Empirical Analysis of the Changing Law of Broad Money Supply: Test Based on China's Data

Pengyue Xu, Ran Xian

School of Business, Shandong University, Weihai, Shandong, China

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Abstract: The broad money supply (M2) is of great significance to evaluate the level of liquidity in the economic system and to formulate future macroeconomic policies. In this paper, the time series data of China's broad money supply (M2) from 2006 to 2019 are analyzed in depth, and on this basis, the ARIMA model is used for high-precision fitting, as well as a short-term forecast is made. The research shows that the ARIMA model has excellent goodness of fit, with the prediction data close to the real data and the prediction accuracy relatively high; China's broad money supply is likely to maintain a rapid growth trend in the future.

1. Introduction

Broad money supply (M2) refers to the sum of cash, current deposit, and quasi-money. Kefeng Pei [1] proposed that M2 has an extremely important reference value for the operation of the national economy. Can Yang [2] also pointed out that M2 is an important tool in China's monetary policy and an important reason why central banks of various countries choose the money supply as the main means of controlling the economy. Chang Wang [3] explains that the Chinese government strives to adjust the price level and actual output by changing the money supply, thereby affecting the economic situation of the entire country.

Many foreign scholars used time series data and the co-integration method of the vector autoregressive model (VAR) to estimate the impact of monetary policy. Hafer and Kutan [4] used the error correction model to examine the co-integration relationship among the money demand of China, real national income, and expected inflation rate from 1952 to 1988 in China. The research of Friedman [5] and Weber [6] also showed that there is a strong correlation between the inflation rate and the growth rate of the money supply. And in the long run, the increase in the money supply will eventually cause the inflation rate to rise to some extent. Blinder [7] used the VAR model and concluded that there is no long-term stable statistical relationship between the three officially defined money supply volumes published by the Federal Reserve Board and nominal GDP. Christiano [8], King [9] used Sims's bivariate model to analyze the logarithmic values of the U.S. money supply M1 and industrial output levels, and concluded that there is a significant Granger causality between the values.

Domestic scholars have also done a lot of work on the research of money supply through various models. Surong Zhu and Zhijian Huan [10] systematically analyzed the principle of STM, applied the STM model to predict China's nominal quarterly GDP, and compared the fitting effects of different models. The empirical study showed that the structural time series model has a good prediction effect. Xiangjun Gu and Lan Gu [11] introduced the state space method for structural economic time series with annual, quarterly and monthly data and provided calculation cases as reference. Qunyong Wang [12] took the quarterly GDP of China as an example to study the seasonal adjustment application of the structured time series method and confirmed that this method is superior to the X11 and SEATS. Yaxing Sun [13], Hui Guan [14], and Xiangshan Lei [15] used the ARIMA model to predict the changing laws and trends of China's money supply and obtained good prediction results.

Based on the historical data of China's money supply, this paper establishes a research model to predict China's money supply in the future, and forms a mechanism to quantitatively study the

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changing trend of China's money supply. The ARIMA model is widely used in data analysis, prediction and control of macroeconomic financial time series. This article uses monthly data instead of the annual data commonly found in previous studies. It has a higher forecast accuracy in the short term and is more suitable for short-term policy guidance. With this model analyzing the broad money supply is of great significance for correctly understanding the various subjects of market economic activities and understanding the macroeconomic situation, studying macroeconomic financial policies, and predicting the development and changes of financial markets.

2. Theoretical knowledge of ARIMA model

The ARIMA model is a well-known time series prediction method proposed by Box-Jenkins in the early 1970s and is often used for short-term analysis and prediction. At the same time, the ARMA model and the SARIMA model have been proposed, which is only suitable for describing the autocorrelation of a stationary sequence. Time series data from economic data is different from cross-section data where there is repeated sampling. It is the only record of a random event. If the mean, variance and auto-covariance of a time series u_t do not depend on the time t, the time series u_t is called to be weakly stationary or covariance stationary, that is, to satisfy the following three properties:

(i) $E(u_t) = \mu$, for all *t*.

(ii) $\text{var}(u_t) = \sigma^2$, for all *t*.

(iii) $\text{cov}(u_t, u_{t-s}) = \gamma_s$, for all t and *s*.

The randomness of a stationary sequence is subject to a certain probability distribution, which means that we can build a model to fit based on the information of past time points of the time series, and then realize the prediction of future information. However, for a non-stationary time series, the randomness of the time series at each time point is different, and it is difficult to grasp the overall randomness of the time series through known information. Most data in economic operations such as GDP and consumer price index are non-stationary time series.

If the time series is non-stationary, it should be transformed into a stationary sequence through difference operation before building the model. This sequence is called an integrated series. If the sequence y becomes a stationary sequence by d times difference, and this sequence is not stationary when it differs by d-1 times, we call the sequence y a single order of order d, denoted as y ~ I (d), and

$$w_t = \Delta^d y_t = (1-L)^d y_t \tag{1}$$

w_t is a stationary series. The ARMA (p,q) model can be built for w_t:

$$w_t = c + \phi_1 w_{t-1} + \ldots + \phi_p w_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{2}$$

Expressed as a causal operator as:

$$\phi(L) w_t = C + \Theta(L) \varepsilon_t \tag{3}$$

In the formula:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p \tag{4}$$

$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q \tag{5}$$

The ARMA (p, q) model after the d-order difference transformation is called the ARIMA (p, d, q) model. The difference is that the characteristic polynomial of the autoregressive part contains d unit roots. Therefore, we need to perform unit root test on the time series to determine whether it is stationary before modeling.

3. Empirical study

The data used in this paper comes from the National Bureau of Statistics and the People's Bank of China. The selected sample interval is the value of the broad money supply in each month from 2006 to 2019. The data of each month from 2006 to 2018 is used for model fitting, and the data of each month of 2019 is used to verify the prediction effect of the model, and the predicted value of 2020 is calculated according to the model. M2 is selected as the original time series of the broad money supply.

3.1 Sequence Preprocessing

Select the statistical software Eviews to get the original time series chart of the money supply. As shown in Figure 1.

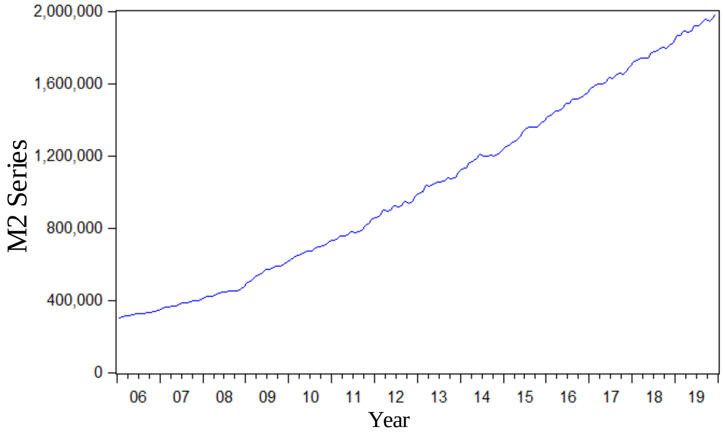


Figure 1 M2 original time series.

The abscissa is time, and the ordinate is the broad money supply. It can be found in the figure that M2 has a strong upward trend, which is a very typical non-stationary time series.

The original hypothesis of the ADF test is $\eta=0$, that is, there is at least one unit root in the sequence. The alternative assumption is $\eta\neq0$, there is no unit root. We conduct an ADF test on the broad money supply M2 and its second-order differential DDM2. According to the SIC criterion, it determines that the lag phase required to eliminate sequence correlation are 12 and 10. Eviews test results are shown in Tables 1 and 2.

According to Table 1, The ADF statistical value of sequence M2 is greater than 1%, 5% and 10% statistical values. And the accompanying probability is obviously greater than 0.05, which cannot reject the null hypothesis, that is, the sequence M2 has at least one unit root. The P statistic of the sequence DDM2 after two differential operations is obviously less than 1%, indicating that after the second order difference, the non-stationary time series M2 becomes a stationary sequence, that is, d = 2. The DDM2 time series is shown in Figure 2. The abscissa is time, and the ordinate is DDM2 data.

3.2 Model Recognition

The order of the ARIMA model depends on the analysis of the autocorrelation coefficient (AC) and the partial autocorrelation coefficient (PAC). The correlation diagram of the time series DDM2 is shown in Figure 3.

It can be found that when k = 12 or 24, the autocorrelation coefficient will have a relatively large peak, indicating that the sequence contains a certain seasonality, and further seasonal differences need to be made. Make the seasonal difference of the period S = 12 for DDM2. The autocorrelation coefficient and partial correlation coefficient of the time series fall into the random area relatively quickly, and the sequence trend is basically eliminated, so the first-order seasonal difference is adopted. According to the above theory, the ARIMA (p, d, q) $(P, D, Q)_{12}$ model is established to predict the broad money supply, where d and D are the orders of the difference, and through the above judgment, we can see that d = 2 and D = 1. When the seasonal period = 12, the autocorrelation coefficient is not zero, so P = 0, Q = 1. Observe the characteristics presented by the correlation graph, try using different p and q values, and select the smallest model with AIC and SC criteria to obtain p = 2 and q = 0. Therefore, the ARIMA (2, 2, 0) $(0, 1, 1)_{12}$ is selected as the final prediction model.

Table 1 Augmented dickey-fuller unit root test on M2

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.7787	0.9997
Test critical values:	1% level	-3.4728	
	5% level	-2.8801	
	10% level	-2.5767	

Table 2 Augmented dickey-fuller unit root test on DDM2

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.0320	0.0000
Test critical values:	1% level	-3.4728	
	5% level	-2.8801	
	10% level	-2.5767	

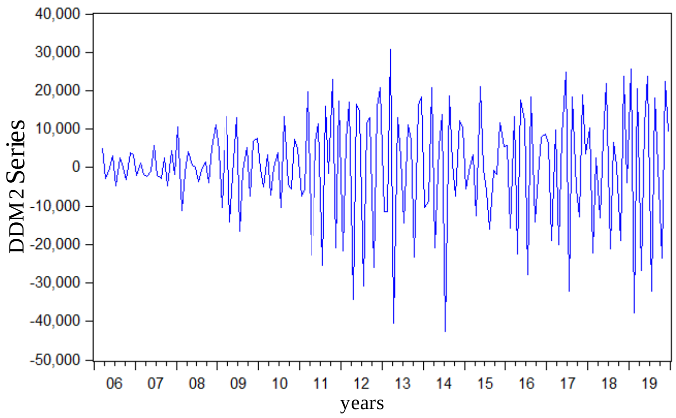
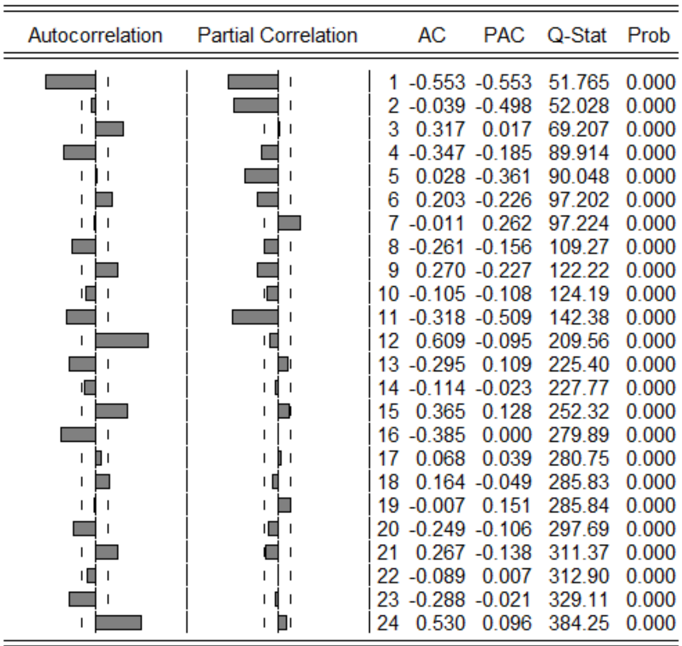


Figure 2 DDM2 time series.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.553	-0.553	51.765	0.000
		2	-0.039	-0.498	52.028	0.000
		3	0.317	0.017	69.207	0.000
		4	-0.347	-0.185	89.914	0.000
		5	0.028	-0.361	90.048	0.000
		6	0.203	-0.226	97.202	0.000
		7	-0.011	0.262	97.224	0.000
		8	-0.261	-0.156	109.27	0.000
		9	0.270	-0.227	122.22	0.000
		10	-0.105	-0.108	124.19	0.000
		11	-0.318	-0.509	142.38	0.000
		12	0.609	-0.095	209.56	0.000
		13	-0.295	0.109	225.40	0.000
		14	-0.114	-0.023	227.77	0.000
		15	0.365	0.128	252.32	0.000
		16	-0.385	0.000	279.89	0.000
		17	0.068	0.039	280.75	0.000
		18	0.164	-0.049	285.83	0.000
		19	-0.007	0.151	285.84	0.000
		20	-0.249	-0.106	297.69	0.000
		21	0.267	-0.138	311.37	0.000
		22	-0.089	0.007	312.90	0.000
		23	-0.288	-0.021	329.11	0.000
		24	0.530	0.096	384.25	0.000

Figure 3 Correlation diagram of DDM2 sequence.

3.3 Inspection of the Model

3.3.1 Model stationarity test

To ensure the stability of the model, the reciprocal of the characteristic roots of the model is required to be less than 1, that is, the roots are in the unit circle. Figure 4 shows the reciprocal distribution of the characteristic roots of the model.

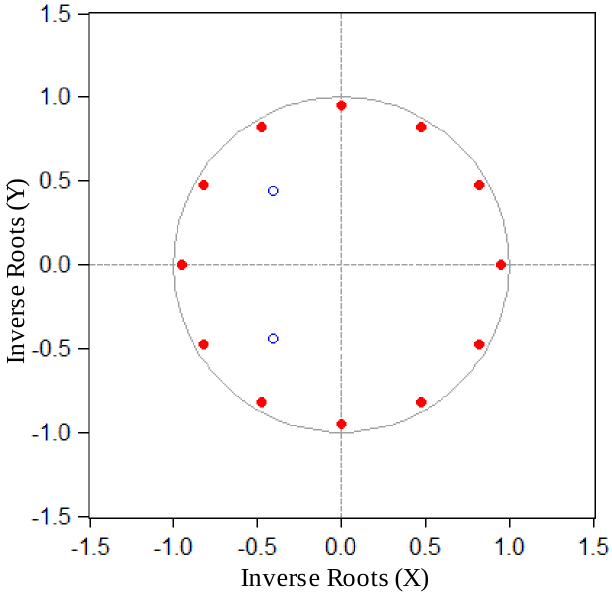


Figure 4. Inverse roots of AR/MA polynomial(s).

As is vividly portrayed from the picture, the reciprocal of all the characteristic roots of the ARIMA (2, 2, 0) $(0, 1, 1)_{12}$ model lies in the unit circle, so it shows that the model is stable.

3.3.2 Model parameter test

The parameter test of the model is shown in Table 3.

Table 3 The parameter test of the model

	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C	-3.719218	142.3789	-0.026122	0.9792
AR(1)	-0.813910	0.071250	-11.42331	0.0000
SAR(12)	-0.362739	0.063301	-5.730400	0.0000
MA(12)	-0.535354	0.056895	-9.409537	0.0000
R-squared	0.570699	Mean dependent var		34.24838
Adjusted R-squared	0.559174	S.D. dependent var		11817.01
S.E. of regression	7845.873	Akaike info criterion		20.83633
Sum squared resid	9.17E+09	Schwarz criterion		20.93493
Log likelihood	-1599.398	Hannan-Quinn criter.		20.87638
F-statistic	49.51891	Durbin-Watson stat		2.100494
Prob(F-statistic)	0.000000			

It can be seen from Table 3 that the P value of each parameter is less than 0.05, indicating that each parameter is significant at the 5% significance level. The DW statistic is 2.100494, which is close to 2. It can be considered that there is no positive correlation between residuals. By observing the residual autocorrelation coefficient and partial autocorrelation coefficient, the residual is close to the white noise sequence, indicating that the model has a good fitting effect, and the model can be used for fitting and prediction. The model fitting diagram is shown in Figure 5.

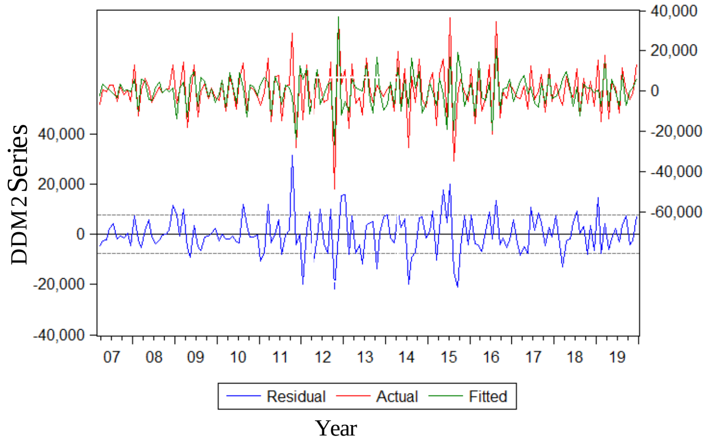


Figure 5 Model fitting diagram.

3.4 Model Prediction

3.4.1 Model prediction accuracy

The following methods are used to evaluate the prediction accuracy of the model:

(i) Mean square error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{x}_i - x_i\right)^2 \tag{6}$$

(ii) Mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}_i - x_i}{x_i}\times 100\right| \tag{7}$$

Use the fitted model to make static predictions on the broad money supply data from January 2019 to December 2019. Static prediction uses the actual value of the previous period when forming the predicted value, so its prediction effect will be more accurate than dynamic prediction. Table 4 compares the predicted data with the real data.

It shows that the broad money supply (M2) shows a rising trend in the short term. The overall forecast accuracy of the model is good, the overall error rate is low, and the MSE value is 3.85E + 07. The prediction ability is excellent when MAPE is less than or equal to 10%; the prediction ability is good when 10% -20%; the prediction ability is reasonable when 20% -50%; and the prediction is not accurate when it exceeds 50%. Based on the above analysis, the ARIMA (2, 2, 0) (0, 1, 1)$_{12}$ model has a MAPE value of 0.28% from January 2019 to December 2019, and the prediction effect is excellent.

Table 4 Comparison between M2 static prediction data and real data

Month	The actual data	Forecast data	Absolute error	Error rate %
1	1865935.33	1851458.39	-14476.9	-0.78%
2	1867427.45	1874489.51	7062.06	0.38%
3	1889412.14	1884626.04	-4786.1	-0.25%
4	1884670.33	1890226.37	5556.04	0.29%
5	1891153.7	1892723.22	1569.52	0.08%
6	1921360.19	1918668.78	-2691.41	-0.14%
7	1919410.82	1922640.8	3229.98	0.17%
8	1935492.43	1932351.33	-3141.1	-0.16%
9	1952250.49	1945730.53	-6519.96	-0.33%
10	1945600.55	1950865.24	5264.69	0.27%
11	1961429.56	1965435.36	4005.8	0.20%
12	1986488.82	1980797.16	-5691.66	-0.29%

3.4.2 Dynamic prediction of the model

Using the fitted effective model to dynamically predict the broad money supply (M2), the forecast range is from January 2020 to December 2020. Dynamic prediction is different from static prediction. It has the characteristics of multi-step forward, that is, according to a certain estimation interval selected, each step uses the prediction value of the previous period to calculate the current prediction value. The specific forecast data is shown in Table 5.

Table 5 M2 predicted values from January 2020 to December 2020

Time	point estimation	95% lower confidence limit	95% higher confidence limit
January 2020	2019008.41	2003516.59	2034500.24
February 2020	2027408.51	2003426.34	2051390.68
March 2020	2048804.23	2013545.19	2084063.27
April 2020	2047397.85	1998317.17	2096478.53
May 2020	2057430.16	1994052.82	2120807.51
June 2020	2088072.23	2008755.22	2167389.24
July 2020	2090862.68	1994457.27	2187268.08
August 2020	2107784.25	1993321.99	2222246.51
September 2020	2123772.08	1990144.70	2257399.45
October 2020	2122392.55	1968666.53	2276118.56
November 2020	2141871.94	1967130.87	2316613.01
December 2020	2167282.84	1970630.98	2363934.71

4. Conclusions and policy recommendations

The ARIMA (2, 2, 0) $(0, 1, 1)_{12}$ model of time series is suitable for high-precision fitting and forecasting of non-stationary time series of China's broad money supply. After repeated verification, the ARIMA (2, 2, 0) $(0, 1, 1)_{12}$ model can be built, and then the model can be used to analyze and reasonably predict China's broad money supply. From the static prediction results, the absolute error between the actual data and the predicted data is relatively small, and the relative error rate is basically stable within 1%. The higher R-squared of the model indicates that the model has a good fit. At the same time, the broad money supply also exhibits certain seasonality and periodicity. From the trend of broad money supply, it can be seen that it exhibits a volatility upward trend similar to exponential growth. The root cause of this exponential trend is the increase in the overall productivity and economic development level of Chinese society, leading to the demand for money getting bigger. Since 1998, China has achieved tremendous success in implementing a stable monetary policy. It is mainly reflected in the steady growth of the total amount of money and credit, the substantial adjustment of the credit structure, and the stability of domestic finance and RMB exchange rates. In order to maintain stable growth of the broad money supply, there are several optimization paths and ideas: (i) China should further accelerate the process of interest rate marketization reform, establish and improve an interest rate system based on central bank interest rates and mediated by the market interest rates, further play the role of market players in currency allocation. (ii) China's monetary policy should actively respond to potential threats and effectively write off, replacing high-growth targets with high-quality growth targets. With the current novel coronavirus pneumonia raging across the world, the slowdown in domestic demand growth, and increasing downward pressure on the economy, it is more important for China to use monetary policy to ensure steady economic growth. (iii) China should focus on optimizing the structure of monetary liquidity, make full use of new monetary policy tools and targeted support measures, guide commercial banks to increase credit to small and micro enterprises and private enterprises, and strive to use monetary policy to support the real economy and prevent and resolve financial risks. At the same time, China must actively explore the path of reforming the financial regulatory system, formulate macro- and micro-prudential regulatory policies, access rules, and codes of conduct in the financial market to promote the orderly and efficient operation of the financial system.

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