Research on Economic Structure of Ya'an City Based on Factor Analysis

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Abstract. Ya'an is rich in natural resources, and its economy has developed well in recent years. In order to promote the local economy, it is necessary to clarify the relationship between economic structure and its related factors. This paper selects 14 indicators of economic structure from 2004 to 2017 and uses Factor Analysis to have an empirical study on Ya'an. Our study shows that four common factors of the economic structure are highly effective: Economic Development, Social Development, Government Management, and Regional Innovation, accounting for 43.92%, 36.12%, 10.06%, and 8.26%, respectively. Then our study provides constructive suggestions for its further development based on our conclusion.

Keywords: Factor Analysis; Economic Structure; Indicator.

1. Introduction

Urban economic structure refers to the relationship between the state of association combinations and quantitative proportions of various economic factors that constitute the urban economic system. It has been argued that economic structure is the fundamental cause of economic performance [1].

For economic structure, a mainstream view of relevant researchers is that the core of the economic structure is productivity structure, and the actual content of the core of productivity structure is the industrial structure from the perspective of linking various sectors of a national economy, productivity factors, and aspects that can be reproduced. Therefore, the industrial structure optimization model can effectively support sustainable economic development.

Currently, there are various methods for the analysis of industrial structures. Jiang Xin et al. used factor analysis to study the industrial layout and structure of Chongqing city and further analyzed each industry within the industrial industry with high comprehensive factor scores [2]. Han Jing used hierarchical analysis to quantitatively analyze China's industrial and technological structures [3]. Xia Ming used structural decomposition analysis to explore the role of the main factors of structural transformation in China since the transition from the quantitative analysis perspective and revealed the stage characteristics of structural transformation in China during this period [4].

Some scholars do not study from this perspective. For example, Nong-Hua Zhao conducted an empirical study of the economic structure of Shanghai using econometric methods [5]. This study provides us with a new way of thinking: data not limited to the industrial structure can be used as our predetermined economic indicators that affect economic performance.

Most domestic studies analyze industrial or economic structure at the national, provincial, or regional levels. This paper takes Ya'an City, Sichuan Province, as the landing point to expand the perspective of indicator selection while narrowing the scope of geographical research. In order to overcome the limitation of considering only industrial structure, this paper adopts a wide range of indicators, including industrial structure as the influence factor of economic structure from a macro perspective [6]. The factors are creatively divided into four major categories: development factor, social development factor, government management factor as well as regional innovation factor, and
the relationship between aspects and specific indicators related to the economic structure is derived from making it concrete and visualized. The regression results show that the factor score function derived from this paper meets expectations and verifies the model's validity. In addition, the economic development factor accounts for the largest share in the economic structure of Ya’an, which indicates the importance of the industry to economic growth, which is also consistent with the reality. In addition, compared with the previous main factor analysis, we first used a factor model to divide the economic structure into four main influencing factors, namely social development (F1), economic development (F2), regional innovation (F3), government management (F4). In these four aspects, only 14 indicators are centralized under the four main factors. Compared with previous research, the main factors have been processed twice, which makes the obtained results more accurate and precise. The effect on the factor is more intuitive.

At the same time, in the process of establishing the factor analysis model, we also introduced the extreme value method standardization, correlation analysis, factor extraction and other steps, so as to ensure that the determined factor parameters are more accurate and reduce the error in the data processing process.

2. The basic fundamental of Factor analysis model

2.1 Standardization of extreme values

First, log in to the official website of the Ya'an Statistics Bureau to search for data related to the economic structure in recent years. Because the data dimensions are inconsistent, this article uses the extreme difference method to standardize these related data [7].

2.2 Correlation analysis

Pearson product-moment correlation coefficient is used to measure the linear correlation between the two fixed-distance variables [8]. If the value of the correlation coefficient is relatively high, they are all measured in economic structure.

Because correlation analysis is processed after the data is standardized, the result is no dimension, which can be compared under the variables of different units.

2.3 Load matrix solution and factor extraction

We used the orthogonal factor model in this paper. The skewing-factor model has excellent uncertainty, and it is challenging to estimate the coefficient. Compared to the skewing-factor model, the orthogonal rotation is easier to be quantified and can make the various with no correlation between each other.

The core part of factor analysis is to interpret most of the information about the initial variables with a few independent factors. We assume the standardized initial variables are: $x_1, x_2, \ldots, x_p$, whose mean and standard deviation are respectfully 0 and 1. We express those initial variables by the factors as a series of linear combinations:

$$
\begin{align*}
x_1 &= a_{11}f_1 + a_{12}f_2 + \cdots + a_{1k}f_k + \varepsilon_1 \\
x_2 &= a_{21}f_1 + a_{22}f_2 + \cdots + a_{2k}f_k + \varepsilon_2 \\
& \vdots \\
x_p &= a_{p1}f_1 + a_{p2}f_2 + \cdots + a_{pk}f_k + \varepsilon_p
\end{align*}
$$

This formula expresses the mathematical model of factor analysis and expresses a linear equation of initial variables X with a common factor as the independent variable and a load factor matrix as the coefficient. $a_{ij}$ is a load of initial variable i on factor j, which is also called the factor load matrix. $\varepsilon$ represents a particular factor with a mean of 0 and whose initial variable cannot be explained by F.
The prerequisites of model is

\[
\begin{align*}
E(F) &= 0, \text{Cov}(F) = E(FF^T) = I \\
E(\varepsilon) &= 0, \text{Cov}(\varepsilon) = E(\varepsilon\varepsilon^T) = \psi^2 = \text{diag}(\psi_1^2, \psi_2^2, \ldots, \psi_p^2) \\
\text{Cov}(F, \varepsilon) &= 0
\end{align*}
\]  
(2)

There is no correlation between the factor $\varepsilon$ and the factors $F$. There is no correlation between the factors $F$, and their variance is 1. Moreover, the covariance matrix between the factors is and there is no correlation between them.

The common degree of variables, also known as the variance of variables, represents how much the information of the initial variables is covered by all common factors. Factor variance contribution can be used to measure whether a factor is essential. The information that the initial variable should be explained mainly.

Firstly, we used the principal component analysis to extract the variables factors, and provide corresponding initial solutions. The $p$ standardized initial variables $x_i$ converted into another unrelated set of variables $y_i$ through linear combination\[^9\].

\[
\begin{align*}
y_1 &= \mu_{11}x_1 + \mu_{12}x_2 + \mu_{13}x_3 + \cdots + \mu_{1p}x_p \\
y_2 &= \mu_{21}x_1 + \mu_{22}x_2 + \mu_{23}x_3 + \cdots + \mu_{2p}x_p \\
y_3 &= \mu_{31}x_1 + \mu_{32}x_2 + \mu_{33}x_3 + \cdots + \mu_{3p}x_p \\
\vdots \\
y_p &= \mu_{p1}x_1 + \mu_{p2}x_2 + \mu_{p3}x_3 + \cdots + \mu_{pp}x_p
\end{align*}
\]  
(3)

Among them,

\[
\mu_{i1}^2 + \mu_{i2}^2 + \mu_{i3}^2 + \cdots + \mu_{ip}^2 = 1 (i = 1, 2, 3, \ldots, p)
\]  
(4)

After the transformation, the new variables $y_1, y_2, y_3, \ldots, y_p$ are used as $x_1, x_2, x_3, \ldots, x_p$ the first, second, ..., and $p$-th principal components of the original variables respectively\[^9\]. In order to reduce the number of variables represented and reflect most of their information, the principal components with larger variance contribution rate are selected in order from high to low.

Therefore, the core is to reduce the dimensionality of all the original variables and extract the factors through the principal component method\[^10\].

After performing these steps, the corresponding principal components are obtained by using $y_i = \mu_i x_i$. Afterwards, factor analysis obtains $p$ eigenvectors and corresponding eigenvalues by extracting by the principal component method, and the correlation coefficient matrix is $U = (u_1, u_2, \ldots, u_p)$, the correlation coefficient matrix is decomposed as follows,

\[
R = \begin{bmatrix}
r_{11} & r_{12} & \cdots & r_{1p} \\
r_{21} & r_{22} & \cdots & r_{2p} \\
\vdots & \vdots & \ddots & \vdots \\
r_{p1} & r_{p2} & \cdots & r_{pp}
\end{bmatrix} = U\Lambda U^T = (u_1, u_2, \ldots, u_p) \begin{bmatrix}
\lambda_1 \\
\lambda_2 \\
\vdots \\
\lambda_p
\end{bmatrix} = \begin{bmatrix}
u_1 \\
u_2 \\
\vdots \\
u_p
\end{bmatrix} = \lambda_1 u_1^T + \lambda_2 u_2^T + \cdots + \lambda_p u_p^T
\]  
(5)
Which is,
\[ AA^T = \lambda_1 u_1 u_1^T + \lambda_2 u_2 u_2^T + \cdots + \lambda_p u_p u_p^T \]  \hspace{1cm} (6)

When solving A, the first step is to solve \( F_1 \) the factor with the largest variance contribution rate to all initial variables, and then decompose R to select the next largest variance contribution rate among the remaining factors, and then solve A. First construct the Lagrangian helper function

\[ L = \frac{1}{2} V_1^2 - \frac{1}{2} \sum_{i,j=1}^{p} \lambda_{ij} \times (r_{ij} - r_{ij}^*) \]  \hspace{1cm} (7)

Where, \( \lambda_{ij} \) is the Lagrange multiplier \( (\lambda_{ij} = \lambda_{ji}) \), according \( V_j^2 = \sum_{i=1}^{p} a_{ij}^2, j = 1, 2, ..., k \) to

\[ L = \frac{1}{2} \sum_{i=1}^{p} a_{ij}^2 - \frac{1}{2} \sum_{i,j=1}^{p} \lambda_{ij} \times (\sum_{m=1}^{k} a_{im} a_{jm} - r_{ij}^*) \]  \hspace{1cm} (8)

Taking the partial derivative of the above formula, we get

\[ \frac{\partial L}{\partial a_{im}} = \delta_{im} a_{i1} - \sum_{j=1}^{p} \lambda_{ij} a_{jm} = 0, i = 1, 2, \ldots, p; m = 1, 2, \ldots, k ; \delta_{im} = \begin{cases} 0, m \neq 1 \\ 1, m = 1 \end{cases} \] \hspace{1cm} (9)

Then use \( a_{i1} \) left multiplication and accumulate and sum i with

\[ \delta_{im} \sum_{i=1}^{p} a_{i1}^2 - \sum_{i,j=1}^{p} \lambda_{ij} a_{ij} a_{jm} = 0 \]  \hspace{1cm} (10)

When the value of m is 1, there is
\[ \sum_{i=1}^{p} \lambda_{ij} a_{i1} = a_{j1} \], so it can be transformed into

\[ \delta_{im} V_i^2 - \sum_{j=1}^{p} a_{j1} (\sum_{m=1}^{k} a_{im} a_{jm}) = a_{i1} V_i^2 - \sum_{j=1}^{p} r_{ij} a_{j1} = 0, i = 1, 2, \ldots, p \] \hspace{1cm} (11)

Solved, \( a_{i1} V_i^2 = \sum_{j=1}^{p} r_{ij} a_{j1}, i = 1, 2, \ldots, p \), its matrix form is

\[ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{p1} \end{bmatrix} = \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{p1} \end{bmatrix} \] \hspace{1cm} (12)

When \( a_i = (a_{i1}, a_{i2}, \ldots, a_{ip})^T \), the characteristic equation of the above formula is \( Ra_i = V_i^2 a_i \). When
the variance contribution rate of the constraint condition $V_i^2$ is the largest, it is known that it is the largest eigenvalue $\lambda_i$. Then multiply $U^TU = 1$ by right to get $a_i^T a_i = \lambda_i u_i u_i^T$ then the first column of the A matrix

$$a_i = \sqrt{\lambda_i} u_i$$

Thus, each factor and the corresponding loading matrix are calculated

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pp} \end{bmatrix} = \begin{bmatrix} u_{11} \sqrt{\lambda_1} & u_{21} \sqrt{\lambda_2} & \cdots & u_{p1} \sqrt{\lambda_p} \\ u_{12} \sqrt{\lambda_1} & u_{22} \sqrt{\lambda_2} & \cdots & u_{p2} \sqrt{\lambda_p} \\ \vdots & \vdots & \ddots & \vdots \\ u_{1p} \sqrt{\lambda_1} & u_{2p} \sqrt{\lambda_2} & \cdots & u_{pp} \sqrt{\lambda_p} \end{bmatrix}$$

(14)

Because the number of factors is often much smaller than the total number of original variables. Therefore, when calculating each factor loading matrix, only the first $k$ eigenvectors and their corresponding eigenvalues need to be selected, as shown below

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pk} \end{bmatrix} = \begin{bmatrix} u_{11} \sqrt{\lambda_1} & u_{21} \sqrt{\lambda_2} & \cdots & u_{1k} \sqrt{\lambda_k} \\ u_{12} \sqrt{\lambda_1} & u_{22} \sqrt{\lambda_2} & \cdots & u_{2k} \sqrt{\lambda_k} \\ \vdots & \vdots & \ddots & \vdots \\ u_{1p} \sqrt{\lambda_1} & u_{2p} \sqrt{\lambda_2} & \cdots & u_{pk} \sqrt{\lambda_k} \end{bmatrix}$$

(15)

In order to make the extracted factors representative, the cumulative variance contribution rate of the factors is finally determined to determine the number of factors finally extracted. In the first extracted factor, the cumulative variance contribution rate formula is as follows

$$a_1 = S_1^2 / p = \lambda_1 / \sum_{i=1}^{p} \lambda_i$$

(16)

It can be known from the formula that in the first factor extracted, the variance contribution rate is divided by its variance contribution by the total variance. In the second factor extracted, its cumulative variance contribution rate formula is as follows

$$a_2 = (S_1^2 + S_2^2) / p = (\lambda_1 + \lambda_2) / \sum_{i=1}^{p} \lambda_i$$

(17)

Therefore, among the first $k$ factors extracted, the formula for the cumulative variance contribution rate is:

$$a_k = \sum_{i=1}^{k} S_i^2 / p = \sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{p} \lambda_i$$

(18)

Calculate the variance of each factor and its cumulative variance contribution rate according to the above formula. Usually, the minimum cumulative variance contribution rate of all extracted factors
shall not be lower than 50%, the higher the better.

\[
\begin{align*}
  y_1 &= \mu_{11}x_1 + \mu_{12}x_2 + \mu_{13}x_3 + \cdots + \mu_{1p}x_p \\
  y_2 &= \mu_{21}x_1 + \mu_{22}x_2 + \mu_{23}x_3 + \cdots + \mu_{2p}x_p \\
  y_3 &= \mu_{31}x_1 + \mu_{32}x_2 + \mu_{33}x_3 + \cdots + \mu_{3p}x_p \\
  &\vdots \\
  y_p &= \mu_{p1}x_1 + \mu_{p2}x_2 + \mu_{p3}x_3 + \cdots + \mu_{pp}x_p
\end{align*}
\]

(19)

where,

After transformation, \( y_1, y_2, y_3, \ldots, y_p \) is used as the \( p \) principal components of \( x_1, x_2, x_3, \ldots, x_p \) \(^{[10]}\). In order to reduce the number of variables and reflect the vast majority of information, we chose the principal component with larger variance contribution rate from high to low.

Therefore, the core is to reduce dimension of all initial variables and extract factors through principal component method \(^{[11]}\). When we got \( p \) corresponding principal components from \( y_i = \mu_i x \), we can also get \( p \) eigenvectors and its eigenvalues which constituted an eigenmatrix \( U = (u_1, u_2, \ldots, u_p) \) called the correlation coefficient matrix

Which is

\[
AA^T \approx \lambda_1u_1u_1^T + \lambda_2u_2u_2^T + \cdots + \lambda_pu_pu_p^T
\]

(20)

Therefore, the formula of cumulative variance contribution rate of the first \( k \) factors extracted is

\[
a_k = \frac{\sum_{i=1}^{k} \lambda_i}{p} = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i}
\]

(21)

The variance of each factor and its cumulative variance contribution rate are calculated according to the above formula. Generally, the minimum cumulative variance contribution rate of all extracted factors should not be less than 50%.

2.4 Maximum Variance Method to named factor

In naming, to have a clearer understanding of the factors and to keep no correlation between each factor, when the meaning of the obtained factors is fuzzy, the maximum variance method in the orthogonal rotation method of the principal component method can be chosen. When only the orthogonal rotation of two factors is considered, factor loading matrix \( A \) right multiply an orthogonal matrix is the matrix \( B \).

\[
B = \begin{bmatrix}
  b_{11} & b_{12} \\
  b_{21} & b_{22} \\
  \vdots & \vdots \\
  b_{p1} & b_{p2}
\end{bmatrix}
\]

(22)

In order to use one factor to represent the information of the original two variables as much as possible after the orthogonal rotation of the factors, the variance of the two sets of data
(b_{11}, b_{21}, ..., b_{p1}) \text{ and } (b_{12}, b_{22}, ..., b_{p2}) \text{ should be summed up as large as possible. In other words, the following formula should be maximized after comprehensive consideration.}

\[ G = V_1 + V_2 = \frac{1}{p^2} \left[ p \sum_{i=1}^{p} \left( \frac{b_{i1}^2}{h_i} \right)^2 - \sum_{i=1}^{p} \left( \frac{b_{i2}^2}{h_i} \right)^2 \right] + \frac{1}{p^2} \left[ p \sum_{i=1}^{p} \left( \frac{b_{i2}^2}{h_i} \right)^2 - \sum_{i=1}^{p} \left( \frac{b_{i2}^2}{h_i} \right)^2 \right] \] (23)

### 2.5 Maximum Variance Method to named factor

Factor analysis is used to establish the mathematical model of economic structure to determine the selected factors, the final need to calculate the weight of the factors on each variable, the value of these weight is called factor score, the selected variables are also called factor variables.

The factor score is first described by the initial variable, and the value of factor \( j \) on the \( i \) observation is

\[ F_{ji} = \sigma_{ji} x_{i1} + \sigma_{j2} x_{i2} + \cdots + \sigma_{jp} x_{ip} \ (j = 1, 2, 3, ..., k) \] (24)

The above formula is also called the factor scoring function. In this paper, the least square method is used to estimate the value coefficients of factors \(^{[12]}\), and the least square estimation of regression coefficients meets the requirement

\[ W/R = S_j \] (25)

In order to get the score after factor weighting and establish the corresponding economic structure model, it is necessary to calculate the total score of factor weighting, and the mathematical formula is as follows:

\[ F = \lambda_1 F_1 + \lambda_2 F_2 \] (26)

Where, \( \lambda \) is the characteristic root corresponding to each extracted factor, and \( F \) is the weighted total score of each factor.

So far, the weight of each factor of Ya’an economic structure and its ranking are obtained.

### 3. Construction of economic structure factor analysis model

#### 3.1 Establishment of economic indicators

The quality of economic development involves many aspects. This paper selects indicators from a macro perspective. We chose 14 indexes related to Ya’an economic structure, respectively is: urban per capita disposable income, per capita net income of rural residents, total retail sales of consumer goods, gross investment in fixed assets, the primary industry, secondary industry, and tertiary industry, revenue in the general budgets of local governments, local governments generally Expenditure, total export-import volume, actual foreign direct investment, government funding for research and education, students enrollment, patent application quantity.

#### 3.2 Pearson correlation analysis

Here, the correlation coefficient matrix between variables is used for testing. As can be seen from the result, the correlation coefficients of most initial variables are relatively high, and there is a robust linear relationship between them. Therefore, the choice of initial variables is reasonable and can be factor analyzed.
3.3 Extracting factors by principal component method

A conclusion can be drawn by calculation when the eigenvalues of initial variables are extracted by principal component analysis, the degree of commonality of variables is relatively high, and the information loss of each initial variable is relatively small, indicating that the overall effect of factor extraction is relatively good.

Table 1. Factors and their variance contribution rates

|   | 1   | 2   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| aggregate | 11.62 | 1.2 | 0.24 | 0.101 | 0.068 | 0.03 | 0.02 | 0.006 | 0.003 | 0.002 | 0 | 0 | 0 |
| Percentage of variance | 83.00 | 8.57 | 1.71 | 0.72 | 0.49 | 0.22 | 0.14 | 0.04 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 |
| accumulative total % | 83.00 | 91.57 | 98.35 | 99.08 | 99.56 | 99.78 | 99.92 | 99.96 | 99.98 | 100.00 | 100.00 | 100.00 | 100.00 |

Table 2. Sum of the squares of loads before and after rotation

|   | aggregate | 11.62 | 1.2 | 0.71 | 0.24 | aggregate | 6.148 | 5.056 | 1.408 | 1.156 |
|---|-----------|-------|-----|------|------|-----------|-------|-------|-------|-------|
| Percentage of variance | 83.00 | 8.57 | 5.07 | 1.71 | Percentage of variance | 43.92 | 36.12 | 10.06 | 8.26 |
| accumulative total % | 83.00 | 91.57 | 96.64 | 98.35 | accumulative total % | 43.92 | 80.04 | 90.09 | 98.35 |

As seen from Table 1 and Table 2 above, in the first group of data items, the first factor extracted explains 83.00% of the original 14 variables, and its cumulative variance contribution rate is 83.00%. In the second group of data items, its inner four factors explained 98.35% of the total original variables. In the third group of data items, the cumulative variance contribution rate after factor rotation does not change and does not affect the common degree of the initial variable, but redistributes the eigenvalues of each factor and explains the variance contribution of the original variable, making the extracted factor easier to name [13].

Figure 1. Lithotripsy of extracted factors

As can be seen from Figure 1, the number of common factors extracted is 4.

3.4 Name each factor in the economic structure and calculate its score

Here, the maximum variance method is adopted for orthogonal rotation of factor load matrix to make each factor more explanatory. The results are shown in Table 3 below:
Table 3. Factor load matrix after rotation

|                              | 1    | 2    | 3    | 4    |
|------------------------------|------|------|------|------|
| urban per capita disposable income | 0.646 | 0.691 | 0.304 | 0.102 |
| total retail sales of consumer goods | 0.71  | 0.644 | 0.267 | 0.072 |
| gross investment in fixed assets | 0.421 | 0.678 | 0.252 | 0.015 |
| Per capita income of rural residents | 0.679 | 0.717 | 0.309 | 0.066 |
| Revenue in the general budgets of local governments | 0.58  | 0.559 | 0.653 | 0.195 |
| Expenditures in the general budgets of local governments | 0.603 | 0.177 | 0.544 | 0.186 |
| total export-import volume | 0.292 | -0.133 | 0.628 | -0.075 |
| Actual foreign direct investment | 0.647 | 0.444 | 0.517 | 0.189 |
| Government funding for research and education | 0.082 | 0.004 | 0.09  | 0.491 |
| students enrollment | -0.574 | 0.409 | -0.224 | 0.405 |
| patent application quantity | 0.487 | -0.602 | 0.292 | 0.323 |
| primary industry | 0.862 | 0.596 | 0.239 | 0.045 |
| urban per capita disposable income | 0.723 | 0.506 | 0.282 | 0.147 |
| total retail sales of consumer goods | 0.823 | 0.414 | 0.232 | 0.03 |

As can be seen from Table 3, according to the rotated component matrix and the actual analysis, it can be concluded that the first factor can be named the development factor (F1). The second factor can be named the social development factor (F2). The third one can be named the government-managed factor (F3). The fourth factor can be named the regional innovation factor (F4). Thus, the final relationship between economic structure-related aspects and specific indicators is shown in Figure 2 below.

![Figure 2. Economic structure indicators](image)

The factor score coefficient is estimated by regression method. The output results are shown in Table 4 below:

Table 4. Factor score coefficient matrix

|       | UPCDI | TRSCG | GIFA | PCIRR | RRGBLG | EGBLG | TEIV | AFDI | GFRE | SE | PAQ | PI | SI | TI |
|-------|-------|-------|------|-------|--------|-------|------|------|------|----|-----|----|----|----|
| 1     | 0.001 | -0.065 | 0.499 | -0.083 | 0.428 | -0.38 | -0.328 | 0.085 | -0.052 | -0.595 | -0.413 | 0.248 | 0.307 | -0.277 |
| 2     | 0.094 | 0.177 | -0.263 | 0.152 | -0.104 | -0.103 | 0.572 | -0.092 | 0.033 | 0.309 | 0.406 | -0.038 | -0.126 | 0.359 |
| 3     | 0.088 | 0.074 | -0.34 | 0.179 | -0.581 | 1.395 | -0.187 | 0.254 | -0.244 | 0.472 | 0.394 | -0.214 | -0.203 | 0.196 |
| 4     | 0.004 | -0.006 | -0.086 | -0.032 | 0.152 | -0.118 | -0.011 | 0.031 | 0.988 | 0.087 | 0.049 | -0.036 | 0.046 | -0.024 |
According to Table 4, the four factors of economic structure and the specific index relationship formula. And the factor scoring function of the final economic structure (symbol :F) is as follows:

\[ F=0.43918F_1+0.36118F_2+0.10058F_3+0.08259F_4 \]  \hspace{1cm} (27)

The scatterplot of the factor score variables for each year is shown in Figure 3 below. In the figure, from 2004 to 2017, the economic structure of Ya'an city is constantly adjusting, and the economy of Ya'an city is developing better and better. It not only meets expectations but also verifies the effectiveness of the established model [14].

Through the above analysis, we found that the economic structure is mainly regulated by four factors: social development, economic development, regional innovation and government management. At the same time, we estimated its factor score coefficients through regression as 0.43918, 0.36118, 0.10058, and 0.08259. Compared to the actual situation, our results can be guaranteed with 96% confidence, which is higher than previously reported studies [5]. Therefore, the adjustment of Ya'an's economic structure in the future will be mainly affected by social development and economic development, while the disposable income of urban residents, the total retail sales of social consumer goods, the disposable income of rural residents and the total investment in fixed assets are the main factors affecting social development; It is determined by the primary, secondary and tertiary industries. It is precisely by adjusting the structure of these two aspects that the Ya'an Municipal Government has made the economic development continue to improve.

![Figure 3. Score coefficient of economic structure factor](image)

4. Conclusions

From the economic structure model of Ya'an City, the economic development factor accounts for the largest proportion (43.918%), which shows the importance of industry to economic growth, which is also in line with the actual situation. At the same time, the impact of other factors on the economic structure is also relatively. Judging from the overall score of the economic structure factor, with the progress of the times and the development of society, the economic structure of Ya'an is constantly being optimized, which has played a very good role in promoting economic development.

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