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Time Series Analyze for Chinese Total Output

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Abstract: Adopting times series model to directly forecast the Chinese total output. The framework I present circumvents the simple linear models and allow me to forecast the next month trade surplus directly. Instead of doing simple linear regression, I use ARIMA model selection to construct the optimal predict function. The dataset we used is after differenced once, since the original data is not stationary enough. There are no simple regression models to compare since other scholars had shown the performance of linear regression is not well. After doing ACF, PACF, EACF and BIC to draw two alternative ARIMA model, I use maximum likelihood and least square methods to estimate the parameters. Then, I obtain the predicted value of Chinese total output surplus of April 2022, and make comparisons with the true value. The model I selected gives the wrong trend, but the true value is in the significant level. For further studies, times series analysis can add more samples into dataset and take machine learning into consideration to draw a more precious prediction.

Keywords: China, Trade, Times, Series output.

1. Introduction

Imports and exports volume of a country is an important factor that illustrate the economic situation of the country in the world trade. The trade amount is determined by supply and demand for each country, the relatively power one would export more and input less in general. Under multiple challenges such as the epidemic and the US trade war, National Bureau of Statistics shows that Chinese total imports and exports amount still reached 3.91 trillion yuan in 2021, an increase of 21.4% over the previous year, where the amount of exports is 2.17 trillion yuan, an increase of 21.2%. As the largest exporter in the world, Chinese trade data serve as indicators for the development level of national as well as global trade. A trade surplus is an economic measure of a positive balance of trade, where the amount of a country's exports exceed its imports. It means that Chinese production and resource reserves are superior in global, which makes an important impact on economic growth.

For trade surplus prediction, researches are divided into two categories. One is macroscopic economic analysis and another is regression analysis. Wei points out that the vertical specialization in processing and manufacturing has boost the Chinese trade surplus to grow rapidly. In specific, for a long period, the trade among China, the US and East Asia has support the trade surplus growth trend to continue. Moreover, foreign direct investment (FDI) should also be accounted for the reason of the growth of Chinese trade surplus [1]. Moreover, for the importance of trade surplus, Wang and Li argues that imports and exports volume of a country reflect its degree of frequency and

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competitiveness in world trades. The process of import and export come from a country depend on other countries for goods and services they lack, while they also require export of what they have advantages for profit. However, in the late 1970s, as the fair trade theory gradually replaced the free trade theory, western developed countries led by the United States usually used economic means to sanction other countries, resulting in frequent trade frictions [2]. Wang argues trade surplus from a macroscopic perspective, the overall trade surplus for China will continue to grow, while the trade module is changing. In world trade, the proportion for traditional processing industry will decrease, on the contrary, the proportion of high-tech industry (phone, new energy car) in export would increase [3].

From the regression analysis, Wang points out a linear regression model to estimate and predict the trade surplus, the coefficients contain of Chinese GDP, exchange rate, and the variance of exchange rate. Through his analysis, the results are not significant in short-term or long-term (20 years). The reasons can be the variance of exchange rate has no relationship with trade surplus [3]. In addition, Chou and Pozo apply GARCH model to illustrate the problem. Chou points out that the exchange rate variability has a negative impact on Chinese trade surplus in long term. The exchange rate variability is calculated from by the conditional variance of exchange rate from an ARCH model. Detailed categories like manufactured goods, mineral fuels, foodstuffs, etc are all being considered to draw the final relationship of the exchange rate variability and trade surplus [4]. Pozo argues that the real exchange rate volatility reduces the volume of trade, based on the exports data from Britain to the US from 1900 to 1940. The result is conducted by two methods, which are rolling standard deviation measure and conditional variance of exchange rate from a GARCH model [5]. The method is similar to the Chou's approach.

Regression has relatively high credibility in predicting future values. However, depending on linear regression, the result of predictions are just passable. Therefore, a time series analysis can be used in Chinese total trade surplus to replace simply regression. In addition, the trade surplus data itself is a time series data since it is collected from different time and used to reflect the rise-fall phenomenon over time [6,7].

This paper attempts to draw the Chinese total output surplus predicted value by using times series analysis. Apply residual diagnose to examine the models that selected from criterions such as ACF, PACF, EACF and BIC. After diagnose, obtain the most suitable model to forecast future values.

2. Method

The final goal is to estimating an ARIMA model that is most suitable to our data and then give precise prediction. A general ARIMA is:

$$Y_t \ = \beta Y_{t-1} + \ e_t + \theta e_{t-1} \tag{1}$$

Where $\boldsymbol{Y_t}$ refers to Chinese trade surplus at time t; $\boldsymbol{Y_{t-1}}$ means autoregressive processes item; $\boldsymbol{e_{t-1}}$ refers to moving average processes; $\boldsymbol{e_t}$ refers to the random error.

$$W_t \ = \beta Y_{t-1} + \ e_t + \theta e_{t-1} \tag{2}$$

$\boldsymbol{W_t}$ refers to Chinese trade surplus at time t after taking differences. The first phase is identification of a model. This paper first takes logarithm and difference to deal with the data, which aims to obtain a stationary process. Then, it uses some important functions (ACF, PACF and EACF) and Bayesian information criterion (BIC) to confirm the fittest model. The second phase is parameter estimates. The best model is selected according to the specific model obtained in previous and then examining the rationality of the estimate results. The third phase is model diagnose. The research expects to

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evaluate the goodness of fit of the resulting model. As an effective way, to examine different characteristics of residuals such as randomness, normality and autocorrelation. The last phase is to forecast the future value of the time series model by using the minimum mean square error.

3. Results

The study here use the data from East money choice database, which is public available and include 105 months Chinese total trade surplus. The selected periods are January 2013 to April 2022. However, the data is unstationary to see.

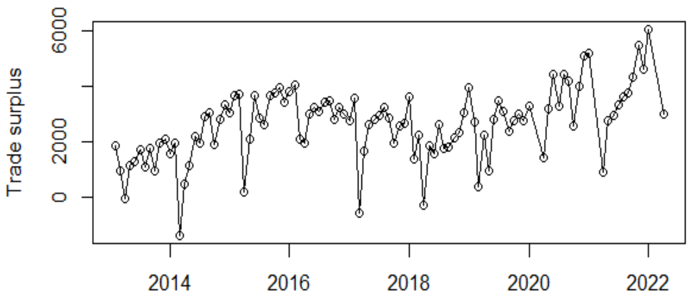

Figure 1: Chinese total trade surplus.

As shown in Figure 1, an upward trend clearly, which do not satisfy our expectation for a stationary series. Therefore, taking differences and logarithm to adjust the data. Moreover, as shown in Figure 1, the variances do not show a considerably swing through time. As a result, taking differences to remove the upward trend. By conducting difference once and twice, the figures 2 and 3 are drawn.

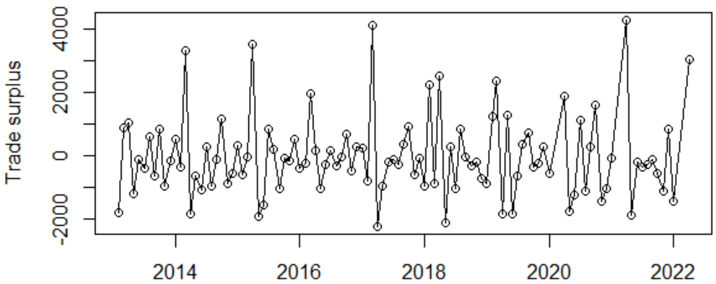

Figure 2: Chinese total trade surplus with first difference.

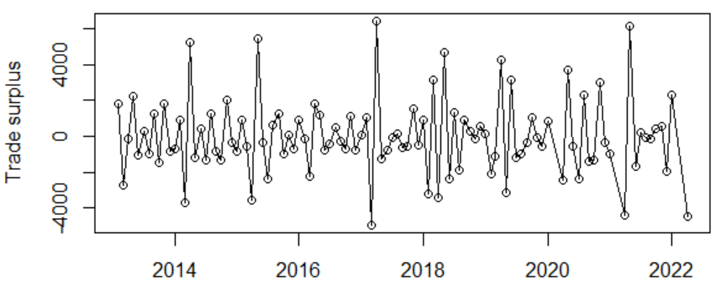

Figure 3: Chinese total trade surplus with second difference.

After analysing two figures 2 and 3, taking difference once is better than twice since it move between -2000 to 2000 in general, while the number move between -4000 to 4000 in the case of difference twice. Moreover, figure 2 is more concentrated around 0 and an overfitting situation is

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unwilling to see, which will lead to a biased prediction. In addition, it is efficient to apply Augmented Dickey-Fuller Test to examine the stationarity. The p-value is less than 0.01 in lag order 4. The p-value is considerably small, and there is no significant evidence to reject Ho (There is an unit root existed in series), so there are reasons to believe that the data after taking difference one is stationary. For the volatility, since the variance is not wave severely, so logarithm is not necessary. As a result, taking difference once is the optimal choice and then get a stationary series. From the autocorrelation function (ACF) and partial autocorrelation function (PACF) 's figures 4, 5, clearly, ACF cuts off at lag 1(lag 0 do not show in the figure, the first line is lag 1) and PACF is dying out pattern. Therefore, ACF & PACF suggest a MA(1) model. Since the data have been taken difference once in the previous operation, the model should be ARIMA(0,1,1) instead.

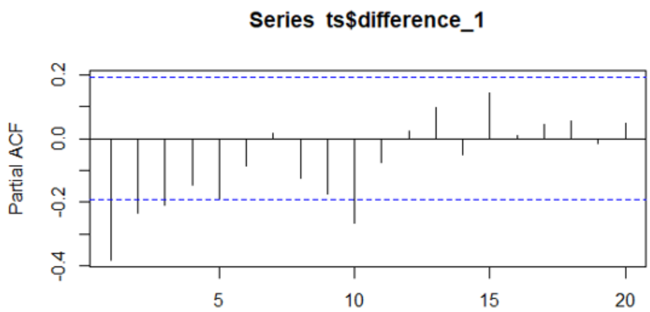


Figure 4: Autocorrelation function of the first difference series.

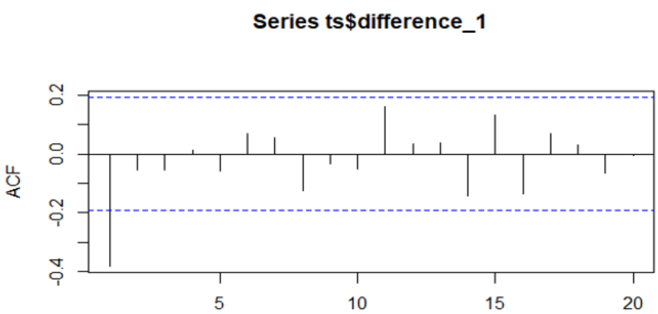
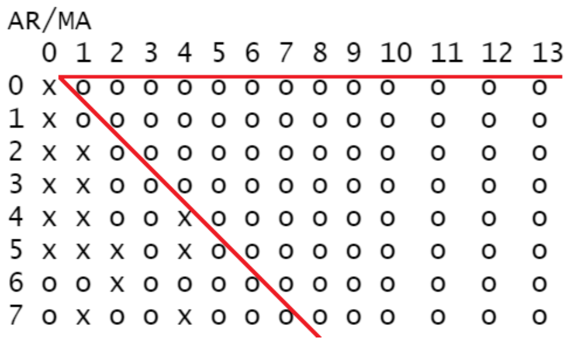


Figure 5: Partial autocorrelation function of the first difference series.



AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	o	o	o	o	o	o	o	o	o	o	o	o	o
1	x	o	o	o	o	o	o	o	o	o	o	o	o	o
2	x	x	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	o	o	o	o	o	o	o	o	o	o	o	o
4	x	x	o	o	x	o	o	o	o	o	o	o	o	o
5	x	x	x	o	x	o	o	o	o	o	o	o	o	o
6	o	o	x	o	o	o	o	o	o	o	o	o	o	o
7	o	x	o	o	x	o	o	o	o	o	o	o	o	o

Figure 6: EACF of the first difference series.

Moreover, the EACF figure shows EACF plot from the first difference data. From the red line I drawn in the plot, the EACF also suggest an ARIMA(0,1,1), which is the same result as ACF&PACF suggested.

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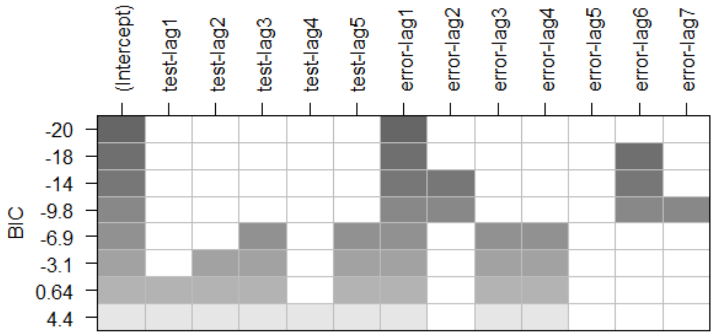

Figure 7: BIC result of the first difference time series.

Figure 7 shows BIC result, which suggest an ARIMA(0,1,1) model as well. In general, ACF, PACF, EACF and BIC all suggest the same model, which is ARIMA(0,1,1). Moreover, apply R studio software to indicate the best model by itself (Code is auto.arima). It gives the table 1.

Table 1: Best ARIMA model suggested by R.

Suggest model: ARIMA(1,1,1)		
	AR1	MA1
Coefficient	0.1940	-0.8399
Standard error	0.1203	0.0609
AIC = 1752.4	AIC_c = 1752.64	BIC = 1760.34
$\sigma^2 = 1161451$	log likelihood = -873.2	

The underlying logic for R studio to choose the best model is an information criterion (AIC). R would choose the model with the smallest AIC, which means the model is best fitting the data with punishment for excess factors. The result is ARIMA(1,1,1). In general, there are two models generated, which are AIRMA(0,1,1) and ARIMA(1,1,1).

For estimate parameters, there are three methods: the method of moments, least Squares and maximum likelihood. Since our model related to MA(q) model, so the Method of Moments is not suitable. For models containing moving average terms, the variance of the method-of-moments estimators is larger than variance of the maximum likelihood estimators. The table 2 and 3 are the results of conditional least Squares and maximum likelihood.

Table 2: LS method estimate results for ARIMA(0,1,1).

Estimate Model: ARIMA(0,1,1), method = “CSS”	
Coefficient： -0.7693	Standard error: 0.0777
Estimated σ^2 = 1203546	Part log likelihood = -875.61

The ARIMA(0,1,1) conducted by least square method should be:

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$$W_t \ = \ e_t + 0.7693e_{t-1} \tag{3}$$

Table 3: ML method estimate results for ARIMA(0,1,1)

Estimate Model: ARIMA(0,1,1), method = "ML"		
Coefficient： -0.7716	Standard error: 0.0708	
Estimated σ^2= 1203546	log likelihood = -874.48	AIC = 1750.97

The ARIMA(0,1,1) conducted by maximum likelihood method should be:

$$W_t \ = \ e_t + 0.7716e_{t-1} \tag{4}$$

By conducting the same procedure, the best estimation for ARIMA(1,1,1) is as shown in table 4.

Table 4: ML method estimate results for ARIMA(1,1,1)

Estimate Model: ARIMA(1,1,1), method = "ML"		
	AR1	MA1
Coefficient	0.1938	-0.8399
Standard error	0.1203	0.0609
Estimate σ^2= 1139114	log likelihood = -873.2	AIC = 1750.4

The ARIMA(1,1,1) conducted by maximum likelihood method should be:

$$W_t \ = \ 0.1938Y_{t-1} + e_t + 0.8399e_{t-1} \tag{5}$$

4. Discussion

4.1. ARIMA(1,1,1)

The model is:

$$W_t \ = \ 0.1938Y_{t-1} + e_t + 0.8399e_{t-1} \tag{6}$$

From table 4, the t-value of ARIMA(1,1,1) is smaller than 2. By applying t-test, the coefficients are not significant in 95% confidence level. And standard errors for parameters are larger than those in ARIMA(0,1,1). Since the parameters are not significant, the model is unbiased from the reality. Other test and prediction is not necessary. Since the ARIMA(1,1,1) performs poor, there is no need to consider more about ARIMA(1,1,1).

4.2. ARIMA(0,1,1)

Both of the methods provided coefficients and variance of the parameter nearly the same, and passed the t-test (t-value>2). So, the two methods estimate significant parameters, and I chose to use

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maximum likelihood just because its standard error for coefficient is slightly smaller. So the model for ARIMA(0,1,1) is

$$W_t \ = \ e_t + 0.7716 e_{t-1} \tag{7}$$

Then I use residual test to verify whether the model contain all the information in the dataset. I check its standardized residuals plots first.

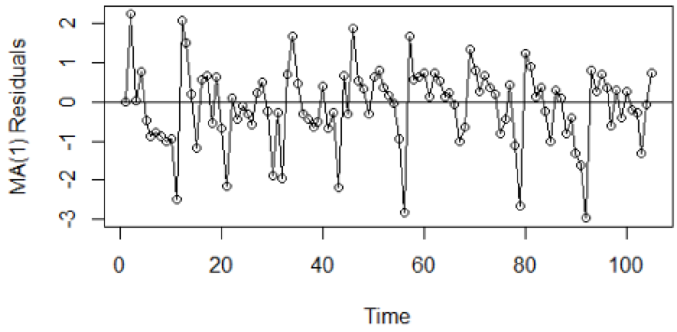

Figure 8: Standardized residuals of trade surplus ARIMA(0,1,1) model.

In general, residuals move inside a rectangular. Residuals do have some extreme values, but it moves like ‘white noise’ for most lags. By eyes, an absolute conclusion cannot be guaranteed, so I used detection() in R to detect whether there are outliers or not. From R studio, is shows “No IO detected”, which means there is no outliers in defaulted 5% confidence interval. Next, Applying Q_Q plot, ACF and PACF of model residuals, and Ljung-Box test to verify normality. According to Chambers et al., Q-Q plot is significant at detecting deviations from normality than classical normality tests [8]. Through Q-Q plot, the majority of values located in the normal line, while some small values do not strictly locate in the normal line. Consider our sample size is 105, which is not a relatively big, the normality performs in acceptable range.

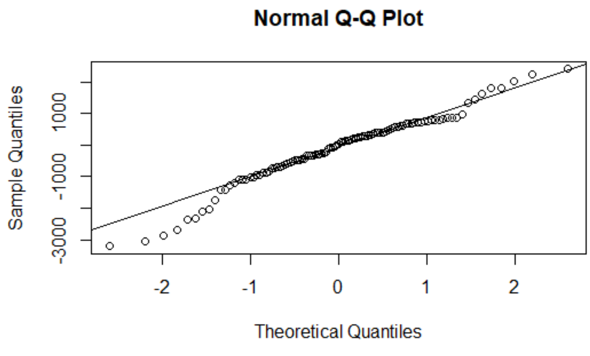

Figure 9: Q-Q plot of trade surplus ARIMA(0,1,1) model residuals.

The ACF and PACF of model residuals show that almost all the lags are significant expect for lag 11 while almost all the lags are independent from each other (in 5% significant level). Since the lag 11 is a quite large lag and lag 11 is the only one that slightly crosses the confidence limit, the impact to normality can be ignored.

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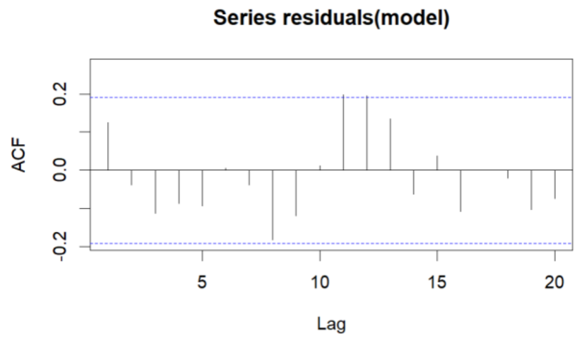

Figure 10: ACF of trade surplus ARIMA(0,1,1) model residuals.

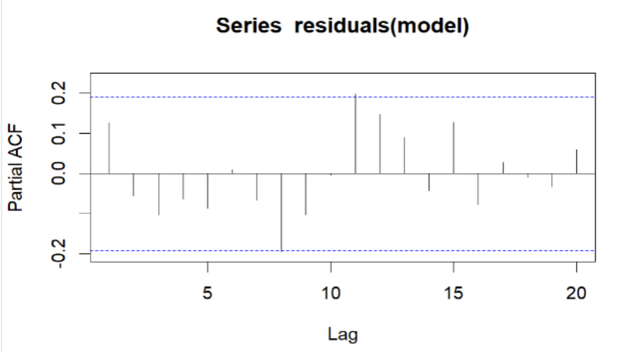

Figure 11: PACF of trade surplus ARIMA(0,1,1) model residuals.

In addition to looking at residual correlation at individual lags, it is useful to have a test that takes into account their magnitudes as a group. It is poosible that most of the residual autocorrelations are moderate, some even close to their critical values, but, take together, they seem excessive. So, Ljung-Box test is created and to address the problem. According to Di Lorenzo, The Ljung–Box test is one of the most important tests for time series diagnostics and model selection [9]. The origin hypothesis in Ljung–Box test is error terms are uncorrelated [10]. By conducting Ljung-Box test, all the p-values for ARIMA(0,1,1) are above 0.1, there are enough significant evidences to reject H0, which says residuals are independent. Depending on our fixed model to forecast the next month data, the forecast plot with 95% confidence interval is as shown in figure 12.

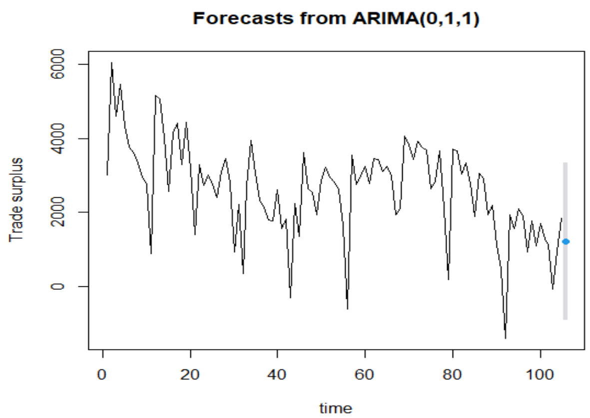

Figure 12: Forecast for the next month (April 2022) value.

The blue point is the exact forecast point for the following one month trade surplus. The grey area is the 95% confidence interval for the forecast value. It is estimated that the trade surplus in April 2022 would decrease about 500 (unit is 100 million) RMB in total. Moreover, the next 3 months forecast values are shown as shown in figure 13:

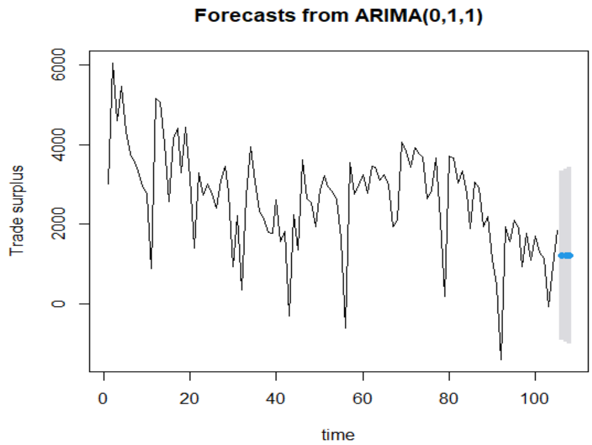

Figure 13: Forecast for the next three months future values.

The forecast values are all the same because the property of MA(1), but the error variance increases as time increases, which means our forecast will be less precise. It proves that 1-step forecast is more accurate since forecast error variance increases as more steps used. The real trade surplus at time April 2022 is 2300 , which is higher than the trade surplus in March 2022. The predict value is around 1800, lower than the true value, while it is in the confidence interval. ARIMA(0,1,1) gives a relatively precise forecast (one-step forecast), but the model mistakes the trend. The shortage of sample size should be responsible for the model misspecification, and the normality for residuals can be improved by adding more data. Moreover, Although the data seems stationary and passed ADF-test, it may be more stationary if do normalization to remove impact caused by variance. In the prediction part, the method of roiling window and machine learning with large sample size can achieve a more precise forecast.

5. Conclusion

Following the path clarified in framework part, after getting a relatively stational data, there are two alternative models for us to test. It is need to mention that ACF, PACF, EACF and BIC all suggest the same model (ARIMA(0,1,1)), which is relatively strong to believe. After we deal with the parameters, the model suggested by ACF, PACF, EACF and BIC is the one suitable. Another one is dropped since it failed to pass t-test. Moreover, the model (ARIMA(0,1,1)) passed all the test in the residual diagnose part. Then, the model provides an approximate forecast for the April 2022 trade surplus, which is around 1500 (unit is 100 million). The gap between prediction value and true value is 500 (unit is 100 million). Some scholars had done linear regression and I did times series analysis to predict the trade surplus, but the result is less-than-perfect. For further researches, I suggest increase the sample size and apply machine learning and neural network to analysis the trade surplus. By powerful computing, the prediction can be more precise to the true value.

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