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Analysis on the Impact of Chongqing Urban and Rural Residents' Consumption Behavior under External Conditions Based on Provincial Panel Data

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Abstract: Based on the principles of economics, this paper comprehensively applies the principal component analysis method to establish a mathematical model, analyzes the differences between urban and rural consumption levels in Chongqing, makes reasonable predictions according to the gray prediction model, and forecasts the establishment of Chengdu Chongqing economic circle and the subsequent impact of the epidemic. The results show that: (1) the proportion of the output value of the tertiary industry in the GDP of the region will increase steadily in the next five years. (2) Chongqing Municipal Government should promote the three major industries and guide the growth of residents' income and economic development simultaneously.

1. Introduction

Since December 2019, COVID-19 has continued to spread around the world, which not only seriously threatens the physical and mental health of people all over the world, but also has an immeasurable impact on the international economic environment, bringing a huge impact on social and economic operations Consumption, investment and export demand, the three carriages driving economic development, decreased at the same time. Insufficient domestic demand has become an important factor driving down China's economic growth The "Fourteenth Five Year Plan" requires in-depth implementation of expanding domestic demand, strengthening the fundamental role of consumption in economic development and the key role of investment in optimizing the supply side structure, and building a high-quality domestic market with strong demand for both consumption and investment.

Li [1] used super SBM model and Markov chain to calculate and analyze the ecological efficiency value of Chengdu Chongqing Economic Circle from 2004 to 2018. At the same time, he used geographical weighted regression model to conduct spatial analysis on ecological efficiency. Zhou [2] analyzed the fairness of health resource allocation in Chengdu, Luzhou and Chongqing, and provided scientific basis for promoting Luzhou's health industry to integrate into Chengdu Chongqing economic circle Huang [3] constructed a human capital measurement model through factor analysis, and measured the human capital of cities in the Chengdu Chongqing economic circle The results show that education capital has the greatest influence on human capital Based on Ni Pengfei's urban competitiveness model, Xu [4] proposed the concept of improving urban competitiveness through urban innovation through the analysis of various macro and micro indicators. The urban innovation diamond structure map effectively expresses the relationship between urban innovation subsystems, thus leading to specific strategic choices

Based on the above scholars' research results, this paper focuses on the economy of Chongqing and studies the impact of the epidemic on the economy, which is of great significance for the economic recovery of Chongqing.

2. Consumption characteristics and differences of rural and urban residents in Chongqing

First of all, this paper selects M=8 samples: food, clothing, household equipment and services, medical care, transportation and communication, other and services, education, entertainment and cultural services, and residence. The orders are $\{X1,\ X2, \ldots,\ X8\}$. Each sample has N=10 dimensional characteristics. The data of 2011-2020 is selected, and the orders are:

(1)

Each characteristic x_j has its own characteristic value. First, all the features are centralized: the mean value is removed. Calculate the average value of each feature, and then subtract the average value of each feature from all samples.

$$\overline{x_i} = \sum_{i=1}^{M} x_i, \bar{x}_i = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{2}$$

$$C = \begin{bmatrix} cov(x_1, x_1) & cov(x_1, x_2) \\ cov(x_2, x_1) & cov(x_2, x_2) \end{bmatrix} \tag{3}$$

In the above matrix, the diagonal is the variance of characteristic x_1 and x_2 respectively, and the non-diagonal is the covariance If the covariance is greater than 0, it means that if one of x_1 and x_2 increases, the other also increases; Less than 0 means an increase and a decrease; When the covariance is 0, the two are independent. The greater the absolute value of covariance, the greater the influence of the two on each other, and vice versa. The vector element is solved as follows:

$$cov(x_n, x_n) = \frac{\sum_{i=n}^{M}(x_n^i - \overline{x_n})(x_n^i - \overline{x_n})}{M-1} \tag{4}$$

According to the above formula, the covariance matrix C of eight samples under this ten dimensional feature can be obtained.

The third step is to find the eigenvalues and corresponding eigenvectors of the covariance matrix C.

Calculate the eigenvalue of covariance matrix C according to matrix knowledge λ Eigenvectors corresponding to and μ:

$$C_\mu = \lambda_\mu \tag{5}$$

Each λ_i corresponds to *a* eigenvector μ_i. Sort the eigenvalues from large to small, select the largest first *k* eigenvectors, and take out their corresponding *k* eigenvectors to get a group:

$$\{(\lambda_1, \mu_1), (\lambda_2, \mu_2), \ldots\ldots (\lambda_k, \mu_k)\} \tag{6}$$

The original feature is projected onto the selected feature vector to obtain a new *K* dimension feature after dimension reduction.

For each sample X^i, the original characteristics are:

$$(x_1^i, x_2^i, \ldots\ldots x_n^i)^T \tag{7}$$

The features after projection are:

$$(y_1^i, y_2^i, \ldots\ldots y_n^i)^T \tag{8}$$

The calculation formula is as follows:

$$\begin{bmatrix} y_1^i \\ y_2^i \\ \vdots \\ y_k^i \end{bmatrix} = \begin{bmatrix} u_1^T \cdot (x_1^i, x_2^i, \ldots\ldots x_n^i)^T \\ u_2^T \cdot (x_1^i, x_2^i, \ldots\ldots x_n^i)^T \\ u_k^T \cdot (x_1^i, x_2^i, \ldots\ldots x_n^i)^T \end{bmatrix} \tag{9}$$

So far, each sample X^i is converted from the original $X^i=(x^i_1, x^i_1)^T$ to $X^i=y^i_1$.

Based on factor analysis and principal component analysis, this paper conducts quantitative analysis on residents' consumption, divides residents' consumption into eight categories: food, clothing, household equipment and services, medical care, transportation and communication.

2.1 Factor analysis of urban residents' consumption structure

In Table 1, the observed value of Bartlett sphericity test is 116.649, with a significance of 0 [5] Because the P value is less than 0.05, the data is spherical distribution, and it is considered that there is a significant difference between the correlation coefficient matrix and the unit matrix; At the same time, the KMO value is 0.728>0.5, which shows that the selected data has structural validity, and the indicators are suitable for factor analysis [6]

Extract factors and factors to explain the original variables, and make a tentative analysis According to the correlation coefficient matrix of the original variable, the principal component analysis method is used to extract the factor, and the characteristic root whose eigenvalue is greater than 1 is selected.

Table 2 is the interpretation table of total variance, reflecting the contribution rate of principal components to variable interpretation. In general, the higher the variance interpretation rate is, the more important the principal component is, and the higher the weight proportion is. According to the calculation results, the characteristic root value of the first factor is 5.925, explaining 74.058% of the total variance of the original eight variables, and the cumulative variance contribution rate is 74.058%; The characteristic root of the second factor is 1.750, the total variance of the original eight variables is 21.874%, and the cumulative variance contribution rate is 95.932%. It can be seen that the information of the original variables is generally less lost, and the effect of factor analysis is better.

Table 1: KMO value and Bartlett test (City)

KMO value	0.728	
Bartlett's sphericity test	Approximate chi square	116.649
	Freedom	28.000
	Significance	0.000***

Note: ***, **,* represent the significance level of 1%, 5% and 10% respectively.

Table 2: Interpretation of Total Variance of Urban Consumption Data

Component	Characteristic root	Percent Variance	Accumulate
F(Food)	5.925	74.058%	74.058%
C(Clothing)	1.750	21.874%	95.932%
H(Home equipment and services)	0.176	2.195%	98.127%
M(Medical care)	0.113	1.418%	99.545%
T(Transportation and communication)	0.017	0.212%	99.758%
O(Others and Services)	0.011	0.139%	99.897%
E(Education, entertainment and cultural services)	0.005	0.066%	99.963%
L(Live)	0.003	0.037%	100.0%

2.2 Factor analysis of rural residents' consumption structure

Now we will analyze the consumption of urban residents from 2011 to 2020. Before factor analysis, it is necessary to check whether the above selected variables are suitable for factor analysis and whether the variables are mutually independent or have a linear relationship. In this paper, KMO test and Bartlett test are used.

Table 3: KMO value and Bartlett test (Rural)

KMO value	0.728	
Bartlett's sphericity test	Approximate chi square	199.684
	freedom	36.000
	Significance	0.000***

Note: ***, **,* represent the significance level of 1%, 5% and 10% respectively.

In Table 3, the observed value of Bartlett's sphericity test is 199.684, and the significance is 0. Because the P value is less than 0.05, the data is spherical distribution, and it is believed that there is a significant difference between the correlation coefficient matrix and the unit matrix; At the same time, the KMO value is 0.654>0.5, which shows that the selected data has structural validity.

Table 4: Interpretation of Total Variance of Urban Consumption Data

Component	Characteristic root	Percent Variance	Accumulate
F	7.915	87.948%	87.948%
C	0.919	10.21%	98.158%
H	0.109	1.214%	99.373%
M	0.035	0.393%	99.766%
T	0.011	0.122%	99 888%
O	0.008	0.085%	99.973%
E	0.002	0.026%	99.999%
L	0.000	0.001%	100.0%

Table 4 is the interpretation table of total variance, reflecting the contribution rate of principal components to variable interpretation. In general, the higher the variance interpretation rate is, the more important the principal component is, and the higher the weight proportion is. According to the calculation results, the characteristic root value of the first factor is 7.915, explaining 74.058% of the total variance of the original eight variables, and the cumulative variance contribution rate is 74.058%; The characteristic root of the second factor is 1.750, the total variance of the original eight variables is 21.874%, and the cumulative variance contribution rate is 95.932. It can be seen that, on the whole, the information of the original variables is less lost, and the effect of factor analysis is ideal.

3. Key indicators affecting the largest consumption of rural and urban residents in Chongqing

It can be seen from Table 4 that health care, clothing, education, entertainment and cultural services have a high load on the first factor, which mainly explains the lifestyle consumption variables; Food, health care, transportation and communication variables have a high load on the second factor, which mainly explains the survival consumption variables.

In this paper, regression method is used to estimate and output factor score coefficient [7,8]. According to Table 3, factor score function can be written. Principal component 1 and component 1 are selected from urban data, and principal component 2 and component 2 are from rural data.

Table 5 is the component matrix table, which is used to describe the factor score coefficients contained in each component. The factor formula is calculated by the formula: linear combination coefficient * (variance interpretation rate/cumulative variance interpretation rate), and normalized to obtain the factor weight score

Table 5: Composition Matrix

Name	Component 1 (City)	Component 2 (Countryside)
F	0.149	1.017
C	-0.077	0.093
H	0.167	0.044
M	0.168	0.161
L	0.167	-0.028
E	0.082	-0.073
T	0.165	0.073
O	0.151	0.064

City: F1=0.149F-0.077C+0.167H+0.168M+0.167L+0.082E +0.165T+0.151O

Rural: F2=1.017F +0.093C+0.044H+0.161M-0.028L- 0.073E+0.073T+0.064O

Table 6: Results of urban main component weight

Name	Variance interpretation rate	Cumulative variance interpretation rate	Weight
C	0.741	0.741	75.472%
E	0.219	0.959	22.291%
F	0.022	0.981	2.237%

Table 7: Weight Results of Rural Principal Components

Name	Variance interpretation rate	Cumulative variance interpretation rate	Weight
F	0.879	0.879	88.503%
M	0.102	0.982	10.275%
C	0.012	0.994	1.222%

Table 6 and Table 7 are the principal component weight analysis based on the load coefficient and other information. The calculation formula is: variance interpretation rate/cumulative variance interpretation rate after rotation.

For cities, the weight calculation results of principal component analysis show that the weight of principal component 1 (clothing) is 75.472%, and the minimum weight is food (2.237%).

For rural areas, the weight calculation results show that the maximum weight of the indicator is food (88.503%), and the minimum weight is clothing (1.222%).

4. The impact of Chengdu Chongqing double city economic circle on Chongqing residents' consumption [9, 10]

The grey prediction GM (1:1) model is used to predict the consumption level of Chongqing residents in the next five years. Taking the ratio of the output value of the tertiary industry to the GDP as an example, the model is established as follows:

Suppose that the proportion of the output value of the tertiary industry in the GDP of the region from 2011 to 2021 is $x^{(0)}(k)$, k=1,2..., 9, which is called the original series. The new sequence $x^{(1)}(k)$ can be obtained by accumulating the original sequence, and

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2 \dots .9 \tag{10}$$

The grey prediction system GM (1:1) is a first-order linear dynamic model of a single sequence. Establish differential equation for new sequence $x^{(1)}(k)$:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = u \tag{11}$$

First order one variable differential equation model, in which parameters a and u can be fitted by the following least square method:

$$\left[\frac{a}{u}\right] = (B^{\tau}B)B^{\tau}y_n \tag{12}$$

$$B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2), 1] \\ \dots \dots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n), 1] \end{bmatrix} \tag{13}$$

First, the existing data series of the proportion of the output value of the tertiary industry to the GDP of the region are preliminarily tested to test their regularity and model suitability. This paper checks by calculating the stage ratio. If the stage ratio is between [0.982, 1.0098], it indicates that the data is suitable for model construction. The calculation result of stage ratio is as follows:

It can be seen from Table 8 that the GM (1:1) model was built for the proportion of the output value of the tertiary industry in the GDP of the region for the establishment of the Chengdu Chongqing Economic Circle. The results show that the maximum value of the grade ratio is 1.015, which is within the scope of application [0.982, 1.0098]. The adaptability is good, so the modeling can continue.

After the model is constructed, the posterior error ratio C value, namely residual variance, is obtained. The more C value is, the better the fitting accuracy of the model is. If C value is less than 0.35, the model precision grade is very good. If C value is less than 0.65, the model precision is qualified. If C value is more than 0.65, the model precision grade is unqualified. The calculation results are shown in Table 9:

Table 8: Grade Ratio

Particular year	Original value	Grade ratio
2011	47.2%	-
2012	46.6%	1.013
2013	46.8%	0.996
2014	46.9%	0.998
2015	48.4%	0.969
2016	50%	0.968
2017	51.1%	0.978
2018	52.6%	0.971
2019	53.6%	0.981
2020	52.8%	0.996
2021	53%	1.015

Table 9: Posterior Error Ratio

Coefficient of development	Grey action b	Posterior error ratio C
-0.018	45.056	0.082

The C value of the posterior error ratio is 0.082<0.35, which means that the precision grade of the model is very good (Table 9).

The grey prediction GM (1:1) prediction model is used to predict the impact of the establishment of Chengdu Chongqing Economic Circle on the consumption of Chongqing residents in the next five years (Figure 3).

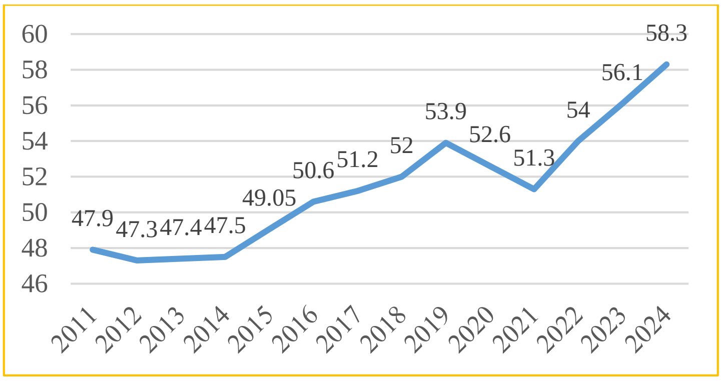

Figure 3: Fitting prediction diagram

Using the same method to calculate the forecast results of GDP in the next five years are as follows (Table 10):

Table 10: Regional GDP

Year	2022	2023	2024	2025	2026
One hundred million)	1.49	1.53	1.57	2.99	4.34

5. Conclusion

1) In order to recover the consumption ability of residents in Chongqing as soon as possible after the epidemic control, the Chongqing Municipal Government should issue corresponding innovation and entrepreneurship policies, encourage the people greatly affected by the epidemic to join the wave

of innovation and entrepreneurship, release more jobs for the society, increase per capita disposable income, and accelerate the recovery of the consumption level of residents in Chongqing. Although the COVID-19 will cause huge losses to various industries in Chongqing and seriously hinder the recovery of Chongqing's economy, if targeted policies can be effectively implemented, it will significantly promote the early recovery of consumption level of Chongqing residents.

2) In recent years, there has been a partial outflow of consumption in Chongqing. The Chongqing Municipal Government and the Chongqing Municipal Education Bureau should greatly increase their investment in research and development of various project teams in colleges and universities, strengthen the regional intellectual property parks based on colleges and universities, improve the scientific research background of various colleges and universities in Chongqing, and cultivate outstanding talents in Chongqing.

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