Predictive Analysis of China's Broad Money Supply (M2) Based on ARIMA-GARCH Model

Xiangyao Liu[1], Lei Wang[2]

[1]Sino-German School, Shanxi University of Finance and Economics, Wucheng Road, Taiyuan, China

[2]Faculty of Finance &Banking, Shanxi University of Finance and Economics, Taiyuan, Shanxi, China

Keywords: Broad money supply; ARIMA; GARCH; Prediction

Abstract: The formation process of China's money supply has its particularity, and monetary policy plays an important role in China's macroeconomic operation. Since 1998, the People's Bank of China has proposed the M2 and M2 two levels of money supply control targets each year when determining the monetary policy goals of the year. After 2007, the People's Bank of China no longer raised the growth target of the narrow money supply M1. The change of the central bank's control objectives indicates that China's monetary policy regulation pays more attention to the broad money supply M2.

Therefore, based on the historical data of China's broad money supply M2, this paper establishes a stable model for predicting the future broad money supply M2 in China, and helps investors predict the direction of future monetary policy by effectively predicting the broad money supply M2, and reduce the risk of buying and selling securities.

1. Introduction

The formation process of China's money supply has its particularity, and monetary policy plays an important role in China's macroeconomic operation. Since 1998, the People's Bank of China has proposed the M2 and M2 two levels of money supply control targets each year when determining the monetary policy goals of the year. After 2007, the People's Bank of China no longer raised the growth target of the narrow money supply M1. The change of the central bank's control objectives indicates that China's monetary policy regulation pays more attention to the broad money supply M2.

Therefore, based on the historical data of China's broad money supply M2, this paper establishes a stable model for predicting the future broad money supply M2 in China, and helps investors predict the direction of future monetary policy by effectively predicting the broad money supply M2, and reduce the risk of buying and selling securities.

2. Research steps

This paper mainly uses ARIMA model and GARCH model. The modeling steps for the predictive model of the broad money supply M2 growth rate are presented.

1) Perform the ADF stability test on the generalized money supply M2 year-on-year growth rate sequence. If the original sequence does not satisfy the stationarity condition, it can be differentially transformed or otherwise transformed to determine its single order (generally less than 3).

2) Calculate the autocorrelation coefficient and partial autocorrelation coefficient of the d-order single-sequence of the original sequence, and determine the order p and q of the ARIMA model, and d is the minimum order that the original sequence satisfies the stationarity.

3) Estimate the unknown parameters of the model and test the significance of the parameters and the rationality of the model itself.

4) Perform an ARCH-LM test on the residuals obtained in the ARIMA model. If there is a conditional heteroscedasticity in the residual sequence, the ARIMA-GARCH model is established; if there is no conditional heteroscedasticity, only the ARIMA model is established.

  DOI: 10.25236/etmhs.2019.302

5) If there is a conditional heteroscedasticity in the residual sequence, the error term of the GARCH model needs to be corrected. It is possible to test the hypothesis of normal distribution, t-distribution and generalized error distribution, and to correct the error distribution with the highest prediction accuracy.

6) Perform a diagnostic analysis to verify that the resulting model does match the observed data characteristics.

3. Empirical analysis

3.1 Time series smoothing

There are three commonly used methods for stationarity test: time series test, autocorrelation chart test, and unit root test.

According to the time series, from January 1997 to October 2017, the national monthly power generation increased year by year, with a clear upward trend and seasonal periodicity. In the past 20 years, the broad-term growth rate of broad money supply M2 has slightly decreased. Before and after 2009-2010, the year-on-year growth rate has strong fluctuations.

In order to confirm this conclusion, the ADF test was further carried out.

Table 1 Unit root test results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.248897	0.1897
Test critical values：	1% level	-3.455585	
	5% level	-2.872542	
	10% level	-2.572707	

In the process of judging the stationarity, using the unit root test to determine the stationarity of the sequence is the most reliable method. By analyzing the above results, it is found that the ADF statistic of the sequence M2 is -2.248897, and the accompanying probability is 18.97%. The original hypothesis that the sequence M2 has a unit root is considered, and the sequence is considered to be unstable. So we make a first-order difference to the sequence and see if it is stable after the difference.

3.2 Differential Process

According to the descriptive statistical analysis results, in order to accurately eliminate the trend and seasonality of the sequence and turn the sequence into a stationary sequence, the sequence M2 is subjected to first-order difference and seasonal difference to form a new sequence DM2.

The first order difference and the seasonal difference of the original sequence M2 are used to obtain the sequence DM2, and the stationarity is analyzed by ADF test.

Table 2 Summary of stationarity test results

Variable	(c,t,p)	Augmented Dickey-Fuller test statistic	Test critical values(5% level)	Prob	Result
M2	(c,0,0)	-2.248897	-2.872542	0.1897	Non-stationary
dM2	(0,0,0)	-8.135836	-2.872542	0.0000	stationary
dM2	(c,0,0)	-8.139173	-2.872542	0.0000	stationary
dM2	(c,1,0)	-8.108441	-2.872542	0.0000	stationary

According to the ADF unit root test results in the above table. The probability of all the test cases of the sequence DM2 is less than 0.05, and the DM2 of the reject sequence has the original hypothesis of the unit root, and the sequence DM2 is considered to be stable.

3.3 Model identification and ordering

The autocorrelation and partial correlation graph analysis is performed on the differential sequence DM2. The accompanying probability of the first 24 periods of the residual sequence is mostly 0.000, which indicates that the residual sequence does not have pure randomness. From the censoring characteristics of autocorrelation and partial autocorrelation, the model can be set to the AMIMA (p, d, q) model.

The following table shows that the adjoint probabilities of the estimated coefficients of the AR(1), AR(3), and SMA(12) terms in the estimation results are less than 0.05, both satisfying the parameter significance requirements, the autoregressive coefficient polynomial and the moving average coefficient polynomial. The reciprocal of the root is within the unit circle and satisfies the reversibility requirement.

Table 3 Model regression results of ARIMA ((1,3),1,0)×(0,1,1)12 model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.274984	0.057400	-4.790699	0.0000
AR(3)	0.272154	0.051381	5.296743	0.0000
MA(12)	-0.492239	0.049646	-9.914965	0.0000
R-squared	0.240781	Mean dependent var		-0.058023
Adjusted R-squared	0.234826	S.D. dependent var		1.227487
S.E. of regression	1.073734	Akaike info criterion		2.991722
Sum squared resid	293.9908	Schwarz criterion		3.033035
Log likelihood	-382.9321	Hannan-Quinn criter.		3.008334
Durbin-Watson stat	1.998071			
Inverted AR Roots	.57	-.42+.55i	-.42-.55i	
Inverted MA Roots	.94	.82-.47i	.82+.47i	.47+.82i
	.47-.82i	.00-.94i	-.00+.94i	-.47-.82i
	-.47+.82i	-.82+.47i	-.82-.47i	-.94

The residual autocorrelation plot of the model shows that the accompanying probability of the Q statistic of the first 24 residuals is much greater than 0.05, indicating that the residual has pure randomness, which means that there is almost no correlation information of the sequence in the residual. The ARIMA((1,3),1,0)X(0,1,1)12 model satisfies the residual randomness condition and simulates the correlation information of the sequence DM2. The parameters of the model are as follows (where is the white noise process).

$$\Delta\Delta_{12}DM2 = \frac{1-0.492239L^{12}}{1+0.274984B-0.272154B^{3}}\varepsilon_{t}$$

3.4 Heteroscedasticity test and establishment of GARCH model

Generally speaking, the ARMA model with parameter significance, stationary reversibility and residual randomness test has been able to reveal the law of time series development. However, China's M2 growth rate sequence often has obvious volatility aggregation characteristics, so it is necessary to further test heteroscedasticity. The results of the heteroscedasticity (ARCH) test using the Lagrangian multiplier (LM) method also show that the F statistic and the TR statistic are accompanied by a small probability, and the residual square sequence of the model is rejected at a significance level of 1%. There is no null hypothesis of sequence correlation, indicating that the residual sequence is heteroscedastic, indicating that the sequence DM2 is heteroscedastic.

Further, this paper establishes a GARCH model. First, the GARCH(1,1) model is estimated. The following figure shows the GARCH(1,1) model parameter estimation results.

Table 4 GARCH model parameter estimation results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.229843	0.065572	-3.505207	0.0005
AR(3)	0.217925	0.061568	3.539608	0.0004
MA(12)	-0.397735	0.043970	-9.045593	0.0000
		Variance Equation		
C	0.060851	0.032430	1.876348	0.0606
RESID(-1)^2	0.145718	0.039945	3.647934	0.0003
GARCH(-1)	0.792802	0.054167	14.63630	0.0000
R-squared	0.232427	Mean dependent var		-0.058023
Adjusted R-squared	0.226407	S.D. dependent var		1.227487
S.E. of regression	1.079625	Akaike info criterion		2.825038
Sum squared resid	297.2256	Schwarz criterion		2.907665
Log likelihood	-358.4299	Hannan-Quinn criter.		2.858263
Durbin-Watson stat	2.058610			
Inverted AR Roots	.53	-.38+.51i	-.38-.51i	
Inverted MA Roots	.93	.80+.46i	.80-.46i	.46+.80i
	.46-.80i	.00+.93i	.00-.93i	-.46+.80i
	-.46-.80i	-.80-.46i	-.80+.46i	-.93

The results show that the estimated coefficients are significant and satisfy the GARCH model's qualifications for parameter non-negative and parameter bounded. The Q-test of the residual square sequence of the GARCH(1,1) model shows that the residual square sequence of the GARCH(1,1) model shows better pure randomness, so the GARCH(1,1) model is better. Interpret the heteroscedasticity of the sequence.

3.5 Model prediction test and prediction

Predictive testing: The US trade deficit from November 2017 to October 2018 can be predicted by the GARCH model. Comparing the predicted value with the actual value, it can be seen that the error between the predicted value and the actual value is small, both less than 10%, so it can be known that the model has a better prediction effect on the growth rate of money supply in the short term.

Table 5 Forecast Error Table

Time	Actual value	Predictive value	Prediction error(%)
2017M11	9.10	9.00	1.12%
2017M12	8.20	8.61	4.94%
2018M01	8.60	9.10	5.54%
2018M02	8.80	9.24	4.73%
2018M03	8.20	8.56	4.24%
2018M04	8.30	8.81	5.76%
2018M05	8.30	8.37	0.78%
2018M06	8.00	8.34	4.02%
2018M07	8.50	8.65	1.79%
2018M08	8.20	8.58	4.44%
2018M09	8.30	8.44	1.63%
2018M10	8.00	8.58	6.72%

Sample prediction: Based on the prediction test, the GARCH model is used to predict the trade deficit of the United States from November 2018 to April 2019. The prediction results are shown in Table 6.

Table 6 Predicted values

Time	Predictive value
2018M11	7.95
2018M12	8.40
2019M01	8.13
2019M02	8.12
2019M03	7.86
2019M04	8.18

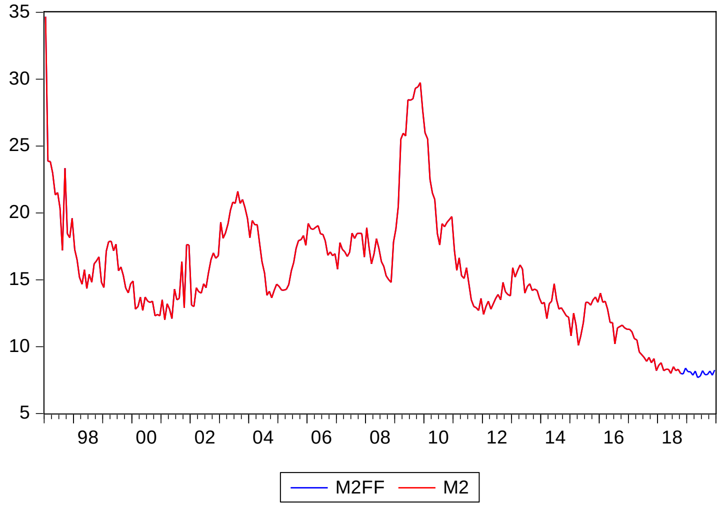

Figure 1 Prediction timing diagram

4. Conclusion

Based on the historical data of China's broad money supply M2 from January 1997 to October 2017, this paper establishes ARIMA ((1,3),1,0)×(0,1,1) of China's broad money supply M2. 12 model, although the model has passed the parameter saliency, stationary reversibility, residual randomness test, but because the money supply M2 itself often has the characteristics of volatility clustering, this paper further tests the heteroscedasticity. In this paper, we find that the original model has significant heteroscedasticity. Therefore, the GARCH (1,1) model is established in this paper. At the same time, in order to overcome the non-negative parameter and the bounded parameter, the EGARCH (5,5) model is also established. Based on the GARCH (1,1) model, this paper conducts an in-sample test on samples from November 2017 to October 2018, which passes the predictive test very well and is from November 2018 to December 2019. The broad money supply M2 is predicted and the fitting effect is good.

It can be seen from the forecast results that it is expected that the growth rate of China's broad money supply M2 will be relatively stable in the next year, and a slight downward trend is conducive to curbing inflation. However, in the future, the central bank may further reduce the standard according to the actual development to stimulate economic development.

References

[1] Yaxing Sun. China's money supply factor decomposition model and ARIMA model prediction [D]. Central South University, 2009.

[2] Yadan Guo. Forecast of China's Money Supply Based on ARIMA Model [J]. Journal of Xiangfu Times, 2012(3):16-16.

[3] Hui Guan. Research on the Change Law of China's Broad Money Supply Based on ARINA Model [J]. Jilin Financial Research, 2012(7): 7-10.

[4] Chang Liu. Prediction and Analysis of China's Narrow-form Money Supply M1——Based on ARIMA Model and Regression Model [J]. China Securities and Futures, 2011(12): 162-163.

[5] Baoning Liu, Zhang Hui. Prediction of China's Money Supply in 2014 Based on ARIMA Model [J]. Foreign Trade, 2014(6): 99-100.

[6] Wei Luo. Research on Gold Price Trend Based on ARIMA-GARCH Model [J]. China Foreign Investment, 2013(6): 31-32.

[7] Beijia Shi. Extrapolation of Money Supply Based on ARIMA Model [J]. Manager, 2015(15):11-12.

[8] Junhua Hu. Regression Model and Forecast of China's Broad Money Supply M2 [J]. China Money Market, 2010(7): 31-35.

[9] Yajie Li, Lei Wang. Futures Forecast Based on ARIMA Model and GARCH Model [J]. Economic Perspectives, 2013(7).

[10] Haibo Li. Research on the Influence of China's Money Supply on Stock Price Index [J]. Journal of Southwest Jiaotong University, 2011(03).

[11] Yanfang Sun. Forecast of Money Supply Based on Adaptive Fuzzy Neural Network [J]. Science and Technology Information, 2011(23).

[12] Junhua Hu. Regression Model and Forecast of China's Broad Money Supply M2 [J]. China Money Market, 2010(07).

[13] Yaxing Sun, Tinglan Xu. ARIMA Model and Forecast of China's Money Supply [J].Mathematical Theory and Application, 2009(04).

[14] Yunxin He. An Empirical Analysis of the Controllability of China's Money Supply [J]. Journal of Finance and Economics, 2006(02).

[15] People's Bank of China. Broad Money Supply (M2) Monthly Data—January 1997 to October 2018 [EB/OL].2018[2018-12-1].http://www.pbc.gov .cn/.

[16] Yi Liu, Jiawen Peng, and Zhihao Yu. 2018. Big Data Platform Architecture under The Background of Financial Technology: In The Insurance Industry As An Example. In Proceedings of the 2018 International Conference on Big Data Engineering and Technology (BDET 2018). ACM, New York, NY, USA, 31-35. DOI: https://doi.org/10.1145/3297730.3297743