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Research on Factors Influencing and Forecasting Regional Gross Domestic Product—A Case Study of Sichuan Province

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Abstract: ***This article analyzes the Gross Domestic Product (GDP) of Sichuan Province from 2012 to 2022 and its influencing factors, selecting ten relevant indicators. Through preliminary linear analysis, weakly correlated indicators were eliminated, ultimately identifying three independent variables: the proportion of the tertiary industry, urban population, and total number of insured individuals at year-end. A multiple linear regression model was constructed to analyze the impact of various economic indicators on GDP. The resulting regression equation was y = -0.008112 - 0.287037x_3 + 1.144240x_5 + 0.130342x_8, indicating a negative correlation between the proportion of the tertiary industry (%) and GDP, while urban population and year-end insured individuals showed a positive correlation with GDP. A time series autoregressive model was utilized to forecast GDP for the next decade. The results confirmed the negative correlation of the tertiary industry proportion (%) with GDP, and positive correlations of both urban population and year-end insured individuals with GDP. The model fit well, explaining 99.71% of the variability in the dependent variable. Forecasts indicate continued growth in urban population and stability in the number of insured individuals at year-end. During the model establishment and resolution process, preliminary linear relationships among the independent variables were defined based on the multiple linear regression model, with significance analysis conducted using R software to derive the regression equation. Subsequently, a dynamic forecast of GDP for the next decade was carried out using the time series autoregressive model, employing differencing to ensure data stationarity. Hypothesis tests of the model revealed that residuals approached normal distribution, with no significant autocorrelation, although heteroscedasticity was present, indicating the need for further model improvement. Transformations of variables (e.g., logarithmic transformation) may be considered to reduce heteroscedasticity.***

Keywords: Multiple linear regression; Time series; Forecasting; Descriptive statistics.

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1. Introduction

In recent years, with the sustained rapid development of China's economy, the Gross Domestic Product (GDP) of various regions has become an important indicator of regional economic vitality. GDP not only reflects a region's overall economic volume and level of development but also provides crucial data for government policy formulation and economic planning. As a significant engine of economic growth in western China, Sichuan Province's economic performance from 2012 to 2022 has garnered considerable attention. Sichuan's advantageous geographical location and rich resources have led to remarkable achievements in infrastructure construction, industrial upgrading, and technological innovation in recent years. However, the province's economic development still faces numerous challenges, such as imbalances in urban-rural development, an unreasonable industrial structure, and increasing resource and environmental constraints.

This paper aims to delve into the Gross Domestic Product of Sichuan Province and its influencing factors during the period from 2012 to 2022. By analyzing the economic data from this timeframe, the research will investigate the driving forces and constraints on Sichuan's economic growth, revealing the specific mechanisms through which different factors affect GDP growth. Researching this topic is significant for several reasons. Firstly, it can provide scientific decision-making support for government agencies, aiding in the formulation of more precise economic development policies. Secondly, it offers market insights to businesses and investors, guiding investment decisions and market strategies. Lastly, this study contributes to enriching and refining the theory of regional economics, offering references and lessons for economic research in other regions.

Researching the GDP of Sichuan Province and its influencing factors from 2012 to 2022 not only holds significant practical implications but also possesses considerable theoretical value. Through an in-depth analysis of this specific region, we hope to draw lessons and experiences regarding regional economic development, providing beneficial references for promoting high-quality economic development in Sichuan Province and the broader western region of China. Li Xiaohan and others examined the relationship between the development of China's maritime economy and transportation using multiple linear regression models. Their research identified key influencing factors through regression analysis and proposed policy recommendations to optimize maritime economic development. Zhang Jie and colleagues employed the ARIMA model to analyze and forecast traffic accident data. The study indicated that the ARIMA model effectively captures the time series characteristics of traffic accident data and accurately predicts future accident frequencies. Hu Yonghong and others applied the ARIMA model to conduct time series analysis of regional water ecological footprints. The findings demonstrated that the ARIMA model could adequately predict the changing trends of regional water ecological footprints, providing valuable insights for the formulation of environmental protection policies. Chen Cong analyzed the primary factors affecting air quality in Shenzhen using a multiple linear regression model. The study revealed that industrial emissions and traffic emissions significantly impact air quality, and quantified the degree of influence of each factor through regression analysis. Zhao Mingrong and others used a multiple linear regression model to analyze the major factors affecting tourism revenue in Liupanshui. The results showed that factors such as tourism infrastructure and promotional activities significantly influence tourism revenue. These studies demonstrate the extensive application of multiple linear regression and autoregressive time series models in domains such as economics, transportation, and the environment, highlighting their capability to identify and quantify influencing factors.

2. Source of Data

In order to ensure the authenticity and accuracy of the research data, the data utilized in this article is sourced from the National Bureau of Statistics. It primarily encompasses relevant data from Sichuan Province for the period 2012 to 2022. The specific indicators include the proportion of various industries (%), final consumption expenditure of urban residents (in billions), total number of urban residents (in ten thousand), urban population ratio (%), per capita disposable income of urban residents (in yuan), average number of students enrolled in higher education institutions (in persons), total number of insured individuals at year-end (in ten thousand), consumer price index, and electricity consumption. The indicators and their meanings are as outlined in Table 1 below:

Table 1: Description of indicators

symbol	index	unit	meaning
x_1	The proportion of primary industry	%	The place of agriculture in the regional economy
x_2	The proportion of the secondary industry	%	The place of industry in the regional economy
x_3	The proportion of the tertiary industry	%	The role of the service sector in the regional economy
x_4	Town residents' final consumption expenditure	100 million yuan	Assess the spending power and economic vitality of urban residents.
x_5	The number of urban populations	10,000 people	Reflects the level of urbanization
x_6	urban per capita disposable income	Yuan	A measure of the income level of the residents
x_7	The average number of students enrolled in higher education institutions	person	Reflect the level of education and the quality of the workforce
x_8	The total number of insured persons at the end of the year	10,000 people	Reflect the degree of perfection of the social security system.
x_9	CPI (Consumer Price Index)	Dimensionless	Reflects the level of inflation
x_{10}	Electricity consumption	Billions of kilowatt hours	Reflects the demand for industrial and residential electricity
y	Gross Domestic Product (GDP).	100 million yuan	A measure of the total economic output of a region

3. Model Assumptions

Assumption One: Residuals approach a normal distribution.

Assumption Two: Residuals exhibit no significant autocorrelation.

Assumption Three: Residuals possess homoscedasticity.

4. Model Introduction

The multiple linear regression model attempts to find the best combination of linear equations to describe the relationship between the dependent variable and multiple independent variables. The model minimizes the discrepancies between the actual data and the predicted values by adjusting the weights of each independent variable, known as regression coefficients. These weights reflect the degree to which each independent variable impacts the dependent variable. By constructing the regression model, I can identify the key factors influencing the GDP of Sichuan Province, understand the mechanisms driving the economy, and evaluate the model's fit for necessary adjustments and optimization. Utilizing a time series autoregressive model, I aim to dynamically forecast the GDP for the next decade based on historical data. I will check the stationarity of the GDP time series and perform differencing if necessary. The time series autoregressive model is a statistical framework for analyzing and predicting time series data, grounded in the idea that future values of the series can be predicted based on its past values. The autoregressive model assumes a dependency between the current data point and its preceding data points. It is crucial for the time series to be stationary, meaning its statistical properties (such as mean and variance) remain constant over time and do not change. Stationarity is an essential prerequisite for time series modeling, as non-stationary data often leads to unreliable predictions.

5. Index Analysis

5.1 Descriptive Statistics

I used R software to perform descriptive statistics on the indicator data from 2012 to 2022. I calculated the sample size, maximum value, minimum value, mean, standard deviation, median, variance, kurtosis, and skewness. I conducted a comprehensive descriptive analysis of each statistical indicator to gain a thorough understanding of the fundamental characteristics of the data. Additionally, I visualized the proportions of the three main industries by creating a line chart.

Table 2: Descriptive statistics of independent and dependent variables

	N	**range**	**minimum**	**maximum**	**mean**		**Standard deviation**	**variance**	**Skewness**		**峰度峰度**	
	统计	**statistics**	**statistics**	**statistics**	**statistics**	**standard deviation**	**statistics**	**statistics**	**statistics**	**标准误**	**统计**	**标准误**
x1	11	3.5116	10.3000	13.8116	11.6817	0.3381	1.1214	1.2570	0.5280	0.6610	-0.4750	1.2790
x2	11	15.5000	36.2000	51.7000	41.9411	1.8422	6.1100	37.3320	0.8410	0.6610	-1.0830	1.2790
x3	11	18.0035	34.5260	52.5295	46.3636	2.1597	7.1630	51.3080	-0.8250	0.6610	-1.0540	1.2790
x4	11	7027.8590	5839.6000	12867.4590	9313.3019	711.4320	2359.5529	5567490.0030	0.0190	0.6610	-1.2900	1.2790
x5	11	1370.0000	3516.0000	4886.0000	4214.2209	143.4051	475.6208	226215.1060	0.0080	0.6610	-1.3230	1.2790
x7	11	22926.2585	20307.0000	43233.2585	31303.2898	2353.0009	7804.0210	60902743.1470	0.1560	0.6610	-1.4140	1.2790
x10	11	1089.6710	2037.0000	3126.6710	2467.8930	101.9013	337.9684	114222.6480	0.8520	0.6610	-1.2810	1.2790
x12	11	2.9000	100.3000	103.2000	101.8571	0.2423	0.8035	0.6460	0.2170	0.6610	-0.9130	1.2790
x13	11	2233.3215	1213.6785	3447.0000	2297.4921	218.0345	723.1386	522929.4250	0.1430	0.6610	-1.4450	1.2790
x14	11	12.4798	12.9002	25.3800	18.5193	1.1459	3.8006	14.4440	0.2840	0.6610	-0.1100	1.2790
y	11	32737.4000	23872.8000	56610.2000	38968.4391	3444.7309	11424.8798	130527878.3390	0.2350	0.6610	-2.1280	1.2790

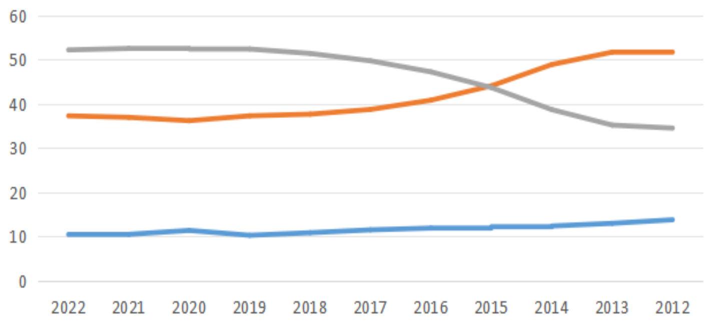
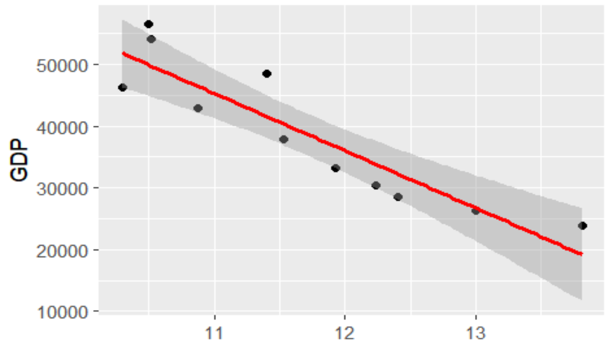


Figure 1: Trends in the share of the three major industries

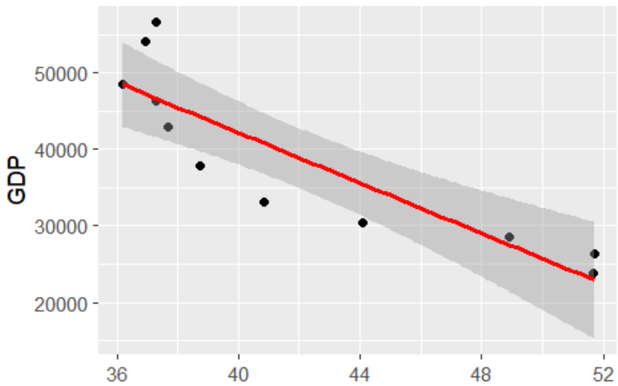
The analysis of Figure 1 indicates that the proportion of the tertiary sector is on the rise, while the primary sector experienced steady growth from 2013 to 2017. In contrast, the secondary sector shows a significant downward trend. This decline may be attributed to the implementation of the Western Development Strategy and the Rural Revitalization Strategy post-2000, which have stimulated the development of agriculture and the rural economy, as well as urbanization and the service industry. The consistent progress in agriculture likely contributes to economic development in rural areas, thereby narrowing the urban-rural gap and promoting balanced overall economic growth. Furthermore, the reduction in the proportion of the secondary sector may be linked to the environmental protection policies implemented in Sichuan Province, aimed at decreasing the development of high-pollution and high-energy-consuming industries, thus fostering green and sustainable economic growth. The overall changes in the proportions of the three major industries indicate that Sichuan Province's economic structure is evolving towards greater optimization and sustainability, facilitating high-quality economic growth in recent years.

5.2 Linear Analysis

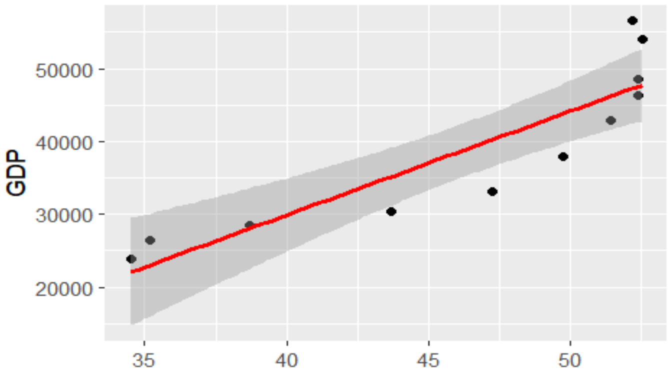
By plotting a scatter plot, I can detect the correlation between the dependent and independent variables. The distribution of the scatter plot allows for a clearer understanding of the linear relationship between the independent and dependent variables. Based on this analysis, I will examine the individual impact of each independent variable on the dependent variable.



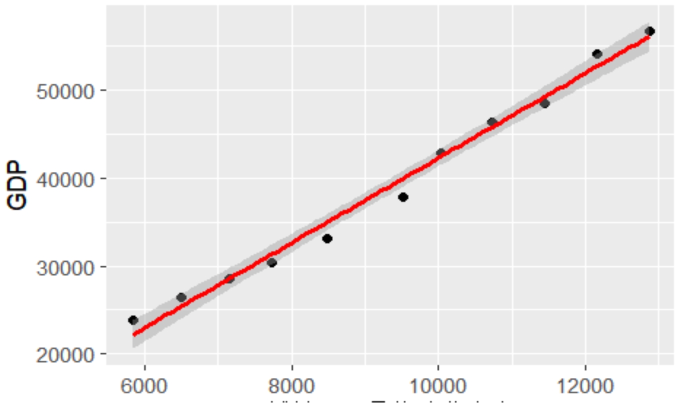
Proportion of the primary sector (%) and GDP



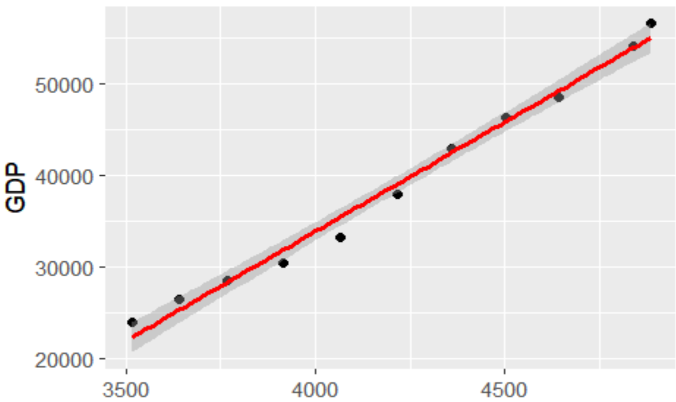
Proportion of the Secondary sector (%) and GDP



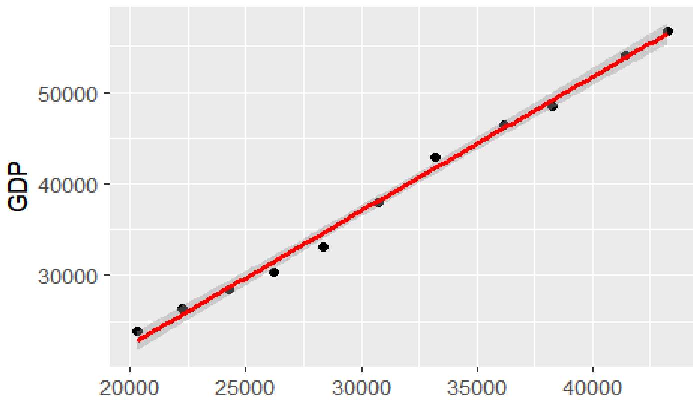
Proportion of the Tertiary sector (%) and GDP



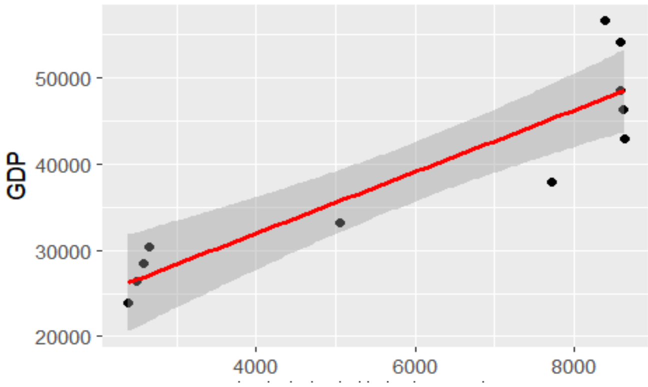
Final consumption expenditure of urban residents and GDP



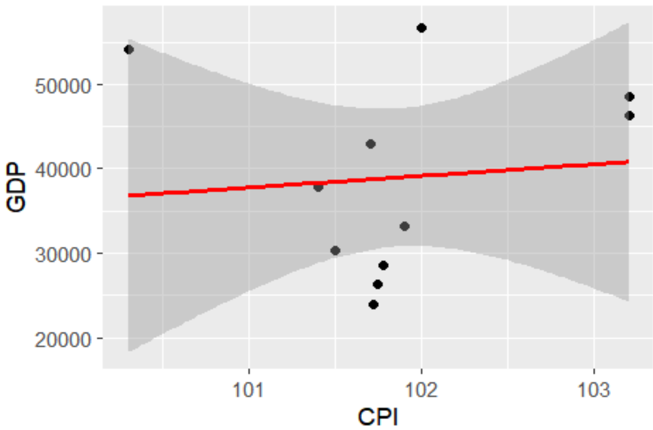
The number of urban populations



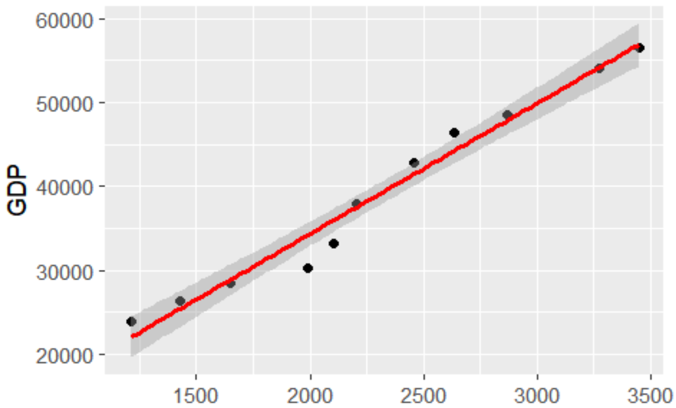
Per capita disposable income of urban residents



The total number of insured persons at the end of the year



CPI&GDP



Electricity consumption vs. GDP

Figure 2: Correlation visualization

Based on the observation from the scatter plot system, it can be seen that there is almost no correlation between CPI and GDP, as the data points are widely dispersed with a very weak linear relationship; therefore, it has been excluded. The proportions of the primary industry and the secondary industry show a negative correlation with GDP, with a relatively dispersed distribution of data points and a weak linear relationship. Conversely, the average number of students in higher education institutions, the urban population, per capita disposable income of urban residents, and the proportion of the tertiary industry all exhibit a positive correlation with GDP, demonstrating a strong linear relationship, with the proportion of the tertiary industry having the strongest linear relationship with GDP.

5.3 Data Preprocessing -- Standardization

Collect and sort out the indicator data, and based on the previous analysis, take the proportion of the tertiary industry (%), the number of urban population (10,000 people), and the total number of insured persons at the end of the year (10,000 people) as independent variables for the model.

Due to the different dimensions of each indicator, standardization processing is performed on each indicator to convert the eigenvalues of different scales to the same scale, in order to improve the convergence speed and stability of the model. The standardization processing in this article is shown in formula 1.

$$z = \frac{x_i - \mu}{\sigma} \quad (1)$$

Among them, x_i represents the original indicator data and $z$represents the standardized data. The normalized data is shown in Table 3 below.

Table 3: Normalized data table

x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	y	y_norm
13.8	51.7	34.5	5840	3516	20307	2037	2384	102	1214	23873	23873
13	51.7	35.2	6503	3640	22228	2140	2486	102	1430	26392	26392
12.4	48.9	38.7	7156	3769	24234	2244	2577	102	1647	28537	28537
12.2	44.1	43.7	7725	3913	26205	2312	2651	102	1992	30342	30342
11.9	40.8	47.2	8475	4066	28335	2314	5057	102	2101	33138	33138
11.5	38.7	49.7	9518	4217	30727	2339	7715	101	2205	37905	37905
10.9	37.7	51.4	10024	4362	33216	2409	8637	102	2459	42902	42902
10.3	37.3	52.4	10735	4505	36154	2546	8617	103	2636	46364	46364
11.4	36.2	52.4	11446	4643	38253	2754	8592	103	2865	48502	48502
10.5	37	52.5	12157	4841	41444	2925	8586	100	3275	54088	54088
10.5	37.3	52.2	12867	4886	43233	3127	8394	102	3447	56610	56610

5.4 Significance Analysis

Table 4: Indicator significance results

	Estimate Std	Error	t value	Pr(>|t|)
(Intercept)	23607.2	499.5	47.265	4.96E-10
x3_norm	-9396.9	1998	-4.703	0.0022
x5_norm	37459.4	1915.2	19.559	2.28E-07
x8_norm	4267.1	1572.4	2.714	0.03

The analysis of the significance of the indicators using R software showed that the intercept term was highly significant, indicating that the constant term in the model played an important role in prediction. The P values of the other three standardized indicators are all less than the significance level of 0.05, indicating good significance. The p-value of x5_norm (2.28E-07) is much smaller than 0.05, indicating a very significant impact on the dependent variable y_norm.

6. Establishment and Solution of Regression Model and Prediction Model

6.1 Multiple Linear Regression

6.1.1 Multiple linear regression model

Based on the linear analysis of respective variables, a preliminary multiple linear regression model is established to explore and model the relationships between multiple independent variables and one or more dependent variables. Following the aforementioned analysis, a multiple linear regression model is constructed, as shown in Formula 2.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon \quad (2)$$

Among these,Y is the dependent variable,x_i is the independent variable.$\beta_i (i = 1,2,3)$ is the parameter of the model, representing the effect of changes in the independent variable on the dependent variable. ϵ represents the error term, indicating the random component that cannot be explained by the model.

6.1.2 Multiple linear regression results

The results of the multiple regression analysis output by R are presented in the table below, and we will proceed to solve for the parameters of the multiple regression function. This yields the multiple linear regression equation 3：

$$y = -0.008112 + -0.287037x_3 + 1.144240x_5 + 0.130342x_8 \tag{3}$$

From the results of the regression equation, it can be observed that for every 1% increase in the proportion of the tertiary industry, GDP will decrease by 0.287037 units. This increase in the share of the tertiary industry may be related to a certain downward trend in GDP. Additionally, for every increase of 10,000 in the urban population, GDP will increase by 1.144240 units. This indicates a positive correlation between urban population numbers and GDP, suggesting that an increase in population may lead to more economic activity and productivity enhancements. Furthermore, for every additional 10,000 insured individuals at the end of the year, GDP will increase by 0.130342 units. An increase in the number of insured individuals typically reflects better social security and economic conditions, and it also shows a positive correlation with GDP. The overall fitting results are illustrated in Figure 3.

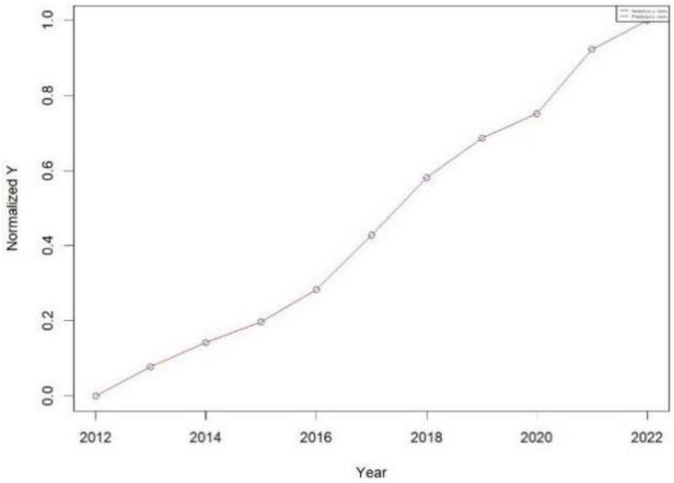


Figure 3: Multiple regression fitting results

6.2 Time Series

6.2.1 Time series prediction model

Some classic time series forecasting models include the Autoregressive Moving Average (ARMA) model, the Autoregressive Integrated Moving Average (ARIMA) model, exponential smoothing methods (such as Simple Exponential Smoothing), and machine learning-based techniques (like Long Short-Term Memory networks, LSTM).

The ARIMA model employs an automatic method to determine its parameters, utilizing an automated ARIMA model for fitting and forecasting, making it suitable for handling unknown data characteristics and seasonality. This article establishes a time series forecasting model based on the aforementioned multivariate analysis models, utilizing an autoregressive model for prediction. First, I will forecast the data for X1, X2, and X3 over the next decade, and then input these values into the regression equation to predict GDP data. The model formula is as follows:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}) + \epsilon_t \tag{4}$$

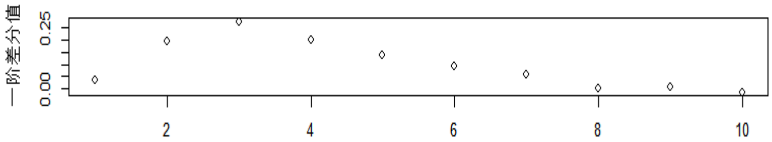
$$Y_t = \emptyset Y_{t-1} + \emptyset Y_{t-2} + \cdots + \emptyset Y_{t-p} + \epsilon_t \tag{5}$$

$$\Delta Y_t = Y_t - Y_{t-1} \tag{6}$$

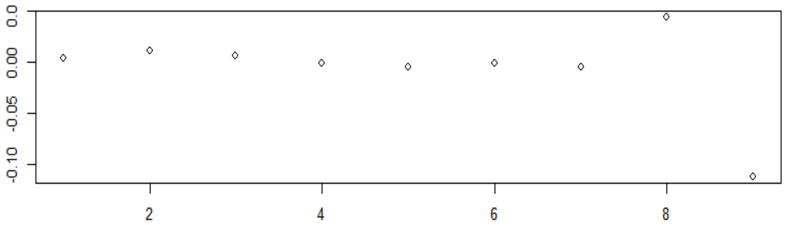
$$Y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} \tag{7}$$

Among them,Y_t is the GDP of a certain year.$Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$ is the observed value from the previous time point.

Since autoregressive models (such as ARIMA) require the input time series data to be stationary, differencing operations are employed to ensure that the time series data meets the criteria for stationarity, thereby guaranteeing the model's stability and accuracy. First-order differencing is applied to the three independent variables to eliminate linear trends, followed by second-order differencing to further remove quadratic trends or more complex patterns. After the second differencing, the indicators for urban population and the total number of insured individuals at year-end both become stable, allowing for subsequent forecasting.

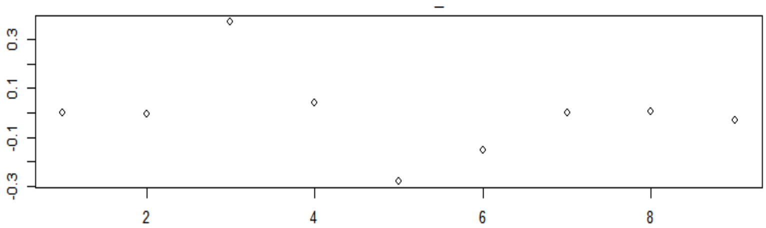


X3_norm after the first-order difference



Time

X5_norm after the first-order difference



X8norm after the first-order difference

Figure 4: Differential plot

6.2.2 Time series forecast results

Using the multiple linear regression model established above, I will predict the GDP for the next decade. Employing a linear trend forecasting method, I will utilize a time series forecasting model to project the three independent variables, with results illustrated in Figure 5 below.

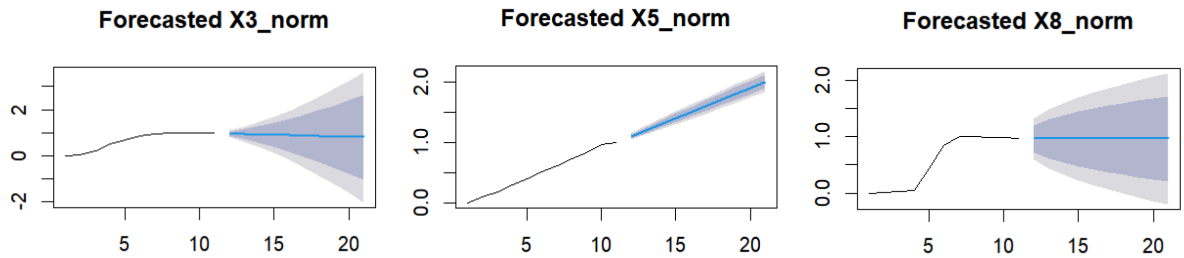


Figure 5: Plot of the three independent variables predicting the results

From the above figure, it can be observed that the predicted proportion of the tertiary industry remains stable over the forthcoming period, with no significant upward or downward trends. Conversely, the projected urban population is expected to exhibit a clear upward trend. This indicates that the urban population is anticipated to continue growing in the future, with the total number of insured individuals initially remaining stable before showing a notable increase. However, towards the end of the forecast period, the growth appears to stabilize again. This may suggest that there will be a significant increase in the number of insured individuals during a certain timeframe, followed by a phase of stabilization. Subsequently, I will input the values of the independent variables predicted through time series analysis into the multiple regression linear equation established previously to forecast GDP for the next decade, with the projected GDP growth trend illustrated below in Figure 6.

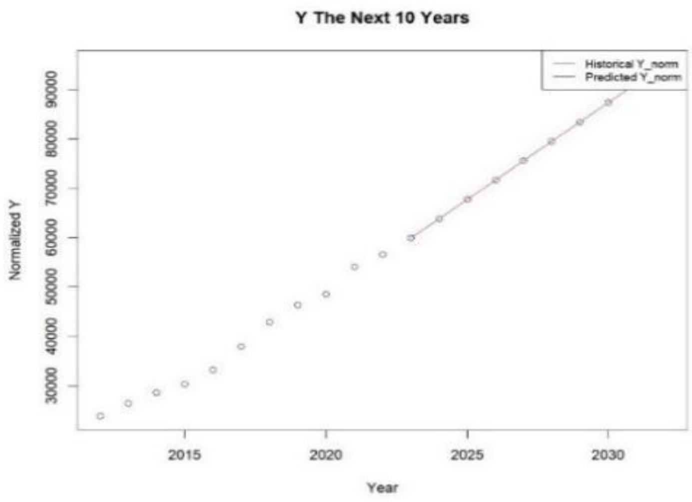


Figure 6: Forecast Result Graph

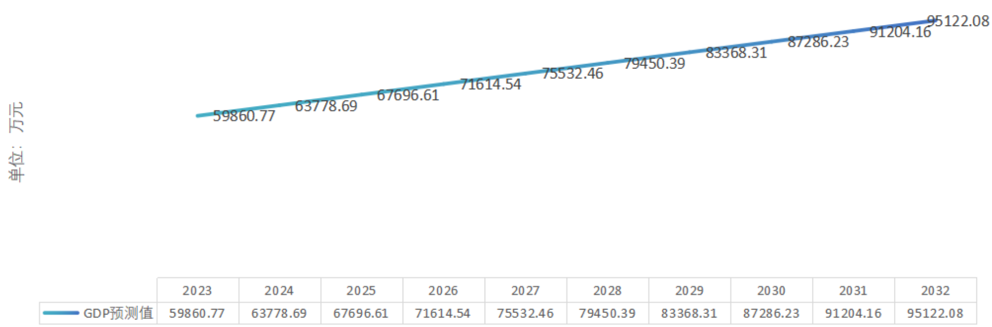


Figure 7: Specific GDP projections for the next decade

7. Model Evaluation

R^2 is a crucial criterion for assessing the goodness of fit of regression models, as it illustrates the explanatory power of independent variables on the dependent variable and provides a basis for model improvement. The results show an R^2 of 0.9971, indicating that the model can explain 99.71% of the variability in the dependent variable, meaning the independent variables almost entirely account for the changes in the dependent variable.

The adjusted R^2 is 0.9959, which takes into account the number of independent variables in the model regarding the goodness of fit and remains very close to 1, suggesting that the model still possesses a high level of explanatory power even after considering the number of independent variables. Subsequent tests for the normality, independence, and homoscedasticity of residuals will be performed to ensure that the model meets the assumptions of regression analysis.

8. Model Testing

After conducting multiple linear regression analysis, it is essential to first perform hypothesis testing for the model before proceeding with predictions. This ensures the robustness and validity of the model, thereby enhancing the accuracy of the predictions. Using R software, I undertake hypothesis testing for the solved multiple linear regression model from the following aspects:

8.1 Multicollinearity

After fitting the regression model, I first conduct a multicollinearity diagnosis to assess the validity of the model. The results of the multicollinearity test indicate that the variance inflation factor (VIF) values for the explanatory variables in this model are all less than 10, suggesting that there is no multicollinearity among the explanatory variables.

8.2 Residual Normality

I analyze the residual normality test to validate the model’s assumptions, thereby improving its reliability and explanatory power. I create a P-P plot to analyze whether the independent variables conform to a normal distribution; the points in Figure 8 are close to the 45-degree line, indicating that the residuals approximate a normal distribution. The p-value is 0.1505, which is greater than 0.05, suggesting that I cannot reject the null hypothesis that the residuals follow a normal distribution.

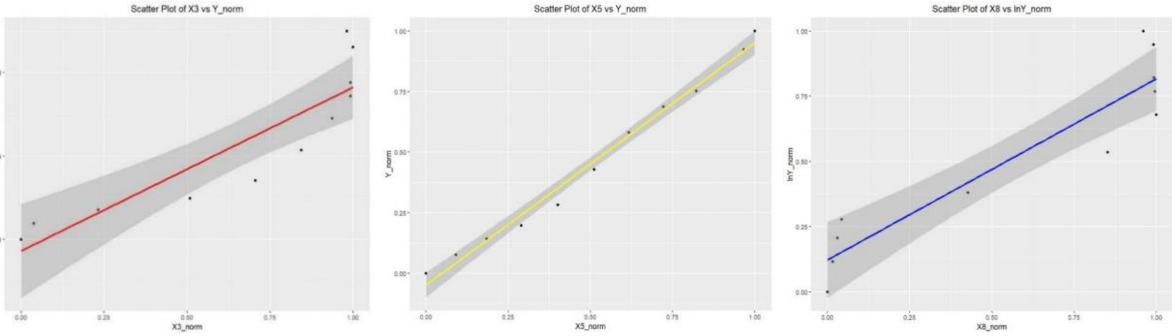


Figure 8: Residual test P-P plot

8.3 Independence Test

The DW statistic is 2.0816, with a p-value of 0.1258, which is significantly higher than the significance level of 0.05. This further supports the null hypothesis that there is no significant positive autocorrelation among the residuals, indicating that the model performs well in this aspect.

8.4 Test for Homocedasticity

The results indicate that the p-value is 0.03546, which is less than 0.05, suggesting that the model may exhibit heteroscedasticity, and it will require further refinement.

9. Model Optimization

The p-value (0.03546) of the regression model I established is less than 0.05, leading to the rejection of the null hypothesis, which indicates that the model's errors exhibit homoscedasticity. This suggests that there may be heteroscedasticity in the model's residuals, and I should consider transforming the variables (such as applying a logarithmic transformation) to mitigate the heteroscedasticity.

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