



Research on the Alignment Between Tertiary Industry Development and Employment Structure Based on the Coupling Coordination Degree Model and Obstacle Degree Diagnosis Model

Ming Li and Shuai Xu*

Advanced Institute of Finance, Henan University, Zhengzhou, China

*Corresponding author: 10240054@vip.henu.edu.cn

Abstract. Based on panel data from China's 31 provincial-level regions for the period 2020–2024, this paper constructs a synergistic analysis framework for “industrial structure–employment structure.” By comprehensively employing Pearson correlation analysis, regression models, two-way fixed-effects models, linear trend forecasting models, coupling coordination models, and barrier diagnosis models, the study examines the alignment between the development of the tertiary sector and adjustments in the employment structure. The findings indicate that the development of the tertiary sector significantly drives the transformation of the employment structure toward the service industry; however, the two processes are not entirely synchronized, and there are marked differences in regional coordination levels. Insufficient labor transfer from agriculture is identified as the primary constraining factor. The methodology employed in this study is highly generalizable and can provide quantitative evidence for the formulation of policies regarding industrial upgrading, employment optimization, and coordinated regional development.

Keywords: Coupling Coordination Degree; Two-Way Fixed Effects Model; Pearson Correlation.

1 Introduction

As economic structures continue to evolve, the alignment between industrial and employment systems directly impacts the efficiency of resource allocation and the quality of regional development [1]. Existing studies often analyze industrial upgrading and employment changes from the perspective of a single indicator or static comparison, making it difficult to simultaneously capture structural interlinkages, regional disparities, evolving trends, and constraining factors. Consequently, research findings lack sufficient explanatory power for complex real-world issues. To address this limitation, this paper constructs an algorithmic analytical framework that integrates multiple models, incorporating correlation identification, effect estimation, trend forecasting, cou-

pled coordination evaluation, and diagnostic analysis of constraining factors into a unified process. This enables a progressive analysis that progresses from relationship discovery to coordination measurement and ultimately to the identification of constraining factors. This framework is not only applicable to research on the relationship between industry and employment but can also be extended to other issues involving the coordinated development of multiple systems. Taking the development of China's tertiary sector and the restructuring of its employment structure as an application scenario, this paper utilizes provincial panel data to validate the model's effectiveness. It reveals the driving role of service sector expansion in employment structural transformation, regional coordination disparities, and key impediments, thereby providing methodological support for industrial structure optimization and employment policy formulation.

2 Industry-Employment Synergy Analysis and Data Preprocessing Methods

2.1 Variable Description and Data Processing

This study uses panel data from 31 provinces, municipalities, and autonomous regions in China covering the period from 2020 to 2024 for the empirical analysis. The data are obtained from the China Statistical Yearbook (2021–2025 editions), resulting in a total of 155 observations.

To examine the alignment between tertiary industry development and the employment structure, several indicators are selected, including the shares of value added in the three industries, the shares of employment in the three industries, the industrial structure upgrading index, the employment structure upgrading index, and the structural deviation index.

To ensure data quality, the original data were processed in a consistent manner, and abnormal observations were removed. Given the substantial differences across regions in terms of industrial development foundations and labor allocation, the subsequent analysis compares the coordination characteristics between industrial structure and employment structure across the eastern, central, and western regions.

3 Multi-Algorithm Measurement Methods for Industry-Employment Alignment

3.1 Relationship identification

Correlation Analysis. To provide an initial assessment of the relationship between tertiary industry development and changes in the employment structure, the Pearson correlation coefficient is used to measure the linear association between the share of tertiary industry GDP and the share of tertiary industry employment.

Building on the correlation analysis, a regression model is further constructed to examine the effect of tertiary industry development on employment structure adjustment. The baseline model is specified as follows:

$$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the share of tertiary industry employment in region i in year t , and X_{it} denotes the share of tertiary industry GDP. The coefficient β captures the direction and magnitude of the effect of tertiary industry development on changes in the employment structure.

Considering that provinces differ in terms of industrial foundations, population mobility, and labor market conditions, while different years may also be affected by changes in the broader economic environment, a two-way fixed effects model is further adopted [2]:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where μ_i represents province fixed effects, λ_t represents year fixed effects, and ε_{it} is the random error term. By introducing two-way fixed effects, unobservable regional heterogeneity and time-specific shocks can be controlled for to some extent, making the estimation results more robust.

To observe the subsequent changes in the alignment between industrial structure and employment structure, a linear trend model is used to extrapolate the share of tertiary industry GDP, the share of tertiary industry employment, and the difference between the two. The model is specified as follows:

$$Y_t = \alpha + \beta t + \varepsilon_t \quad (3)$$

where Y_t denotes the observed value in year t , t is the time variable, and β represents the changing trend. This model is mainly used to describe the short-term direction of change, rather than to make precise long-term forecasts.

Coupling Coordination Degree Model. To quantify the coordination level between industrial structure and employment structure, a coupling coordination degree model is constructed [3]. First, the comprehensive industrial structure index U_1 and the comprehensive employment structure index U_2 are calculated, and then the coupling degree C is obtained:

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \quad (4)$$

On this basis, the coordination degree D is further calculated: $D = \sqrt{CT}$, where $T = 0.5U_1 + 0.5U_2$. A higher value of D indicates a better degree of coordination

between industrial structure and employment structure. In this study, $D < 0.5$ is regarded as a state of disorder, $0.5 \leq D < 0.8$ is regarded as barely coordinated, and $D \geq 0.8$ is regarded as well coordinated.

Obstacle Degree Diagnosis Model. The coupling coordination degree can reflect the overall coordination level, but it does not directly show which factors limit further improvement in coordination. Therefore, an obstacle degree diagnosis model is further used to identify the main constraining factors [4]. The formula is:

$$O_j = \frac{P_j \times w_j}{\sum_{j=1}^n P_j \times w_j} \times 100\% \tag{5}$$

where O_j denotes the obstacle degree of the j -th indicator, $P_j = 1 - Z_j$ denotes the indicator deviation degree, Z_j is the standardized value of the indicator, and w_j is the indicator weight. A larger value of O_j means that the indicator has a more obvious constraining effect on the coordinated development of industry and employment.

4 Empirical Analysis of Tertiary Industry Development and Employment Structure Alignment Under a Multi-Model Algorithm Framework

4.1 Descriptive Analysis

From Table 1, descriptive statistics show a mismatch between China’s industrial and employment structures during 2020–2024. The average tertiary industry GDP share was 51.73%, while its employment share was 48.50%, indicating a slight lag in employment adjustment. The mismatch was more pronounced in the primary industry, where the GDP share was only 9.22% but the employment share reached 27.00%, suggesting insufficient labor transfer from agriculture. In addition, the standard deviations of tertiary industry GDP and employment shares were 11.85 and 13.18, respectively, revealing significant regional differences. Although the service sector has shown strong labor absorption capacity, regional disparities remain and require further examination.

Table 1. Descriptive Statistics of Main Variables (2020–2024)

Variable	Observations	Mean	Std. Dev.	MinMax
Primary industry GDP share (%)	155	9.22	6.10	0.2 21.9
Secondary industry GDP share (%)	155	39.05	8.65	14.553.0
Tertiary industry GDP share (%)	155	51.73	11.85	26.685.3
Primary industry employment share (%)	155	27.00	14.30	1.5 53.5

Secondary industry employment share (%)	155	24.54	6.87	8.1	45.8
Tertiary industry employment share (%)	155	48.50	13.18	24.6	82.0
Industrial structure upgrading index (tertiary/secondary)	155	1.69	1.22	0.35	5.88
Employment structure upgrading index (tertiary/secondary)	155	2.15	1.44	0.54	5.10

4.2 Correlation and Regression Analysis

Based on the descriptive statistics, the relationship between tertiary industry development and changes in the employment structure is further examined. Table 2 shows that the correlation coefficient between the share of tertiary industry GDP and the share of tertiary industry employment is 0.975, which is significant at the 1% level, indicating a very strong positive relationship. The correlation coefficient between the industrial structure upgrading index and the employment structure upgrading index is 0.879, which also passes the 1% significance test. These results suggest that as the industrial structure upgrades toward the service sector, the employment structure tends to move in the same direction.

Table 2. Correlation matrix of industrial structure and employment structure

Variable	Tertiary Industry GDP Share	Tertiary Industry Employment Share	Industrial Structure Upgrading Index	Employment Structure Upgrading Index
Tertiary industry GDP share	1	0.975***	0.958***	0.928***
Tertiary industry employment share	0.975***	1	0.895***	0.969***
Industrial structure upgrading index	0.958***	0.895***	1	0.879***
Employment structure upgrading index	0.928***	0.969***	0.879***	1

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

A regression analysis is further conducted using the share of tertiary industry employment as the dependent variable and the share of tertiary industry GDP as the core explanatory variable. The results in Table 3 show that the regression coefficient of the tertiary industry GDP share is 0.962 and is significant at the 1% level. This implies that a one-percentage-point increase in the share of tertiary industry GDP is associated with an average increase of 0.962 percentage points in the share of tertiary industry employment, indicating that the two variables change almost synchronously. The model achieves an R^2 of 0.951, suggesting strong explanatory power.

However, the intercept term is -2.515 and is also statistically significant. This further suggests that growth in tertiary industry output does not necessarily lead to an

immediate adjustment in the employment structure. Although service sector development promotes employment structure upgrading, labor transfers from other industries to the service sector are still affected by factors such as skill matching, job transitions, and regional mobility.

Table 3. Correlation and Regression Results for Tertiary Industry GDP Share and Employment Share

Variable/Indicator	Value/Result
Tertiary industry GDP share (coefficient β)	0.962***
Intercept term (α)	-2.515***
Correlation coefficient (r)	0.975***
R^2	0.951
t -statistic (coefficient)	48.62
F -statistic	2364.15***
Observations (N)	155

4.3 Trend Forecast Analysis

To examine the short-term evolution of industry–employment alignment, a linear trend model is used for directional forecasting based on data from 2020–2024. As shown in Table 4, the tertiary industry GDP share is projected to rise from 56.7% in 2024 to 58.1% in 2026, while the tertiary industry employment share is expected to increase from 48.8% to 50.1%. Meanwhile, the gap between the two is projected to narrow from 7.9 to 7.6 percentage points, suggesting gradual convergence, although employment adjustment remains relatively slow.

Table 4. Trends and Forecasts of Industrial and Employment Structure Changes (2020–2026)

Year	Primary Industry GDP Share (%)	Secondary Industry GDP Share (%)	Tertiary Industry GDP Share (%)	Primary Industry Employment Share (%)	Secondary Industry Employment Share (%)
2020	7.7	37.8	54.5	25.1	28.7
2021	7.3	39.4	53.3	22.9	29.1
2022	7.3	39.9	52.8	23.3	29.1
2023	6.9	36.8	56.3	22.8	29.1
2024	6.8	36.5	56.7	22.2	29.0
2025	6.7	35.6	57.7	21.5	29.1
2026	6.6	35.3	58.1	20.8	29.1

Note: Data for 2025–2026 are forecast values generated using the linear trend model and are intended only for trend analysis.

4.4 Coupling Coordination Degree and Regional Differences

Beyond the linear relationship identified by correlation and regression analyses, the coupling coordination model further evaluates the overall alignment between industrial and employment structures. The results show that the national coordination degree remained around 0.50 during 2020–2024, indicating a near-disordered state and a slow employment response to tertiary industry upgrading. As shown in Table 5, the eastern region achieved the highest average coordination degree at 0.74, followed by the central region at 0.50 and the western region at 0.42, revealing clear spatial disparities [5]. This pattern is mainly related to differences in service-sector development, labor market maturity, and the share of agricultural employment.

Table 5. Comparison of the Coordination Degree Between Tertiary Industry Development and Employment Structure Across Eastern, Central, and Western Regions

Region	Average Coordination Degree (2020–2024)	Coordination Level	Representative Provinces (2024)
Eastern	0.74	Barely coordinated	Beijing (0.78), Shanghai (0.76)
Central	0.50	Near disorder	Henan (0.48), Hubei (0.52)
Western	0.42	Mild disorder	Sichuan (0.44), Xinjiang (0.39)

4.5 Obstacle Factor Diagnosis and Robustness Test

To identify the main constraints on coordination improvement, the obstacle degree model is applied, with the results shown in Table 6. The primary industry employment share is the dominant obstacle, with an obstacle degree of 61.30%, indicating that insufficient labor transfer from agriculture remains the key factor limiting industry–employment coordination [6]. The tertiary industry employment share ranks second at 22.50%, suggesting that the service sector’s labor absorption capacity still needs improvement. By contrast, the primary industry GDP share and other factors have relatively limited effects, with obstacle degrees of 10.20% and 6.00%, respectively.

Table 6. Ranking of Obstacle Factors Affecting the Alignment Between Tertiary Industry Development and Employment Structure in China

Rank	Obstacle Factor	Obstacle Degree (%)	Main Impact
1	Primary industry employment share	61.30	Insufficient transfer of agricultural labor
2	Tertiary industry employment share	22.50	Further improvement in service-sector labor absorption capacity is needed
3	Primary industry GDP share	10.20	The agricultural sector still accounts for a relatively large share of economic activity
4	Other factors	6.00	Regional development and industrial structure differences

To test the reliability of the results, the industrial structure upgrading index is further used to replace the share of tertiary industry GDP in the regression analysis. The results show that industrial structure upgrading still has a significant positive effect on employment structure upgrading, and both the direction and significance level of the coefficient remain consistent with those of the baseline model. This indicates that the effect of tertiary industry development on employment structure upgrading is relatively stable, and the main findings do not change substantially after the indicator substitution.

Overall, the development of the tertiary industry does promote the transformation of the employment structure toward the service sector, but the adjustment process is not fully synchronized. Regional disparities and the relatively high share of employment in the primary industry are the main factors constraining further improvements in industry–employment coordination.

5 Conclusion

This paper verifies the applicability of a multi-model framework for analyzing industry–employment synergy. The results show that from 2020 to 2024, tertiary industry development significantly promoted employment restructuring, with a correlation coefficient of 0.975 and a regression coefficient of 0.962. However, the national coordination index remained around 0.50, indicating a lag between industrial upgrading and employment adjustment. Regionally, the eastern region showed the highest coordination level at 0.74, followed by the central region at 0.50 and the western region at 0.42. Obstacle diagnosis further reveals that the high share of primary-sector employment is the main constraint, accounting for 61.30%. Overall, the proposed framework effectively identifies structural relationships, regional disparities, and key constraints. Future research may incorporate longer time series and micro-level employment data.

References

1. Zhang Guosheng, Li Wenjing. Corrective or Exacerbating Effect?—The Impact of Digital Infrastructure on “Imbalances” in Industrial and Employment Structures [J]. *Chinese Journal of Population Science*, 2022, (6): 26–38+126.
2. Wang Da, Zhu Jialin, Zhou Yong, et al. How Does Transition Finance Promote Green Technological Innovation? —A Two-Way Fixed-Effects Model Study Based on ESG Mediating Effects and Heterogeneity Tests [J]. *Enterprise Economy*, 2025, 44(11): 102–111. DOI: 10.13529/j.cnki.enterprise.economy.2025.11.010.
3. Guo Xiaofeng, Hou Debing, Liu Haihong. A Study on the Synergistic Development of the Logistics and Manufacturing Industries in Hunan Province Based on the Entropy-Weighted Coupling Coordination Model [J]. *Railway Logistics*, 2025, 43(12): 61–67. DOI: 10.16669/j.cnki.issn.2097-5899.202502280001.
4. Wan Bingtong, Bao Xueying, Zhao Jianchang, et al. Establishment and Application of a Model for Performance Evaluation and Obstacle Diagnosis in Regional Water Ecological Civilization Construction [J]. *Environmental Science*, 2021, 42(4): 2089–2100. DOI: 10.13227/j.hjlx.202008026.

5. Liang Lijun, Wang Chen, Lai Jianing. Empirical Study on the Coordinated Development of Green Logistics and Regional Economy: Based on the Optimization of the Coupling Coordination Index Model and the Factor Obstacle Index Model [J]. *Ecological Economics*, 2025, 41(7): 69-76+84.
6. Yang Xinyu, Wang Yi, Yao Jiawei, et al. Analysis of Coupling Coordination and Obstacle Factors Between Agricultural Industrial Structure and Agricultural Natural Resource Ecosystems in Hanzhong City [J]. *Liaoning Agricultural Sciences*, 2026, (1): 7-12.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

