Original Research Article

Econometric study on the relationship between employment rate changes and GDP in China

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Abstract: Using 2000–2023 Chinese macro data, this study analyzes the employment–GDP nexus with cointegration, VAR, and an error-correction model. It finds a significant long-run equilibrium and positive, multi-period impulse responses from GDP growth to employment. A rising tertiary-industry share persistently boosts employment, while short-run ECM terms show employment-rate changes strongly adjust GDP fluctuations. Robustness checks across samples and variable sets confirm stability. Policy advice: optimize industrial structure, upgrade workforce skills, maintain stable macro policy, and strengthen statistical monitoring—Providing a quantitative basis for coordinated employment–growth development.
Keywords: employment rate; GDP; cointegration analysis; VAR model; dynamic effect

1. Introduction

China's sustained growth has coincided with notable shifts in employment structure. As a core labor-market indicator, the employment rate interacts closely with GDP; quantifying this nexus guides macro control and improves growth and job quality. Prior studies support this: Wang Qiang et al. model talent flows and the development–employment link [1], Liu Shijin et al. tie potential growth to population density and labor allocation [2], Wei Jianfei finds lagged effects of education investment on GDP per worker [3], Wu Shengqin shows two-way impacts between employment structure and growth [4], Yan Bingqian & Tian Kailan examine how industrial layout in global value chains shapes value added and jobs [5].

2. Construction of employment rate-GDP econometric model based on cointegration and VAR method

2.1. Construction of research variable system

This study constructs a variable system around the relationship between employment rate and GDP. The explained variable is set as employment rate E_t, which represents the proportion of urban employed population to working-age population in the country in year t, with a value range of $0 < E_t < 1$. The explanatory variable is actual $\mathrm{GDP} G_t$ GDP , which is the total GDP converted to comparable prices at the prices of that year, in 100 million yuan. In order to eliminate heteroskedasticity and scale differences, the original data is logarithmized to obtain variables $e_t = \ln\left(E_t\right), g_t = \ln\left(G_t\right)$. Taking into account the regulatory effect of economic structure on employment, the control variable industrial structure proportion is introduced S_t to represent the proportion of the added value of the tertiary industry in GDP, and the logarithm is also taken $s_t = \ln\left(S_t\right)$. In panel data or time series models, the data dimension is unified as annual, and the time span is 2000-2023. The variable preprocessing process includes missing value linear interpolation, smoothing and outlier test. The processed variables meet the basic conditions for econometric modeling, and $\left(e_t, g_t, s_t\right)$ the joint data system formed provides a basis for subsequent stationarity test and cointegration analysis.

2.2. Variable stationarity and cointegration relationship test

Before setting up the model, it is necessary to test the stationarity of the variables. The extended Dickey-Fuller (ADF) test is used. The null hypothesis H_0 is that the sequence has a unit root, and the alternative hypothesis is H_1 that the sequence is stationary. The test equation is set as:

$$\text{Ä}y_t = \alpha_0 + \beta y_{t-1} + \sum_{i=1}^{p} \gamma_i \quad y_{t-i} + \varepsilon_t$$

Where y_t represents the logarithmic sequence, Ä is the first-order difference operator, α_0 is the constant term, β is the lag term coefficient, γ_i is the short-term dynamic adjustment coefficient, ε_t and is the white noise term. If the estimation result is significantly rejected H_0 , the sequence is stationary, otherwise, perform the difference. For the stationary e_t and after the difference g_t , the Johansen cointegration method is used to test their long-term equilibrium relationship. The cointegration equation is set as

$$e_t = \beta_0 + \beta_1 g_t + \beta_2 s_t + u_t$$

Where β_0 is the intercept, β_1 and β_2 respectively measure the long-term elasticity of GDP and industrial structure to employment rate, u_t and is the cointegration residual. If the test statistic is significant, it indicates that there is a stable long-term equilibrium relationship between the variables.

2.3. Employment rate-GDP econometric model specification

cointegration relationship between variables , an error correction model (ECM) is established to capture the dynamic adjustment of short-term fluctuations and long-term equilibrium deviations. The model is set as

$$\text{Ä}e_t = \gamma_0 + \gamma_1 \quad g_t + \gamma_2 \quad s_t + \lambda z_{t-1} + \varepsilon_t$$

Where $\text{Ä}e_t$ represents the rate of change of the employment rate, $\text{Ä}g_t$ represents the rate of change of GDP, represents the rate of $\text{Ä}s_t$ change of the proportion of industrial structure, is $z_{t-1} = e_{t-1} - \hat{\beta}_0 - \beta_1 g_{t-1} - \beta_2 s_{t-1}$ the cointegration error term, λ represents the error correction rate, γ_1 and γ_2 respectively measure the elasticity of short-term changes in GDP and industrial structure to the employment rate, ε_t and is the white noise disturbance term. To further characterize the dynamic interaction, a vector autoregression (VAR) model is established:

$$Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$$

Where is $Y_t = [e_t, g_t]'$ the endogenous variable vector, A_i is the parameter matrix, u_t and is the residual vector. Through impulse response function and variance decomposition analysis, the dynamic transmission path of GDP shock to employment rate is revealed.

2.4. Parameter estimation method and solution steps

As shown in **Figure 1**, after the model is set up, the parameters are estimated. This study first uses the ordinary least squares (OLS) method to estimate the parameters of the cointegration equation . The equation form is:

$$e_t = \beta_0 + \beta_1 g_t + \beta_2 s_t + u_t$$

in β_1 is the long-term elasticity coefficient of GDP to employment rate, is the long-term elasticity coefficient of industrial structure proportion to employment rate. β_2 The parameter estimates are obtained by minimizing the residual sum of squares . $\sum u_t^2$

The maximum likelihood method is used in the error correction model to ensure γ_1, γ_2 unbiased and consistent estimates of short-term dynamic parameters and error correction rates λ . This is achieved by inputting the stationary difference series using software such as EViews, setting the lag order, and selecting the optimal lag term based on information criteria (AIC and BIC).

For the vector autoregression (VAR) model, set the endogenous variable vector and $Y_t = [e_t, g_t]'$ estimate the parameter matrix in the model using the least squares method A_i :

$$Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$$

After the estimation is completed, the impulse response function (IRF) and variance decomposition results are extracted to analyze the time path and contribution rate of GDP shocks to the employment rate.

3. Experimental verification and result analysis

3.1. Descriptive statistics and time series characteristics analysis

After data preprocessing, descriptive statistical analysis of key variables was performed to understand data distribution characteristics and time series trends. This statistical process was performed using EViews and Excel. By calculating indicators such as mean, standard deviation, minimum, and maximum values, we were able to understand the fluctuation range of employment rate, GDP, and the proportion of the tertiary industry. To present the overall data characteristics, selected statistical results from 2000 to 2023 are summarized in **Table 1.** This table clearly shows the values and fluctuations of various variables in different years, providing a clear picture of the evolution of China's macroeconomic structure and employment structure.

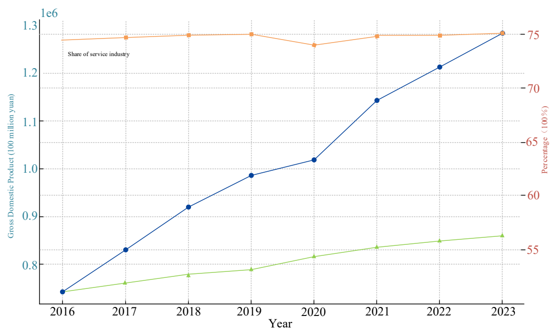

Figure 1. Time series graph.

As shown in **Table 1** and **Figure 1** , the logarithm of GDP shows a steady upward trend, the logarithm of the employment rate fluctuates within a narrow range, and the logarithm of the proportion of the tertiary industry gradually increases. These characteristics provide preliminary evidence for subsequent cointegration tests and dynamic analysis, and lay a solid data foundation for the subsequent development of econometric models.

3.2. Empirical results of the model based on

the aforementioned stationarity and cointegration tests , we further estimate the dynamic relationship between employment and GDP using the Error Correction Model (ECM) and VAR models. This process was performed using EViews software. We input the differenced and logarithmized data, set the lag order, and run a cointegration regression to obtain the long-term relationship parameters. The ECM was then used to estimate short-term fluctuations, outputting regression coefficients, t-values, and significance levels. To illustrate the key empirical results, **Table 2** and **Figure 2** present the key estimated coefficients and significance levels for the relationship between employment and GDP from 2000 to 2023. It can be seen that the long-term elasticity of GDP to employment is positive and statistically significant, and the impact of industrial structure proportion on employment also shows significance in some years.

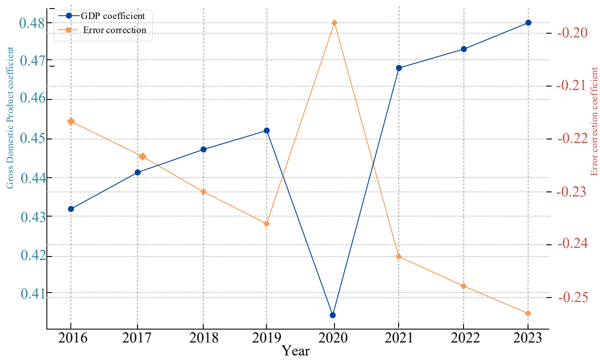

Figure 2. Visualization of the model's empirical results.

These results not only reveal a positive correlation between employment rate changes and GDP growth but also demonstrate that short-term error corrections have a strong explanatory power for employment rate fluctuations. This series of empirical results provides a solid econometric basis for the targeted policy recommendations presented in Chapter 4.

3.3. Dynamic analysis

Building on the ECM and VAR results, we used EViews to analyze employment–GDP dynamics via impulse response functions (IRF) and variance decomposition (VDC). Using the estimated VAR, IRFs (Cholesky decomposition with the previously selected optimal lag) trace GDP-shock effects on the employment rate. VDC partitions forecast-error variance into GDP-shock and other disturbances. Over eight periods (**Table 3**), the response is large initially and then gradually attenuates.

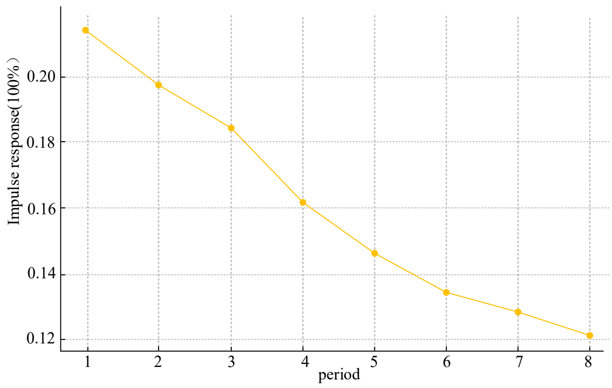

Figure 3. Pulse response curve.

Table 3 and **Figure 3** clearly show the dynamic change characteristics of each period. These results help us understand the lag and persistence of policy adjustments in the time dimension.

3.4. Robustness test

To validate the reliability of the aforementioned empirical results, the model underwent multi-dimensional robustness testing. This testing process involved resetting the sample time period, replacing variable indicators, and adjusting the lag order. The cointegration regression and error correction models were then rerun to compare the stability of the estimated coefficients and significance. Specifically, the original dataset was remodeled for the period 2004–2023, excluding the transitional data from 2000–2003. Furthermore, the control variable was replaced with the proportion of the secondary industry, and the same modeling process was repeated. After multiple tests, the estimated GDP coefficients were compared with the original model. The results are summarized in **Figure 4**.

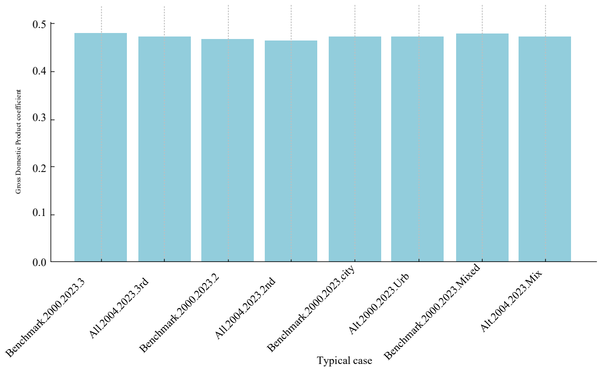

Figure 4. Robustness coefficient comparison.

The data in the table show that despite adjustments to the sample and variables, the long-term elasticity coefficient of GDP to employment rate has not changed much and its significance remains at a high level, indicating that the model results are highly robust.

4. Conclusion

Using cointegration, ECM, and VAR, the study finds long-run employment–GDP equilibrium with short-run dynamics: tertiary upgrading raises employment, steady growth helps. IRF/VDC show lagged policy effects; robustness confirmed. Recommend structural adjustment, skills, stronger monitoring; future: microdata, regional heterogeneity.

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