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Analysis and Prediction of the Contribution Rate of China's Tertiary Industry Based on ARIMA Model

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Abstract: *In order to explore the evolution law and future state characteristics of China's tertiary industry contribution rate, this paper selects the contribution index data of China's tertiary industry to GDP from 1990 to 2020. It uses the ARIMA model to predict the future data of China's tertiary industry contribution index to GDP from 2021 to 2022. A stationary time series data is obtained through the stationary processing of time series, and finally, a prediction model of ARIMA (1,1,3) is established. The results show that the contribution index of China's tertiary industry to GDP shows a cyclical fluctuation of increase and decrease. The rising trend indicates that China's economic restructuring has achieved specific results. The validity of the predicted data is verified by using the actual tertiary industry contribution index data of GDP in 2020, proving the rationality of the predicted results. Furthermore, the predicted data in 2022 show a downward trend. On this basis, relevant suggestions are put forward to develop the tertiary industry vigorously and steadily promote the transformation and upgrading of economic structure.*

Keywords: *Contribution of tertiary industry to GDP; ARIMA model; Time Series Predictions*

1. Introduction

The tertiary industry contribution rate refers to the proportion of incremental tertiary industry to incremental GDP. It is used to analyze the extent of the role of various factors in economic growth. It should be calculated by excluding the price change factor and using the total amount of comparable prices. 2013 was the first time that China's tertiary industry accounted for more than the secondary industry in terms of GDP. In the first half of 2014, the proportion of the tertiary industry continued to increase, and the added value of the tertiary industry reached 46.6% of GDP. The continuous increase in the share of the tertiary industry indicates that China's economic structure is undergoing significant changes, and the transformation and upgrading have reached a critical stage, which deserves attention. Through the analysis of various trend factors, the continuous increase of the proportion of tertiary industry will be trendy. Its leading role will be further revealed, and it will be the norm for the service industry (i.e., tertiary industry) to overtake the manufacturing industry as the primary driver of China's economic growth. This means that China's economy is changing from an industrial-led economy to a service-led economy. This trend will have a profound and lasting impact on China's economic growth, employment, and other aspects. The vigorous development of tertiary industries, especially the elderly, health services, information consumption, cultural creativity, and design services, will be the new potential and space for China's current and next stage of economic growth.

Feng Qiong, Bi Zhongfei, and Liu Jun [1] used the ARIMA model to explore the spatial-temporal evolution and prediction of agricultural water resources in the Huaihe River Basin, analyzed the change characteristics of water resources from 2000 to 2020, and used the ARIMA model to forecast and explore the water resources pressure data from 2021 to 2025, and finally concluded that the overall water resources pressure in the Huaihe River Basin showed a downward trend. Moreover, it will face certain pressure on water resources in the future. Yao Jinhai and Zou Jiajun [2] analyzed and predicted CPI by constructing the SVM-ARIMA model and verified the validity of forecast data using actual CPI data in 2020. Yao Jinhai [3] built the combined prediction model of SVR-ARIMA to forecast future asset prices and found that compared with the traditional time series model, this combined model has a more significant improvement in prediction accuracy. Wang Xiangqian, Wu Donglong, and Zheng Jiantong [4]

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established the combined prediction model of SVR-ARIMAX to analyze and forecast the port cargo throughput. The empirical analysis shows that the combined model has higher prediction accuracy. Zhou Xiaoliang, Feng Xu, Yan Maolin [5] et al. established the ARIMA model to analyze and forecast the future supply of three major woody oils, camellia seed oil, walnut oil, and olive oil in China and the future supply of woody oil.

Combined with the forecast results and relevant national development goals, they put forward relevant suggestions for promoting the high-quality development of the woody oil industry. Lun Runqi, Luo Qiyou, Gao Mingjie [6] et al. forecast and analyzed the wholesale market price of potatoes by establishing the ARIMA prediction model. The prediction results show that the wholesale market price of potatoes will have a downward trend in 2020, hurting the potato market. On this basis, put forward relevant production strategies to reduce the economic losses caused by price decline. Xie Xianfen, Wang Binhui, and Gu Wanrong [7] et al. analyzed and predicted the innovation environment index using the ARIMA method and finally concluded that the data was more consistent with reality. The government and relevant enterprises could use these data to evaluate the regional innovation environment and make decisions. Liu Jinpei, Wang Piao, Huang Yanyan [8] et al. analyzed and predicted WTL crude oil prices by establishing ArMI-SVR combined prediction model and BP neural network method. CAI Chengzhi, Jiang Xingzi, Liang Ying [9] et al. predicted and analyzed the world wheat supply and demand situation based on the ARIMA model. The results showed that the world wheat total output increased faster than the population growth rate, and the supply increased somewhat. The wheat total output increased faster than the population growth rate in China, but the supply needed to be increased in general, and a small number of imports were needed. Chen Yanming, Bai Ziyu, and Liu Dan [10] analyzed and predicted the export volume of plastic products in China by establishing the ARIMA model. The results showed that the prediction accuracy of the ARIMA model was higher than that of the regression model, the predicted value of the export volume of plastic products from 2019 to 2021 was given, and relevant suggestions were put forward.

Based on the research of the current results, it is realized that the prediction accuracy of the ARIMA model is more accurate, and the fitting effect is better than that of the regression model. Based on existing achievements, combined with China's current economic development trend and the general background of economic restructuring, this paper takes the contribution index of the tertiary industry to China's GDP as the innovation entry point, uses the ARIMA model to forecast and analyze the contribution rate data of the tertiary industry, and innovatively adopts the method of combining practice and prediction. The actual tertiary industry in 2020 is used to verify the validity of the forecast data. Combined with the forecast data, relevant suggestions are finally put forward to develop the tertiary industry and promote high-quality economic development vigorously.

2. Model Introduction and Data Adoption

2.1 Model introduction

The ARIMA model, also known as the single-integer autoregressive moving average model (B-J model), is a well-known time series forecasting model created by Box, an American statistician, and Jenkins, a British statistician, in the early 1970s. The B-J forecasting method is suitable for forecasting time series for which it is difficult to judge the typical characteristics of the time series. Finding explanatory variables requires less time than the regression analysis method. The ARIMA model can be used for forecasting non-stationary time series and is a short-term forecasting model with high accuracy. It mainly contains three parameters - autoregressive order (p), difference order (d), and moving average order (q), and the general form of the model is noted as ARIMA(p, d, q). In addition, ARIMA models can be divided into three types: (1) autoregressive models (AR models); (2) moving average models (MA models); and (3) single integer autoregressive moving average models (ARIMA models).

The ARIMA model can be expressed as follows: Φ (L) is the autoregressive operator of the smooth process, and Θ(L) is the moving average operator of the smooth process.

$$\Phi(L) \cdot \nabla^d x_t = \Theta(L)\, ut \tag{1}$$

$$E(ut) = 0, Var(ut) = \sigma 2, E(usut) = 0, s \neq t \tag{2}$$

$$E(xsut) = 0, Vs < t \tag{3}$$

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The essential plunge of ARIMA model establishment: (1) Data smoothing process. The non-stationary time series is converted into a stationary time series through differencing or other transformations. The value of the differencing order, i.e., the parameter d, is determined to make the time series meet the stationarity requirement. (2) Model identification. It is mainly to determine the values of parameters p and q. According to the time series model identification rules, the corresponding model is established, and its parameter values are determined. In general, the order of the time series is initially determined based on the autocorrelation and partial correlation plots. Then the type and order of the model are determined by exploring from lower order to higher order one by one. (3) Parameter estimation and model diagnosis. After determining the p, d, and q values, the specific type of the model is also determined. From there, the specific values of each parameter can be estimated, and then the estimates can be tested to see if the test criteria conditions are met. (4) Model prediction. That is, the optimal model with specific parameter values has been determined to predict the future value or trend of the series[11-13].

2.2 Data Adoption

The data in this paper are mainly from the National Bureau of Statistics 1990-2020 data, Table 1 lists the contribution rate of tertiary industry in China from 1990 to 2020, from Table 1, can be clearly seen that the contribution rate of tertiary industry in China has increased rapidly from only 20% since 1990 to 54.9% in 2020, with exponential multiple growths every year. From the line graph of China's tertiary industry contribution rate in Figure 1, this exponential multiple growths is even more obvious. Obviously, the time series has obvious non-stationarity and is a non-stationary time series.

Table 1: The contribution rate of tertiary industry in China in 1990-2020

Unit: %

Year	Contribution of tertiary industry(%)	Year	Contribution of tertiary industry(%)
1990	20.0	2006	45.9
1991	32.2	2007	47.3
1992	28.7	2008	46.2
1993	28.0	2009	43.7
1994	27.4	2010	39.0
1995	28.5	2011	43.9
1996	28.5	2012	45.0
1997	34.5	2013	47.2
1998	33.0	2014	49.9
1999	37.4	2015	55.9
2000	36.2	2016	60.0
2001	49.0	2017	61.1
2002	46.5	2018	61.5
2003	39.0	2019	63.5
2004	40.8	2020	47.3
2005	44.3		
variance	124.41	mean value	42.30

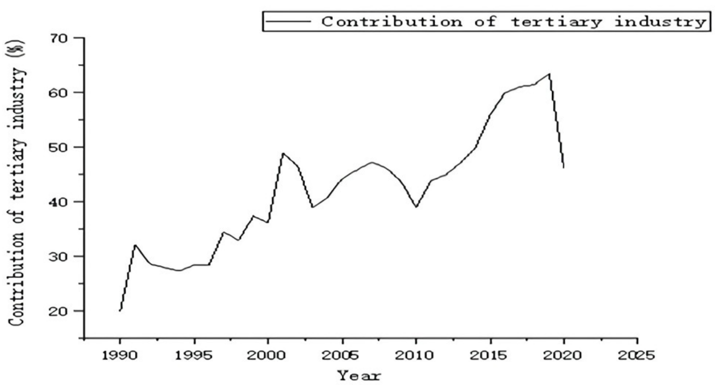

Figure 1: A line graph of the contribution of China's tertiary sector

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3. Authentic proof analysis— ARIMA Model Building

3.1 Model Building

3.1.1 Stability test

The EVIEWS software was used to generate the time series graphs. From the time series plot of the contribution of the domestic tertiary sector from 1990 to 2021 (as shown in Figure 2), it can be roughly judged that the data in this column shows a non-cyclical growth trend and is a non-stationary series.

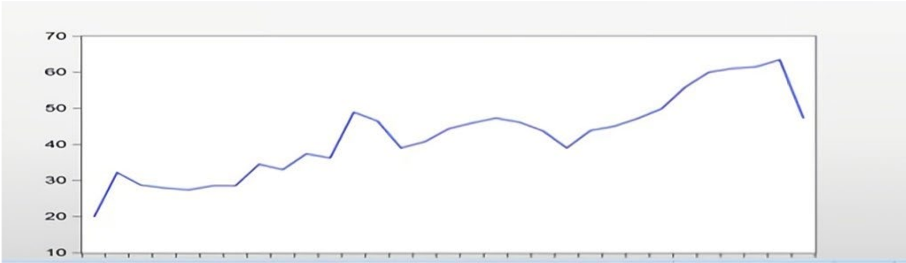

Figure 2: Domestic tertiary sector contribution rate time series chart

3.1.2 Pure Randomness Test

From the autocorrelation-partial autocorrelation plot of the data in this column (shown in Figure 3), it can be concluded that the p-values corresponding to the Q statistics are less than 0.05, which should reject the original hypothesis, indicating that the series is not a purely random series, that is, the series contains relevant information, and the historical information of the series has an influence on the future and has research value[13-16].

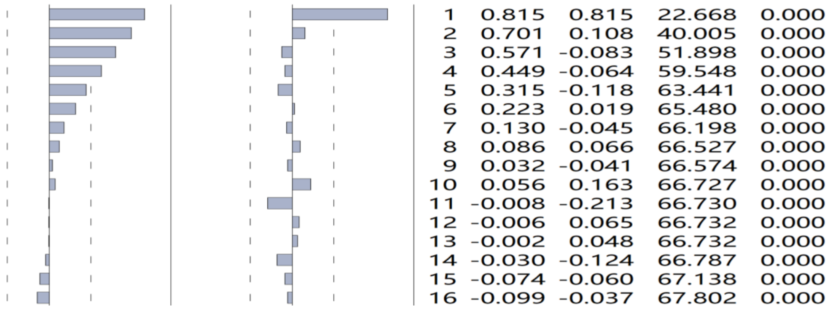

Figure 3: Autocorrelation-partial autocorrelation plot of the tertiary sector contribution rate series

3.1.3 Smoothening Treatment

The original data can be judged as a non-stationary time series through the original data time series plot for further investigation, and the ADF test is performed on the original data, as shown in Table 2, the t-test statistic is significantly larger than the critical value provided by each significance level, so it can be concluded that the original series is a non-stationary series.

Table 2: Unit root test results of the original series

Null Hypothesis: GXL has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.146200	0.2291
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

The first-order difference of the sequence is generated using the the eviews command (genr dgxl=d(resid)), and after the first-order difference of the sequence, the sequence plot is obtained (Figure 4). Next, to investigate whether the series is smooth, a unit root test is also required.

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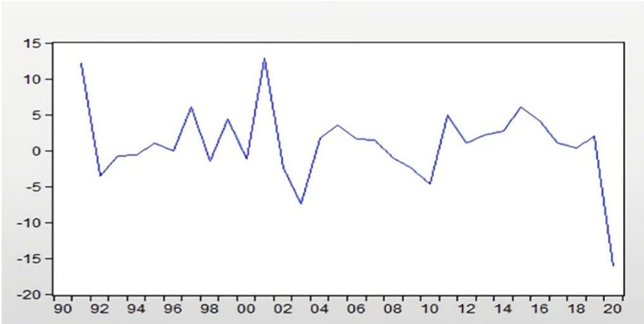


Figure 4: First-order post-differential sequence diagram

Through the unit root test, the results are shown in Table 3, where the original hypothesis of a first-order difference has a unit root. From Table 3, it can be obtained that the statistics of the t-test of the series after the first-order difference are significantly smaller than the critical values provided by each significance level, so it can be concluded that the time series after the first-order difference is smooth.

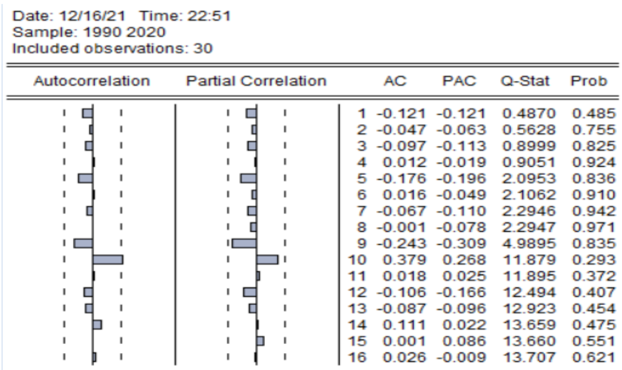
Table 3: ADF test results for first-order post-differential series

Null Hypothesis: DGXL has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.386376	0.0001
Test critical values:	1% level	-3.679322	
	5% level	-2.967767	
	10% level	-2.622989	

3.1.4 Model Identification and Estimation

The resulting autocorrelation function, partial autocorrelation function, and correlation statistics for the sequence after performing first-order differencing are shown in Figure 5.



Date: 12/16/21 Time: 22:51
Sample: 1990 2020
Included observations: 30

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.121	-0.121	0.4870	0.485
		2	-0.047	-0.063	0.5628	0.755
		3	-0.097	-0.113	0.8999	0.825
		4	0.012	-0.019	0.9051	0.924
		5	-0.176	-0.196	2.0953	0.836
		6	0.016	-0.049	2.1062	0.910
		7	-0.067	-0.110	2.2946	0.942
		8	-0.001	-0.078	2.2947	0.971
		9	-0.243	-0.309	4.9895	0.835
		10	0.379	0.268	11.879	0.293
		11	0.018	0.025	11.895	0.372
		12	-0.106	-0.166	12.494	0.407
		13	-0.087	-0.096	12.923	0.454
		14	0.111	0.022	13.659	0.475
		15	0.001	0.086	13.660	0.551
		16	0.026	-0.009	13.707	0.621

Figure 5: Autocorrelation of first-order difference series - partial autocorrelation plot

From the above analysis, we can build ARIMA (p, 1, q) model for the studied data and choose the AIC criterion (AIC =-2l /T + 2(k + 1) /T) and SBC criterion (SC =-2l /T + [(k + 1) lnT]/T) for the fixed order of ARIMA model. The model is determined by analyzing the autocorrelation function of the smooth time series and the nature of the trailing or truncated partial autocorrelation function. In general, if the autocorrelation function is trailing and the partial autocorrelation function is p-order truncated, the AR(p) model is chosen; if the partial autocorrelation function is trailing and the partial autocorrelation function is q-order truncated, the MA(q) model is chosen; if the autocorrelation function and the partial autocorrelation function are trailing, the ARMA(p, q) model is chosen The model determination criteria are shown in Table 4From the above analysis, we can build ARIMA (p, 1, q) model for the studied data and choose the AIC criterion (AIC =-2l /T + 2(k + 1) /T) and SBC criterion (SC =-2l /T + [(k + 1) lnT]/T) for the fixed order of ARIMA model. The model is determined by analyzing the autocorrelation function of the smooth time series and the nature of the trailing or truncated partial autocorrelation function. In general, if the autocorrelation function is trailing and the partial autocorrelation function is p-order truncated, the AR(p) model is chosen; if the partial autocorrelation function is trailing and the partial autocorrelation function is q-order truncated, the MA(q) model is chosen; if the autocorrelation

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function and the partial autocorrelation function are trailing, the ARMA(p, q) model is chosen The model determination criteria are shown in Table 4.

Table 4: Model Order Determination Principle

	AR(p)	MA(q)	ARMA(p,q)
Autocorrelation function	Tailing	Trim	Tailing
Partial autocorrelation function	Trim	Tailing	Tailing

We identify the model by the autocorrelation function and partial autocorrelation function of the series after differencing the data once, and it can be observed from the partial autocorrelation function of the first-order difference that the partial autocorrelation function and autocorrelation function are trailing, and according to the principle of model fixing order, two models are tried to be constructed here, which are ARIMA(1,1,1) and ARIMA(1,1,3).

3.2 Model Test

The next most important thing is to perform diagnostic tests on the parameter estimation results. Figure 6 presents the results of parameter estimation for the ARIMA (1, 1, 1) model. First, the estimated coefficients t-statistics of the AR (1) and MA (1) terms are accompanied by large probabilities and do not satisfy the parameter significance. The model diagnostic test does not pass.

Dependent Variable: DGXL
Method: Least Squares
Date: 12/16/21 Time: 23:23
Sample (adjusted): 1992 2020
Included observations: 29 after adjustments
Convergence achieved after 7 iterations
MA Backcast: 1991

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.661311	0.867835	0.762024	0.4529
AR(1)	-0.275114	0.401591	-0.685059	0.4994
MA(1)	0.151727	0.476866	0.318175	0.7529

R-squared	0.027514	Mean dependent var	0.520690
Adjusted R-squared	-0.047293	S.D. dependent var	4.997741
S.E. of regression	5.114554	Akaike info criterion	6.199755
Sum squared resid	680.1253	Schwarz criterion	6.341199
Log likelihood	-86.89645	Hannan-Quinn criter.	6.244054
F-statistic	0.367799	Durbin-Watson stat	1.604616
Prob(F-statistic)	0.695801		

Inverted AR Roots	-.28
Inverted MA Roots	-.15

Figure 6: Estimation results of the ARIMA (1, 1, 1) model

Figure 7 presents the parameter estimation results of the ARIMA (1, 1, 3) model. t-statistics of the estimated coefficients of the AR (1) and MA (3) terms are accompanied by small probabilities to satisfy the parameter significance. Second, the inverse of the polynomial roots of the autoregressive coefficients and the inverse of the polynomial roots of the moving average coefficients below the estimated results are within the unit circle, so the smoothness reversibility is satisfied. Finally, the autocorrelation plot windows of the residuals of the ARIMA (1, 1, 3) model presented in Figure 8 have high concomitant probabilities of the Q statistic, it shows that the residuals of ARIMA (1,1,3) model have pure randomness.. The three diagnostic tests of parameter significance, smooth reversibility, and pure randomness of residuals all pass, indicating that the constructed ARIMA (1, 1, 3) model is appropriate[17-20].

Dependent Variable: DGXL
Method: Least Squares
Date: 12/16/21 Time: 23:28
Sample (adjusted): 1992 2020
Included observations: 29 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 1989 1991

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.058490	0.246894	4.287230	0.0002
AR(1)	-0.363280	0.225113	-1.613768	0.1187
MA(3)	-0.857800	0.063454	-13.51841	0.0000

R-squared	0.116709	Mean dependent var	0.520690
Adjusted R-squared	0.048764	S.D. dependent var	4.997741
S.E. of regression	4.874363	Akaike info criterion	6.103553
Sum squared resid	617.7449	Schwarz criterion	6.244998
Log likelihood	-85.50152	Hannan-Quinn criter.	6.147852
F-statistic	1.717692	Durbin-Watson stat	1.956566
Prob(F-statistic)	0.199227		

Inverted AR Roots	-.36		
Inverted MA Roots	.95	-.48+.82i	-.48-.82i

Figure 7: Estimation results of the ARIMA (1, 1, 3) model

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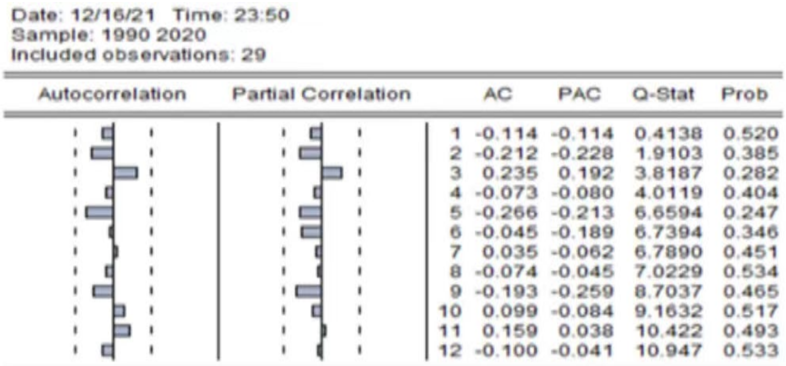
Date: 12/16/21 Time: 23:50
Sample: 1990 2020
Included observations: 29

	AC	PAC	Q-Stat	Prob
1	-0.114	-0.114	0.4138	0.520
2	-0.212	-0.228	1.9103	0.385
3	0.235	0.192	3.8187	0.282
4	-0.073	-0.080	4.0119	0.404
5	-0.266	-0.213	6.6594	0.247
6	-0.045	-0.189	6.7394	0.346
7	0.035	-0.062	6.7890	0.451
8	-0.074	-0.045	7.0229	0.534
9	-0.193	-0.259	8.7037	0.465
10	0.099	-0.084	9.1632	0.517
11	0.159	0.038	10.422	0.493
12	-0.100	-0.041	10.947	0.533

Figure 8: Autocorrelation plot of the residuals of the ARIMA (1, 1, 3) model

4. Model Predictions

Through the above series of analyses and the theoretical knowledge of related literature, we can determine the best-fit forecasting model is ARIMA (1, 1, 3). Through eviews, it is predicted that the contribution rate of the tertiary industry with a data delay of two years is as follows. The data predicted in 2021 is basically consistent with the official data released by the National Bureau of Statistics of China in 2022, and the actual contribution rate of the tertiary industry in 2022 needs to be published, as shown in Table 5.

Table 5: The forecast results of the contribution rate of tertiary industry in the next two years

Year	**2021**	**2022**
Predicted Value (%)	54.606	50.311

5. Conclusion

This paper takes the annual time series of the contribution rate of China's tertiary industry from 1990 to 2020 as the research object. On this basis, the ARIMA (1,1,3) model is constructed to fit and forecast the contribution rate of China's tertiary industry during the sample period using mature time series modeling techniques. The model fitting effect is tested with good results. The forecast results show that from the long-term change trend, China's tertiary industry contribution rate rise is the general trend. From the short-term change trend, the contribution rate of China's tertiary industry has an inevitable fluctuation but an overall upward trend. The development of the tertiary industry will become a necessary feature of the modern economy.

Based on this, some suggestions and measures are put forward to strengthen the development of the tertiary industry. First, actively cultivate and develop a market system, effectively unify production and circulation, establish an efficient and smooth market system, develop a variety of trade forms, open up the professional market of related industrial commodities, agricultural and sideline commodities, and various means of production as a whole, and pay attention to the coordinated development of other industries related to the market system, such as finance, consulting, transportation, and other service industries. Thus, an extensive network of market systems and related industries has been established. Second, we should accelerate the development of the service labor-based tertiary industry, expand the service field, extend the industrial chain, increase employment channels, focus on the development of consulting industry, tourism, purchase and leasing, and other related industries, and handle the relationship between the service industry and economic benefits. Third, we should strengthen scientific and technological research and development, vigorously develop intelligent industries, form high-tech industrial clusters, extensively carry out software research and development, technical consulting, information consulting, and other industrial services, cultivate new advantages in economic development, promote economic benefits with science and technology, and promote the further development of commodity economy.

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