Research on Shanxi Province Gdp Based on Time Series Model

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Abstract: By collecting the GDP data of Shanxi Province from 1978 to 2019, using stata to preprocess the data, select the ARIMA (0,1,1) model from the data features, perform parameter estimation and model testing, and finally make predictions and discover its predictions. The accuracy is high.

1. Introduction

GDP is an important concept of macroeconomics, reflecting the economic strength and market size of a country. The GDP of Shanxi Province will directly reflect the economic conditions of Shanxi Province. Therefore, many scholars try to use mathematical models to analyze this time series, and time series models are more and more widely used. After the reform and opening up, my country's time series analysis and research have become more and more in-depth. Liu Mingding (2013) modeled and analyzed the total GDP of Shandong Province from 2007 to 2011, and made a forecast of the continued growth of GDP in 2012, but did not give an accurate value; Cui Huijuan (2018) established ARIMA (4,1,0) Model, and predict the GDP of Shandong Province within and outside the sample, pointing out the growth trend of GDP; Zhao Zimeng (2019) stabilized the third-order difference of Chengdu GDP from 1991 to 2016 and established ARIMA (2, 3, 0) The model is not rigorous enough to determine the order; Zheng Wei, Zhang Kun, Guan Nanxing (2020) used the ARIMA (2,1,1) model to model the GDP of Yunnan Province from 1993 to 2017, and used the least square method Carry out parameter estimation to improve parameter accuracy. The above-mentioned research is worthy of reference, but also has shortcomings. First, the sample time range is small and the representativeness is weak; secondly, most of them use Eviews software, etc., Stata and others are relatively rare.

2. Data Preprocessing

2.1 Lngdp Stationarity Test

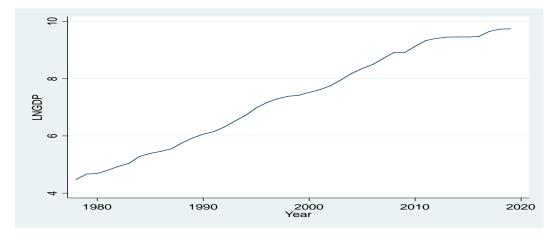


Fig.1 Timing Diagram of Lngdp

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Since financial time series data is generally not stable, we first take the logarithm of GDP to get lnGDP. It can be seen from the figure that lnGDP shows an increasing trend as the years progress, and this series is a non-stationary time series.

2.2 Lngdp First-Order Difference Stationarity Test

Table 1 d.Lngdp Adf Test Results

Dickey-Fu	ller test for unit	root	Number of obs	= 40
		Inte	erpolated Dickey-Ful	ler
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Value	Value	Value
Z(t)	-4.307	-3.648	-2.958	-2.612

MacKinnon approximate p-value for Z(t) = 0.0004

The adf test is performed on the first-order difference of lnGDP, and the results show that -4.307<-2.958 and -4.307<-3.648, that is, at the 95% confidence level or even the 99% confidence level, the first-order difference of the series is stable.

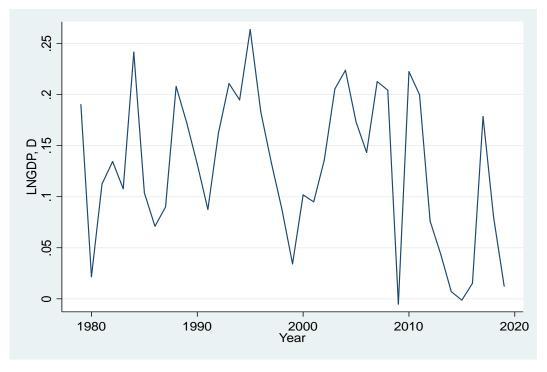


Fig.2 D.Lngdp Sequence Diagram

3. Model Recognition

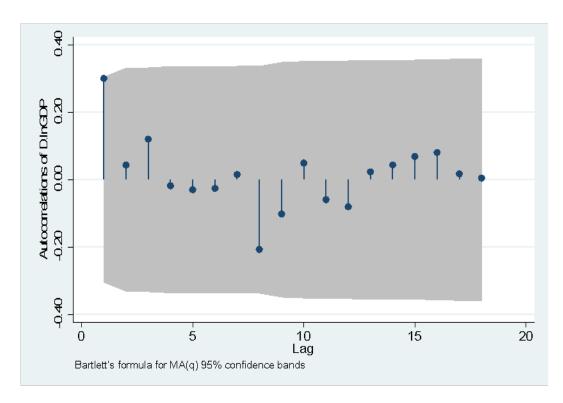


Fig.3 D.Lngdp Autocorrelation Coefficient Diagram

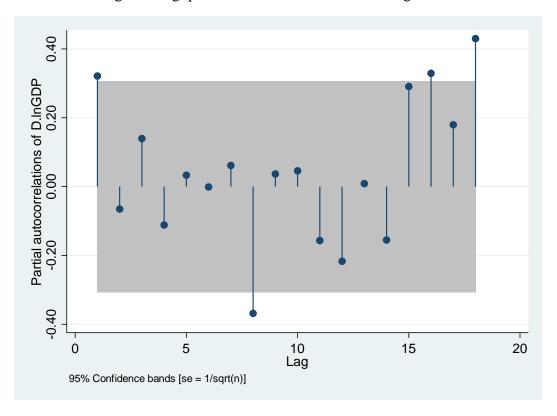


Fig.4 D.Lngdp Partial Autocorrelation Coefficient Diagram

Observing the first-order differential autocorrelation coefficient and partial autocorrelation coefficient of lnGDP, we think that the autocorrelation coefficient and partial autocorrelation coefficient are tailed. For lnGDP, consider the ARIMA (p, d, q) model, and d=1, guarantee its stability.

4. Model Ordering

4.1 Significance Test and Optimization

We consider three cases, ARIMA (1,1,1), ARIMA (1,1,0) and ARIMA (0,1,1). ARIMA (1,1,1) is significantly non-zero at the 90% significance level, and ARIMA (1,1,0) and ARIMA (0,1,1) are at the 95% significance level. Significantly not zero, so ARIMA (1,1,0) and ARIMA (0,1,1) are given priority

Table 2 Arima (0,1,1) Parameter Estimation Results

- 2019 l = 50.93233			Number o			41
50.93233				2(1)	_	
1 = 50.93233			Decele > a		=	5.46
			Prob > 0	chi2	=	0.0195
	OPG					
Coef.	Std. Err.	Z	P> z	[95%	Conf.	<pre>Interval]</pre>
.1285498	.015881	8.09	0.000	.097	4236	.1596761
.3880333	.1660994	2.34	0.019	.062	4845	.7135822
.069726	.0099406	7.01	0.000	.050	2428	.0892092
	.1285498	Coef. Std. Err. .1285498 .015881 .3880333 .1660994 .069726 .0099406	Coef. Std. Err. z .1285498 .015881 8.09 .3880333 .1660994 2.34 .069726 .0099406 7.01	Coef. Std. Err. z P> z .1285498 .015881 8.09 0.000 .3880333 .1660994 2.34 0.019	Coef. Std. Err. z P> z [95% .1285498 .015881 8.09 0.000 .0973880333 .1660994 2.34 0.019 .062069726 .0099406 7.01 0.000 .050	Coef. Std. Err. z P> z [95% Conf. .1285498 .015881 8.09 0.000 .0974236 .3880333 .1660994 2.34 0.019 .0624845

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Table 3 Arima (0,1,1) Information Criterion Value

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
	41		50.93233	3	-95.86467	-90.72395

Note: N=Obs used in calculating BIC; see [R] BIC note.

Table 4 Arima (1,1,0) Parameter Estimation Results

ion						
- 2019					=	41
d = 50.62256		Wald chi2(1) = Prob > chi2 =			4.11 0.0426	
Coef.	OPG Std. Err.	Z	P> z	[95%	Conf.	Interval]
.1278242	.0161739	7.90	0.000	. 09	6124	.1595245
.3175556	.1566002	2.03	0.043	.010	6249	. 6244863
.0703144	.0106725	6.59	0.000	.049	3966	.0912322
	- 2019 d = 50.62256 Coef1278242 .3175556	- 2019 d = 50.62256 OPG Coef. Std. Err. .1278242 .0161739 .3175556 .1566002	- 2019 d = 50.62256 OPG Coef. Std. Err. z .1278242 .0161739 7.90 .3175556 .1566002 2.03	- 2019 Number of Wald chiral of the Prob > 0 OPG Coef. Std. Err. z P> z .1278242 .0161739 7.90 0.000 .3175556 .1566002 2.03 0.043	- 2019 Number of obs Wald chi2(1) Prob > chi2 OPG Coef. Std. Err. z P> z [95% .1278242 .0161739 7.90 0.000 .096 .3175556 .1566002 2.03 0.043 .0106	- 2019 Number of obs = Wald chi2(1) = Prob > chi2 = OPG Coef. Std. Err. z P> z [95% Conf. .1278242 .0161739 7.90 0.000 .096124 .3175556 .1566002 2.03 0.043 .0106249

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Table 5 Arima(1,1,0) Information Criterion Value

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
	41		50.62256	3	-95.24513	-90.10441

Note: N=Obs used in calculating BIC; see [R] BIC note.

Both passed the significance test. The AIC and BIC of ARIMA (0,1,1) are both smaller than the AIC and BIC of ARIMA (1,1,0), so the model ARIMA (0,1,1) is better, we choose ARIMA(0,1,1).

4.2 Validity Check

Table 6 White Noise Test Results of Residual Sequence

Portmanteau	test	for	white	noise	
Portmanteau	ı (Q)	stat	tistic	=	5.0447
Prob > chi2	2 (18)			=	0.9988

The P value is 0.998>0.05, so the null hypothesis cannot be rejected. The residual sequence is a white noise sequence, and the model ARIMA(0,1,1) is valid.

5. Results and Predictions

5.1 Result Analysis

From Table 2 we get $\Delta Yt=0.1285+\epsilon_t+0.3880\epsilon_{t-1}$. This model shows that the first-order difference of lnGDP is only affected by the constant term 0.1285 and the random disturbance term in the current period and the previous period in the moving average.

5.2 Model Prediction

We list the values of the first 10 periods in the sample predicted by the model, and we can find that the error between the predicted y value and lnGDP remains within a certain range, and we can use this model for more analysis and prediction.

Table 7 the Top 10 Prediction Results in the Sample

D.					
LNGDP	хb	sxb	LNGDP	У	sy
	.12854982	.12854982	4.4772754		
.19021956	.12854982	.12854982	4.667495	4.6058253	4.6058253
02166608	.14934813	.12854982	4.6891611	4.8168431	4.7960448
11248747	.07996231	.12854982	4.8016486	4.7691234	4.8177109
.13441835	.14113405	.12854982	4.9360669	4.9427826	4.9301984
.10774652	.12594504	.12854982	5.0438134	5.0620119	5.0646167
.24153571	.12148865	.12854982	5.2853491	5.1653021	5.1723632
.1036751	.17513162	.12854982	5.3890242	5.4604808	5.413899
.0710352	.10082235	.12854982	5.4600594	5.4898466	5.5175741
.08990729	.11699142	.12854982	5.5499667	5.5770509	5.5886093

References

[1] Liu Mingding. The application research of ARIMA model in regional GDP prediction [J]. Journal of Jixi University, 2013, 13(07): 68-70.

- [2] Sun Silong, Li Shaobo, Fan Chen, Liu Hong. The construction and application of GDP prediction model based on ARIMA[J]. Journal of Liaoning University of Science and Technology, 2014, 37(04): 337-342+349.
- [3] Cui Huijuan. Research and Analysis of Shandong Province GDP Based on Time Series Model [D]. Shandong University, 2018.
- [4] Zhao Zimeng. Forecast of Chengdu's GDP based on ARIMA time series model[J]. Communication World, 2019, 26(02): 206-207.
- [5] Zheng Wei, Zhang Kun, Guan Nanxing. Time series analysis and forecast of Yunnan Province GDP based on ARIMA model[J]. Journal of Chuxiong Normal University, 2020, 35(03): 26-32.