)			6.59%

Table 5. Predicted Values of ETS (A, N, A) Model

Time	Piont forecast	Interval estimate of 80% confidence level	Interval estimate of 95% confidence level
2019.07	26012197	(23621427,28402967)	(22355830,29668564)
2019.08	27496730	(24928483,30064976)	(23568936,31424524)
2019.09	28874115	(26139887,31608342)	(24692475,33055755)
2019.10	27073494	(24182801,29964188)	(22652560,31494428)
2019.11	28224219	(25185104,31263333)	(23576294,32872143)
2019.12	27389672	(24209055,30570290)	(22525338,32254007)
2020.01	25847560	(22531472,29163647)	(20776042,30919078)
2020.02	19773579	(16327343,23219816)	(14503016,25044143)
2020.03	21224636	(17652990,24796282)	(15762275,26686997)
2020.04	23540110	(19847311,27232910)	(17892462,29187759)
2020.05	25267428	(21457327,29077530)	(19440381,31094476)
2020.06	25591927	(21667971,29515883)	(19590754,31593100)

4. Analysis of Prediction Results

According to the above empirical evidence and prediction, the summary and analysis are as follows:

First of all, from June 2014-June 2019 real data, months China's exports to the United States trade gross value of the current period has obvious seasonal fluctuations, in February or march of each year will be the lowest of the year, mainly due to the effect of China about 2 month every year the Spring Festival holiday, after the Spring Festival exports gradually recover, generally around November reached the highest value. Although there were frictions between China and the United States during this period, and the United States frequently used the "double-countervailing" investigation, "337" investigation and technical barriers to trade to restrict the import of Chinese products, China's export trade with the United States was still on the rise on the whole, and the surplus was also expanding. Even in 2018, when the United States started a trade war, China's exports to the United States continued to grow.

Secondly, by using the model of A ETS (A, N, A) it is concluded that the July 2018-June 2019 month predicted values and the real value of the mean absolute error rate was 6.59% (remove) in February 2019, error rate is small, relatively than that of ARIMA (0, 1, 1) (0, 0)$_{[12]}$ model, especially in the case of data with the seasonal characteristics, ETS (A, N, A) model to predict trend has more advantages.

Finally, the peak value of the predicted value in November 2019 is lower than the peak value of the actual value in 2018, and the minimum value of the predicted value in February 2020 is higher than that in 2019, indicating that the fluctuation range of China's exports to the United States during the forecast period is smaller than that in 2018, and the total value of exports drops to the level of 2017. The comparison between the predicted value and the real value also shows that the trade war between China and the United States has little impact on 2018. However, due to the long-term trend of the trade war between China and the United States, China's exports to the United States will be restrained to a certain extent during the period from 2019 to 2020, and the prospect of china-us trade is not optimistic.

5. Suggestions

5.1 We Will Continue to Open Up and Expand Multilateral Economic and Trade Cooperation

China should continue to open up to the outside world, strengthen the supply-side structural reform in foreign trade, and improve the tax reduction and exemption policies and measures to support small and medium-sized foreign trade enterprises. We will promote the development of the One Belt and One Road market and the construction of bilateral and multilateral free trade areas, further enhance trade facilitation and create a favorable new environment for opening up the economy, so as to offset the impact of the reduction in exports to the United States.

5.2 We Continue to Negotiate with the United States on the Basis of Ensuring Bottom-Line Thinking

We should stick to the bottom-line principle and the principles of equality, justice and mutual benefit in communication and negotiation with the us, strive for an early conclusion of an agreement conducive to the long-term economic development of the two countries and avoid further deterioration of China-US trade. The recent breakdown of trade talks between China and the us and trump's threat to impose additional tariff rates have further increased the uncertainty of china-us trade, which will also seriously affect the confidence of the export market in the us in the future.

5.3 We Will Strengthen Enterprises' Awareness of Risk Prevention and Intellectual Property Protection, and Foster New International Competitive Advantages

Faced with the trade war between China and the United States, enterprises should be aware of risks, adjust their export markets in a timely manner, and avoid risks of tariffs and exchange rates. Properly handle the industrial cooperation with relevant American enterprises. At the same time, we need to strengthen ipr protection and create a sound business environment in China. We should encourage and intensify enterprise innovation, improve the structure of export products, and cultivate competitive advantages in the quality, technology, brand and service of export products. In particular, we should avoid focusing on 16 categories of products for export to the United States and implement differentiation strategy.

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