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Application of ARMA Model in China's Fixed Assets Investment Forecast

Ying Liu[1], Ping Xiao[2*]
[1](*School of Hunan University of Humanities, Science and Technology, Hunan 417000, China*)
[2](*School of Hunan University of Humanities, Science and Technology, Hunan 417000, China*)
**Corresponding author. applefly13@126.com*

Abstract: With the rapid development of economy, fixed assets investment as an important part of investment is one of the important driving forces of social and economic development, and an important means of social fixed assets reproduction. Therefore, predicting the growth rate of China's fixed assets investment has become an important issue and is of great significance for promoting China's economic growth. This paper uses ARMA model, uses Eviews software to conduct an in-depth analysis of China's fixed assets investment from 1980 to 2017, and predicts the fixed assets investment in China in future. It can be seen from the analysis results that the ARMA model can provide more accurate prediction effects, and can be used to predict the future data and provide a reliable basis for the fixed assets investment of the whole society in China.

Keywords: economic growth, ARMA model, fixed asset investment

I. Introduction

Since the reform and opening up, China's economic development has developed rapidly and has made tremendous achievements. Fixed assets investment is an economic activity for the construction and acquisition of fixed assets, that is, fixed asset reproduction activities, which is a key means of social fixed assets reproduction. The fixed asset investment's amount is the workload of constructing and purchasing fixed assets activities in monetary performance. It reflects the comprehensive indicators of the scale, speed, proportional relationship and direction of use of fixed assets investment.

With the economic development, China's total fixed asset investment's account continued to increase: only 91.09 billion yuan in 1980, but in 1993, the total amount exceeded 1000 billion yuan for the first time, to reach 1,307.23 billion yuan. Since the beginning of the 21st century, with China's accession to the WTO, the foreign investment has increasedsubstantially,andthetotalinvestmenthasdevelopedparticularly rapidly, which has promoted the adjustment and improvement of China's economic policies. By 2016, it has reached to 60,646.56 billion yuan. Compared with the account of the last century.

The ARMA model, also known as the Box-Jenkins model, orBJ model for short, is a time series prediction method .Before, many scholars have conducted relevant research on fixed asset investment. For example, in 2005, Shi Meijuan used the ARMR modeling method to analyze the data which was provided by "Shanghai Statistical Yearbook 2002"in the application of "ARMR model in the prediction of fixed assets investment in Shanghai". The results show that the model ARMR (1 , 1, 10) has accurate prediction effects and provides a reliable basis for the fixed assets of the whole society in Shanghai.

In 2007, BaoBaolin and He Yingdi used the time-series-modeling method in Eviews software system in the article" Application of ARMA Model in Taiyuan City Fixed Assets Investment Forecast" to establish the ARMA model and analysed the total fixed assets investment data of Taiyuan City. The results show that the ARMA (2,1,3) model provides a more accurate prediction effect, providing a convenient and practical method for the forecast of fixed assets investment in Taiyuan City.

Also, in 2010, in the "Application of ARMA Model in China's Fixed Assets Investment Forecast". Based on the relevant data of China's fixed asset investment from 1980 to2007, Li Hui used the principles of statistics and econometrics, starting from the definition of time series, using ARMA modeling method applied to the analysis and forecast of China's fixed asset investment data over the years. It is proved that the ARMA (4, 2, 4) model is thebest. And Li Hui recommended that the government seize the investment opportunity and arrange the investment proportion reasonably to promote the healthy development of the economy.

Just in 2014, in the "Based on the ARMR model: Total Social Assets Investment Forecast", Xue Beibei used the econometric software Eviews to establish a related ARMA based on the total fixed asset investment data of Anhui Province. The model had carried out predictive analysis and provided an objective and scientific basis for the formulation of fixed assets investment in Anhui Province.

From the prediction analysis of these scholars, we can know that the ARMA model can make short-term accurate predictions and indirectly promote the healthy development of the economy. Therefore, this paper regards the total investment in fixed assets in China as a time series. By collecting historical data, using historical data to analyze and obtain the laws, so as to predict the account of future.

II. The Selection of Data

Collect and sort out the total fixed assets investment at the end of the year from 1980 to 2017 from the China Statistical Yearbook (see Table 1)

year	(X)	year	(X)	year	(X)	year	(X)
1980	910.9	1990	4517	2000	32917.73	2010	251683.77
1981	961	1991	5594.5	2001	37213.49	2011	311485.13
1982	1230.4	1992	8080.1	2002	43499.91	2012	374694.74
1983	1430.1	1993	13072.3	2003	55566.61	2013	446294.09
1984	1832.9	1994	17042.1	2004	70477.4	2014	512020.65
1985	2543.2	1995	20019.3	2005	88773.62	2015	561999.83
1986	3120.6	1996	22913.5	2006	109998.2	2016	606465.66
1987	3791.7	1997	24941.1	2007	137323.94	2017	631684
1988	4753.8	1998	28406.2	2008	172828.4		
1989	4410.4	1999	29854.7	2009	224598.77		

Table 1Total social fixed assets investment at the end of 1980-2017 unit(100 million yuan)

III. Empirical Analysis Based on Arma Model

1. Stability test of time series

(1) Modeling by time series data, the precondition is that the data should be stable. Therefore, firstly, it is necessary to perform the stationarity test on the data according to the scatter plot, auto correlation function and partial auto correlation function graph in time series. Drawing the linear -time diagram, we can see that the sequence has a very large upward trend. Therefore, the fixed asset investment amount has a strong non-stationary nature(see Figure 1). Then you need to smooth the data.

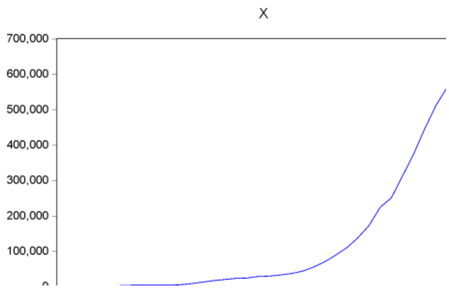


Figure 1 X sequence line timing diagram

(2) Smoothing the non-stationary sequence. First take the natural logarithm of X_t, so$Y_t = \ln X_t$. The results obtained are shown in Table 2 below.

year	(Y)	year	(Y)	year	(Y)	year	(Y)
1980	6.815	1990	8.416	2000	10.402	2010	12.436
1981	6.868	1991	8.630	2001	10.525	2011	12.650
1982	7.115	1992	8.997	2002	10.681	2012	12.834
1983	7.266	1993	9.479	2003	10.926	2013	13.009
1984	7.514	1994	9.744	2004	11.163	2014	13.147
1985	7.841	1995	9.905	2005	11.394	2015	13.240
1986	8.046	1996	10.040	2006	11.609	2016	13.316
1987	8.241	1997	10.125	2007	11.831	2017	13.357
1988	8.467	1998	10.255	2008	12.060		
1989	8.392	1999	10.304	2009	12.323		

Table 2 Social total fixed asset investment logarithm

Then draw a line graph based on the obtained data, as shown in Figure 2.It can be seen that the line graph still has a clear upward trend. Therefore, the fixed asset investment amount still has a strong non-stationary nature after taking the logarithm.

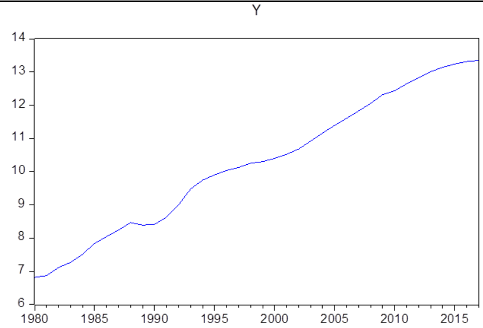


Figure 2 Y sequence line timing diagram

Taking the unit root test of Y_t ,we can get figure 2.The results in the figure also show that the sequence isnot stable, so the data needs to be differentially processedto further smooth the processing.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.905669	0.7746
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

Figure 3 Y-sequence unit root test

(3) For further smoothing, then perform the first-order difference method of Y_t, Commanding $Z_t = Y_t - Y_{t-1}$. Draw a sequence line type timing diagram, as shown in Figure 4. From the figure, we can see that the sequence has a small upward trend and a large amplitude. Therefore, it can be considered that the fixed asset investment amount is basically stable after logarithmic difference method. Then take the unit root test of Z_t , as shown in Figure 5, and the value of P was <0.05,so the sequence was basically stable.

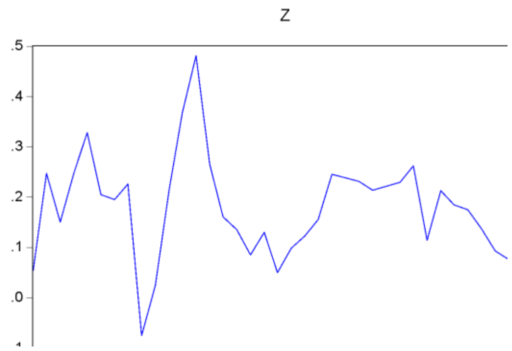


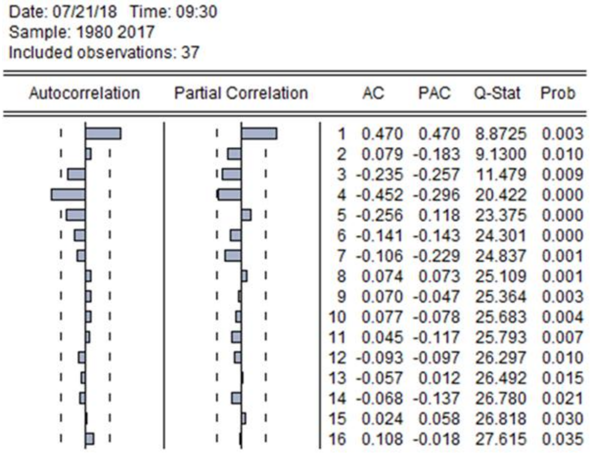
Figure 4 Z sequence line timing diagram

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.713282	0.0086
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

Figure 5 Z-sequence unit root test

2. Model ordering and parameter estimation

To determine the order of the model, at first, screening the p and the q values in the model. The ECF and PACF figures with a lag of 16 were made by using Eviews software. (See Figure 6)



Date: 07/21/18 Time: 09:30
Sample: 1980 2017
Included observations: 37

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.470	0.470	8.8725	0.003
		2	0.079	-0.183	9.1300	0.010
		3	-0.235	-0.257	11.479	0.009
		4	-0.452	-0.296	20.422	0.000
		5	-0.256	0.118	23.375	0.000
		6	-0.141	-0.143	24.301	0.000
		7	-0.106	-0.229	24.837	0.001
		8	0.074	0.073	25.109	0.001
		9	0.070	-0.047	25.364	0.003
		10	0.077	-0.078	25.683	0.004
		11	0.045	-0.117	25.793	0.007
		12	-0.093	-0.097	26.297	0.010
		13	-0.057	0.012	26.492	0.015
		14	-0.068	-0.137	26.780	0.021
		15	0.024	0.058	26.818	0.030
		16	0.108	-0.018	27.615	0.035

Figure 6 Z sequence lags 16 ACF maps and PACF maps

According to the tailing and truncation in Fig. 6, the stationary sequence partial autocorrelation function and the autocorrelation function are both tailed. Then establish the ARMA model .Considering p=3, 4, q=3, 4, 5, make the AIC values for each combination, see Table 3 below.

		q		
		3	4	5
	3		-2.5965	-2.5984
	4	-4.205	-2.2651	-2.5936

Table 3 AIC value

Then, screen by the AIC value. It can be seen from Table 3 that when p=4 and q=3, the value of AIC is the smallest, and according to the principle of the AIC value minimizing, it can be said that the model ARMA（4,1,3）is better.

Perform the parameter estimation process, and the results of Figure 7 can be obtained by estimating parameters using Eviews software.

Dependent Variable: Z
Method: Least Squares
Date: 07/21/18 Time: 09:32
Sample (adjusted): 1984 2016
Included observations: 33 after adjustments
Convergence achieved after 381 iterations
MA Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.174386	0.010658	16.36225	0.0000
AR(1)	0.506492	0.080955	6.256456	0.0000
AR(2)	-0.250795	0.066225	-3.786981	0.0009
AR(3)	0.528028	0.118725	4.447467	0.0002
AR(4)	-0.637205	0.108394	-5.878602	0.0000
MA(1)	-0.009701	0.658259	-0.014738	0.9884
MA(2)	0.128916	0.692352	0.186200	0.8538
MA(3)	-3.220189	0.709541	-4.538410	0.0001

R-squared	0.944608	Mean dependent var	0.177121
Adjusted R-squared	0.929098	S.D. dependent var	0.105627
S.E. of regression	0.028126	Akaike info criterion	-4.097042
Sum squared resid	0.019777	Schwarz criterion	-3.734252
Log likelihood	75.60119	Hannan-Quinn criter.	-3.974974
F-statistic	60.90392	Durbin-Watson stat	1.811969
Prob(F-statistic)	0.000000		

Figure 7ARMA (4,1,3) parameter estimation

Look at Figure 7, it can be seen that the coefficient test of the first-order and second-order lag terms of MA is not significant. Thus, delete the two items, the corrected ARMA (4, 3) is obtained, and use the Eviews software to estimate the parameters, we obtain Figure 8.

Dependent Variable: Z
Method: Least Squares
Date: 07/21/18 Time: 09:34
Sample (adjusted): 1984 2016
Included observations: 33 after adjustments
Convergence achieved after 23 iterations
MA Backcast: 1981 1983

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.180570	0.004430	40.75775	0.0000
AR(1)	0.559456	0.158638	3.526615	0.0015
AR(2)	-0.103137	0.164900	-0.625452	0.5369
AR(3)	0.215804	0.143303	1.505930	0.1437
AR(4)	-0.507740	0.139644	-3.635970	0.0011
MA(3)	-0.911261	0.048206	-18.90354	0.0000

R-squared	0.687044	Mean dependent var	0.177121
Adjusted R-squared	0.629089	S.D. dependent var	0.105627
S.E. of regression	0.064330	Akaike info criterion	-2.486628
Sum squared resid	0.111734	Schwarz criterion	-2.214536
Log likelihood	47.02937	Hannan-Quinn criter.	-2.395077
F-statistic	11.85480	Durbin-Watson stat	1.791756
Prob(F-statistic)	0.000004		

Figure 8 ARMA (4,3) parameter estimation

Looking at Figure 8, it can be seen that the coefficient test of the second-order and third-order lag terms of AR is not significant. Therefore, delete the first-order, second-order, and third-order lag terms, we obtain the modified ARMA (4, 3), and use Eviews software to estimate the parameters to obtain Figure 9, and make a model fit map, as shown in Figure 10.

Dependent Variable: Z
Method: Least Squares
Date: 07/21/18 Time: 11:01
Sample (adjusted): 1984 2016
Included observations: 33 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 1981 1983

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.181369	0.003144	57.68925	0.0000
AR(4)	-0.404530	0.161056	-2.511738	0.0176
MA(3)	-0.896867	0.036360	-24.66624	0.0000

R-squared	0.506893	Mean dependent var	0.177121
Adjusted R-squared	0.474019	S.D. dependent var	0.105627
S.E. of regression	0.076606	Akaike info criterion	-2.213784
Sum squared resid	0.176053	Schwarz criterion	-2.077738
Log likelihood	39.52744	Hannan-Quinn criter.	-2.168009
F-statistic	15.41938	Durbin-Watson stat	0.833604
Prob(F-statistic)	0.000025		

Figure 9 ARMA (4,3) parameter estimation

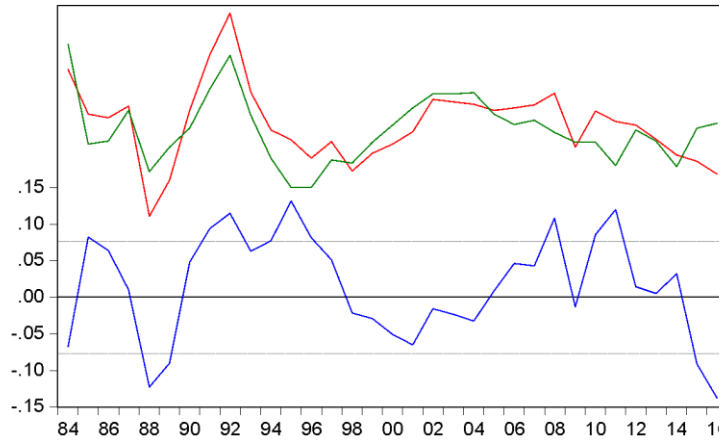


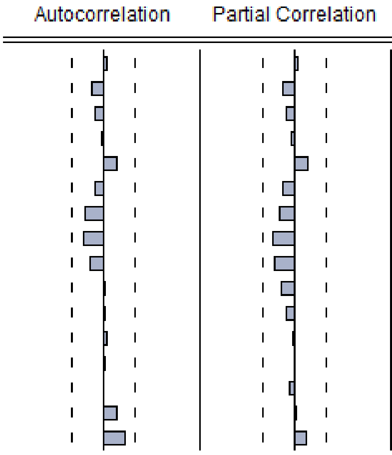
Figure 10 Model fitting map

According to the correction result in Figure 9, the expression of the model is:□ = 0.1813 □ 0.4045□□□4□□□□ 0.8969□□□3.

3. Model hypothesis testing

The model hypothesis test is to test whether the model residual sequence is a white noise sequence. If the model passes the white noise test, it can be predicted. Observing the ACF and PACF maps of the residuals of ARMA (4, 3) (see Figure 11), we can see that the AC values of the auto correlation function of the model residuals and the PAC values of the partial autocorrelation function all fall within the confidence interval. Therefore, the model residual obeys the white noise distribution, so the choice of the parameters of our model ARMA is correct, and the fitting effect is also meeting the requirements.

Date: 07/21/18 Time: 10:06
Sample: 1984 2016
Included observations: 33
Q-statistic probabilities adjusted for 3 ARMA term(s)



	AC	PAC	Q-Stat	Prob
1	0.029	0.029	0.0300	
2	-0.121	-0.122	0.5741	
3	-0.095	-0.089	0.9235	
4	-0.015	-0.025	0.9323	0.334
5	0.154	0.136	1.9083	0.385
6	-0.091	-0.115	2.2617	0.520
7	-0.197	-0.171	3.9938	0.407
8	-0.229	-0.237	6.4204	0.267
9	-0.152	-0.229	7.5261	0.275
10	0.009	-0.141	7.5298	0.376
11	0.011	-0.096	7.5364	0.480
12	0.031	-0.019	7.5903	0.576
13	0.021	-0.003	7.6166	0.666
14	-0.001	-0.064	7.6166	0.747
15	0.134	0.012	8.7753	0.722
16	0.225	0.117	12.221	0.510

Figure 11 11 ACF and PACF maps of model residuals

4. Use the tested model to make predictions

According to the model ARMA (4, 3) of time series {□□}:

□□ = 0.1813 □ 0.4045□□□4□□□□ 0.8969□□□3

The prediction formula for the model ARMA (4, 3) of time series{□□ } is:

□□ = □□□1 + 0.1813 □ 0.4045□□□4□□□□ 0.8969□□□3

Thus the prediction formula for the model ARMA (4, 3) of time series is:

□□ = □ 0.1813□0.4045□ □□4□□□□0.8969□□□3

Therefore, according to the formula, we can make a simple forecast for the next year's fixed asset investment amount: 670, 216.724 billion yuan.

IV. Conclusion

It can be seen from the model formula we have gotten that China's fixed asset investment is closely related to the lag value of the fourth period and the random disturbance item of the third period. From parameter estimates, we can see that: China's fixed asset investment is negatively correlated with the third phase of the random disturbance. Therefore, the government must pay attention to this point when guiding investment. The government should also regulate the proportion of investment rationally, and prevent improper social investment to affect the healthy development of the economy.

Because the ARMR model itself has a defect, that is, with the extension of time, the prediction error may gradually increase, but the ARMA model is more accurate in the short term. Compared with other forecasting methods, the accuracy of its prediction is still relatively high, especially in terms of short-term forecasting.

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