How to promote urban employment in the process of local transformation and upgrading? -- Analysis based on principal component regression

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Abstract: The possible unemployment in the process of industrial upgrading may affect the improvement of residents' well-being, so it is very necessary to study its influencing factors. Based on time series data from 2000 to 2019, this paper selects indicators that may affect urban labor employment from three dimensions: economic growth, structural change and technological progress, and further analyzes the factors affecting urban labor employment through principal component regression on this basis. The empirical results show that although economic growth factors can also have a positive effect on urban labor employment, its impact is not significant compared with the other two types of factors. Therefore, the government should combine various measures to promote employment, accelerate the transformation and upgrading of industrial structure at the same time, increase investment in independent research and development, improve the level of technological innovation, and should also focus on improving the quality of workers.

1. Introduction

The possible unemployment in the process of industrial upgrading may affect the improvement of residents' well-being, so it is very necessary to study its influencing factors. Based on time series data from 2000 to 2019, this paper selects indicators that may affect urban labor employment from three dimensions: economic growth, structural change and technological progress, and further analyzes the factors affecting urban labor employment through principal component regression on this basis. The empirical results show that although economic growth factors can also have a positive effect on urban labor employment, its impact is not significant compared with the other two types of factors. Therefore, the government should combine various measures to promote employment, accelerate the transformation and upgrading of industrial structure at the same time, increase investment in independent research and development, improve the level of technological innovation, and should also focus on improving the quality of workers.

2. Literature review

In view of the importance of employment, domestic and foreign scholars have conducted in-depth and detailed discussions on the factors affecting employment. The existing researches can be summarized into five aspects: economic growth, structural change, technological progress, policy system and demand change.

Okun's law states that there is a negative correlation between unemployment and GDP growth. This law has been confirmed by the experience of developed countries, so it has become one of the main bases for most countries to regulate the macro-economy and solve the unemployment problem. There are a lot of empirical studies on the applicability of Okun's law in China, but the conclusions are not consistent. From the perspective of spatial spillover, Wu and Li (2022) [1]found that from the national level, the impact of economic growth on employment is significantly positive, and there is a positive spatial spillover effect on employment, thus verifying Okun's Law. However, by analyzing the relationship between economic growth rate, employment growth rate, unemployment rate and employment elasticity, Chen (2008) [2]found that China's high economic growth did not bring about a corresponding increase in employment.

Industrial structure also has an impact on employment. The process of industrialization is not only the evolution of industrial structure from the first industry to the second industry, and then from the second industry to the third industry, but also the process of the transfer of labor resources between industries. Guo (2006) [3]believes that the adjustment of industrial structure affects the change of employment structure, and the change trend of the two is consistent in the same period. Zhou and Wu (2008)[4]analyzed the impact of regional industrial structure and industrial competitiveness on regional employment from the perspective of industry and region. It is found that under the condition of the same employment growth rate and the same initial level of

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employment, the difference in the proportion of industry, especially manufacturing industry, and industrial competitiveness are the main reasons for regional employment disparities.

The influence of technological progress on labor employment has been a topic of extensive research, but whether the effect of technological progress on labor employment shows a mechanism of "compensation and creation" (Pissarides,1992)[5]or "creative destruction" has not been reached. In recent years, technological progress and industrial change have promoted the development and application of robotics, artificial intelligence and automated production technology. On the one hand, production automation and intelligence have greatly improved the level of productivity, but on the other hand, the technological transformation represented by "machine replacement" has also caused concerns about large-scale technical unemployment, so the impact of technological progress on employment has once again become a hot topic. Some scholars believe that technological progress will lead to the creation of new industries and jobs, thereby increasing the demand for labor. Yang and Li (2013) [6]argue that technological progress in the information industry increases the relative demand for high-skilled labor and decreases the relative demand for low-skilled labor. Gregory et al. (2016) [7]showed that technological progress does not have a negative impact on total employment. Although process-oriented technological progress will reduce the employment of middle-skill jobs to a certain extent, it can create certain employment opportunities with the increase of product demand and the spillover effect of demand. Li Lei et al. (2021)[8], based on the data of micro-enterprises in China, found that the increase in the use of robots would instead promote the increase in the labor demand of enterprises. However, some scholars believe that technological progress will accelerate the replacement of labor force, which will make the unemployment problem worse. Acemoglu and Restrepo (2020) [9]analyzed the impact of the use of industrial robots on the local labor market in commuter areas in the United States during 1990-2007 and found that an increase of one robot per thousand workers would lead to a decrease of about 0.18%-0.34% in the employment-population ratio. Thus, the existence of the phenomenon of "machine replacement" is verified.

Some scholars try to incorporate policy, system and demand factors into the analysis framework of employment issues, which enricfies the research perspective on factors affecting employment. Zhang and Yue (2022) [10]used UNCTAD data and micro-data of China's population census to construct regional level external tariff change indicators to study the impact of external tariff changes on China's regional labor employment. The higher the decline in external tariffs, the greater the increase in overall employment and in the tradable and non-tradable sectors.

It can be found that most domestic and foreign literatures only analyze the influence of a certain factor on the employment quantity or employment structure, while few scholars can combine the multiple factors affecting employment. On this basis, this paper will select the factors that may affect labor employment, and use statistical measurement methods to analyze the impact of each factor on labor employment.

3. Empirical analysis

3.1. Indicator selection and data source

By combing past literature, it can be found that the factors affecting labor employment can be mainly attributed to economic growth, structural change and technological progress. Urban per capita consumption expenditure (X_1) and urban fixed asset investment (X_2) are selected as the main indicators to measure economic growth. The structure of tertiary industry (X_3) and the level of urbanization (X_4) are used as indicators of structural change. The number of patent applications (X_5), the number of patent grants (X_6) and the number of scientific and technological achievements registration (X_7) are used as evaluation indicators of technological progress. The data in this paper are mainly from the China Statistical Yearbook (2000-2020) and the Annual Statistical Report of the State Intellectual Property Office (2000-2019), and also refer to some data from China Science and Technology Statistics and the State Science Network.

3.2. Principal component analysis

In this paper, the least square method was used for regression in advance, and it was found that the goodness of fit of the model was very good. However, at the significance level of 5%, the T-tests of X_3, X_5, X_6 and X_7 were not significant, which indicated that the model may have serious multicollinearity. In general, it is possible to eliminate the multicollinearity in the model by eliminating the variables that cause collinearity through stepwise regression method. However, this paper aims to analyze 7 subdivision indicators in the three categories of influencing factors, so stepwise regression method is not applicable. In order to solve the multicollinearity problem, this paper decides to choose the principal component analysis method, trying to use the idea of dimensionality reduction to convert this group of highly correlated explanatory variables into a group of independent variables without linear relationship, and the converted variables are called principal components. The advantage of this method is that it can eliminate the multicollinearity in the model without reducing the variables, which helps to better achieve the purpose of research.

After standardized data processing, based on the principle that the eigenvalue is greater than 1, A principal component is finally extracted by SPSS software, and component matrix A is obtained.

Table 1. Eigenvalue contribution

ingredient	Initial eigenvalue		
	total	variance percent	accumulate %
1	6.797	97.094	97.094
2	0.144	2.057	99.150
3	0.047	0.665	99.815
4	0.006	0.088	99.903
5	0.005	0.070	99.974

6	0.001	0.017	99.991
7	0.001	0.009	100.000

Table 2. Component matrix

	Component
ZX_1	0.998
ZX_2	0.986
ZX_3	0.946
ZX_4	0.994
ZX_5	0.997
ZX_6	0.995
ZX_7	0.979

As shown in Table 1 and 2, the cumulative contribution rate of principal component 1 has reached 97.094%. Through the analysis of the component matrix, it can be found that the load of each index on principal component 1 has reached 0.9 or more. The expression of the principal component F1 can be further obtained as follows:

$$F_1 = 0.383ZX_1 + 0.378ZX_2 + 0.363ZX_3 + 0.381ZX_4 + 0.382ZX_5 + 0.382ZX_6 + 0.376ZX_7 \quad (1)$$

Before principal component regression, the unit root test was conducted on the above standardized and logarithmic time series data, and the results were shown in Table 3.

Table 3. Unit root test

variable	ADF test value	test form (c,t,k)	Threshold	onclusion
ZY	-2.052684	(c,0,3)	-2.673459	unstable
D (ZY,2)	-4.805165	(c,0,1)	-3.065585	stable
D (F_1,2)	-7.662069	(c,0,1)	-3.065585	stable

The critical values of ADF in the table are all given by Eviews 8.0 software. The unit root test of explained variable ZY is still not significant even at the significance level of 10%, so it is not stable. After second-order difference, explained variable ZY and explanatory variable F_1 both have second-order monointegrality at the significance level of 5%. Therefore, it is decided to further investigate whether there is a cointegration relationship between ZY and F_1.

Table 4. Johansen cointegration test

Hypothesized No. of CE (s)	Eigenvalue	Trace	5% Critical Value	Prob.**
None *	0.576965	27.60616	25.87211	0.0302
At most 1	0.490015	12.12074	12.51798	0.0582

It can be seen from Table 4 that there is a cointegration relationship between ZY and F_1, so a model with ZY as the explained variable and F1 as the explained variable can be established and its regression can be carried out. The results are as follows:

$$\widehat{ZY} = 0.3819F_1 \quad (2)$$

Bring the formula F_1 about ZX above into the equation:

$$\widehat{ZY} = 0.1462677ZX_1 + 0.1443582ZX_2 + 0.1386297ZX_3 + 0.1455039ZX_4 + 0.1458858ZX_5 + 0.1458858ZX_6 + 0.1435944ZX_7 \quad (3)$$

Table 5. The mean and standard deviation of the variable

variable	Mean	standard deviation
Y	10.4105	0.20749
X_1	9.4289	0.56408
X_2	12.0753	1.12113
X_3	3.8155	0.09992
X_4	-0.7272	0.16042
X_5	13.7321	1.14269
X_6	13.1429	1.13847
X_7	10.6458	0.29861

Using the data in Table 5, the logarithmic regression model obtained by restoring $\widehat{ZlnY}$ is as follows:

$$\hat{Y} = 6.861 + 0.0538X_1 + 0.0267X_2 + 0.2879X_3 + 0.2106X_4 + 0.0265X_5 + 0.0265X_6 + 0.0998X_7 \quad (4)$$

From the regression results, the tertiary industry structure (X_3) has the greatest impact on urban labor employment, with its logarithmic regression coefficient reaching 0.2879; the urbanization level (X_4) has the second greatest impact on urban labor employment, with its logarithmic regression coefficient reaching 0.2106; the number of scientific and technological achievements registered (X_7) also has a great impact on urban labor employment. The logarithmic regression coefficient reached 0.0998. The elasticity of the remaining four indicators to the number of urban employment is not much different. The comprehensive regression results show that technological progress also has a great impact on urban labor employment; Economic growth factors including per capita consumption expenditure of urban residents (X_1) and urban fixed asset investment (X_2) also have a certain positive impact on employment, but this positive impact is not significant compared with the other two factors.

4. Conclusion

In order to eliminate the influence of multicollinearity, this paper adopts the method of principal component analysis to extract a principal component with a cumulative contribution rate of 97.094% from the sample. On this basis, the unit root test and co-integration test are conducted for the explained variables and the principal component, and it is found that there may be a long-term equilibrium relationship between the two. Therefore, the principal component regression model is constructed, and a logarithmic regression model on the influencing factors of urban employment is finally obtained by reducing the standardized variables. The empirical results show that the structural change factors and technological progress factors have a greater impact on urban employment. Among the structural change factors, the tertiary industry structure contributes the most, while among the technological progress factors, the registration of scientific and technological achievements contributes the most. The influence of economic growth factors on urban employment is relatively insignificant. Therefore, this paper suggests that local governments can focus on the following measures:

(1) Accelerating the transformation and upgrading of the industrial structure. The coordination between the development and employment of the tertiary industry is

the best, so it is gradually becoming the main channel of labor transfer and employment. Therefore, the government should not deindustrialize too early in the process of industrial upgrading, but should fully consider the industrial heterogeneity within the industry and the service industry, as well as the upstream and downstream industry chain correlation between departments.

(2) Strengthen independent research and development and promote scientific and technological innovation. To promote scientific and technological innovation is essentially to promote independent research and development. On the one hand, the government can use financial allocations to set up research funds to support the cooperation between leading industries and research institutions in the region to jointly develop new technologies and new products needed for industrial upgrading. On the other hand, funds can be used to support related enterprises to form a public technology research and development platform to break through common technical bottlenecks. Once the research and development process has made significant progress, the government can help enterprises quickly form large-scale production in the short term through procurement, thereby reducing the unit cost of products and creating jobs.

(3) People-oriented, pay attention to improving the quality of workers. On the one hand, urban labor employment is difficult because of the lack of enough employment opportunities, on the other hand, urban workers lack the ability to quickly adapt to environmental changes under the background of the overall economic development level of society and the continuous improvement of scientific and technological innovation level. The government needs to further increase the popularization of education, establish a sound vocational training system, and improve the professional quality and employment skills of workers, so that they can better adapt to the impact of job changes and have the ability to adapt to new jobs under the background of scientific and technological innovation, so as to improve the overall social structural unemployment problem.

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