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PAPER

Analysis and Advice on Employment Forecasts for Graduates Taking into Account the Characteristics of Employment Mobility

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ABSTRACT

In the context of accelerating globalization, the emerging knowledge economy and rapid technological development have brought unprecedented opportunities and challenges to the employment choices of graduates. The employment mobility of graduates has been constantly increasing, and their employment decisions are no longer limited to majors or regions. Instead, graduates can consider various factors more comprehensively, including industrial and urban development, compensation and benefits, etc. This study attempted to understand the characteristics of graduate employment mobility from a more macro perspective, by deeply analyzing the spatial correlation measure and the city-industry integration effect. Then, detailed research and prediction were conducted on the mobility characteristics based on the dynamic decomposition prediction mechanism, which provided not only a more scientific and accurate theoretical basis for graduate employment prediction but also scientific decision-making references for policy makers and educational institutions when formulating relevant policies and educational training plans. The research results contribute to promoting close city-industry integration and have important reference value for promoting urban economic development and optimizing urban industrial structure.

KEYWORDS

graduate employment, employment mobility characteristics, city-industry integration, spatial correlation measure, dynamic decomposition prediction mechanism

1 INTRODUCTION

Affected by globalization, the emerging knowledge economy and constant technological development have brought opportunities for graduate employment choices [1–3]. Graduates are no longer limited to their own majors or regions, and their employment mobility has increased, which has become an important characteristic of today's society. At the same time, the phenomenon of close city-industry

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integration is becoming increasingly evident in the continuous economic and social development of major cities [4–7]. The integration is manifested as a mutual promotion process of urban development and industrial transformation, bringing new opportunities and challenges to urban development. However, it remains a relatively complex and unresolved major issue to more accurately predict and guide the characteristics of graduate employment mobility in the context of city-industry integration [8–10].

The significance of relevant research is that it deeply explores and analyzes the characteristics of graduate employment mobility, especially in the context of city-industry integration [11–14]. By deeply analyzing and evaluating the spatial correlation measure and the city-industry integration effect, this study aims to provide a more scientific and accurate theoretical basis for graduate employment prediction [15–19], which not only helps better understand the employment needs and preferences of graduates but also provides important decision-making references for policy makers and educational institutions when facing the complex and changing job market, helping them formulate more scientific and reasonable policies and guidance plans.

However, existing studies of graduate employment prediction mostly rely on traditional statistical models, which mainly predict future employment trend by analyzing previous data [20–23]. In the environment of globalization and knowledge economy, this mode often overlooks the dynamic nature of the job market, resulting in overly conservative prediction results that cannot accurately reflect the true situation of the market. More importantly, most existing studies have not taken into account employment mobility characteristics and city-industry integration, which often leads to a certain degree of deviation in the prediction results, not fully and accurately reflecting the characteristics of graduate employment mobility.

In view of the above issues, the research contents of this study mainly include city-industry integration measures consisting of spatial correlation measures, city-industry integration effect evaluation analysis, and graduate employment prediction considering employment mobility characteristics based on a dynamic decomposition prediction mechanism. A new measure was used to deeply explore the characteristics of graduate employment mobility in order to obtain more accurate prediction results. At the same time, it is expected that this study can provide more scientific guidance for the industrial layout of cities and the employment decisions of graduates, thereby helping promote the sustained development of city-industry integration. This study is of important theoretical and practical value for research on urban development and graduate employment, providing new perspectives and ways of thinking for research in related fields.

2 GRADUATE EMPLOYMENT PREDICTION CONSIDERING EMPLOYMENT MOBILITY CHARACTERISTICS

Considering the characteristics of graduate employment mobility prediction, it is necessary to predict some key indicators, which reflect various aspects of the mobility, helping better explain the mobility characteristics and provide support for prediction. The three most critical indexes include salary expectation, industry selection, and career mobility. Salary expectation reflects the economic needs of graduates and has a significant impact on their employment choices. Salary expectation prediction helps understand the economic needs and employment pressures of graduates. Industry selection is an important aspect of graduate employment mobility. Different industries are influenced by various factors, such as economic situation, policy orientation, and technological progress, all of which can affect graduates' industry selection. Predicting their potential industry selection helps graduates understand future employment trends. In addition, graduates may experience career mobility based on personal interests, work environments, development prospects, and other factors during the employment process. Predicting this index helps explain the career development trend of graduates.

2.1 Salary expectation prediction

Salary expectation is a continuous numerical variable with high variability and is often influenced by many factors, such as educational background, industry, and geography. The impacts of these factors on salary expectation may vary at different salary levels. For example, the impact of educational background may be more significant in high-salary groups and less significant in low-salary ones. Therefore, quantile regression was used to predict salary expectation, which helped capture differences of salary expectation at different levels, thereby obtaining more precise prediction results. In addition, quantile regression has strong robustness to abnormal values, which is also very useful for dealing with possible abnormally high or low salary values.

It was assumed that the distribution function of random variable Y was given by the following formula:

$$D(t) = O(T \leq t) \tag{1}$$

Then for any $0 < \pi < 1$, the π value satisfying the following formula was the π-th quantile of T:

$$W_T(\pi) = D^{-1}(\pi) = INF(t : LD(t) \geq \pi) \tag{2}$$

Therefore, the asymmetric piecewise linear function serving as the test function was defined by the following formula:

$$\vartheta_\pi(\omega) = \omega(\pi - U(\omega)) \tag{3}$$

Let $U(\varepsilon)$ be the indicative function in the above formula, then there were:

$$U(\omega) = \begin{cases} 0, \omega \geq 0 \\ 1, \omega < 0 \end{cases} \tag{4}$$

If salary expectation and its influencing factors were taken as the dependent variable and independent variables, respectively, it was assumed that there is a linear correlation between them. Let $W_T(\pi|Z)$ be the π-th conditional quantile of T under explanatory variable Z, $\alpha(\pi)$ be the regression coefficient vector, and B be the sample size, then the linear quantile regression model was constructed based on the following formulas:

$$W_T(\pi|Z) = \alpha_0(\pi) + \alpha_1(\pi)Z_1 + \alpha_2(\pi)Z_2 + \cdots + \alpha_k(\pi)Z_j = Z'\alpha(\pi) \tag{5}$$

$$\underset{\alpha}{MIN} \sum_{u=1}^{B} \vartheta_\pi(T_u - Z'_u\alpha) \tag{6}$$

After calculating the estimated value of $\alpha(\pi)$ with different quantiles, the impact of explanatory variables on corresponding salary expectation factors at different levels and other variables was further measured.

2.2 Industry selection prediction

Industry selection is a discrete categorical variable. However, different industries were made numerical according to certain indexes, such as the average salary, development speed, and scale of the industry, and then kernel density estimation was used to predict the industries that graduates might choose. For example, after the frequency of graduates choosing various industries in the previous period was first counted and used to score each industry, the kernel density estimation was used to estimate the distribution of these scores, thereby predicting the industries that future graduates might choose. The probability distribution of those industries was obtained using this method, thereby better explaining the characteristics of graduate employment mobility.

It was assumed that b random samples $Z = \{z_1, z_2, ..., z_b\}$ were identically distributed. Let $d(z)$ be the density function and g be the non-negative constant, then there were:

$$d_b(z) = \frac{D(z+g) - D(z-g)}{2g} \tag{7}$$

Let $J(\cdot)$ be the kernel function satisfying the condition of $\int J(z)dz = 1$, z_u be the u-th sample point, and g be the bandwidth. When b approached $+\infty$, g approached 0, and bg approached $+\infty$, the following formula was obtained according to kernel density estimation:

$$\hat{d}(z) = \frac{1}{b}\sum_{u=1}^{b} J(z - z_u) = \frac{1}{bg}\sum_{u=1}^{b} J\left(\frac{z - z_u}{g}\right) \tag{8}$$

2.3 Career mobility and career development prediction

After introducing the dynamic decomposition prediction mechanism, this study predicted the graduate career mobility and career development trend in the comprehensive integration learning framework. The dynamic decomposition prediction mechanism decomposed the complex career mobility and development trend into multiple sub-trends for analysis, which provided a deep understanding of career selection and development of graduates from different perspectives, thereby providing more comprehensive information. The comprehensive integration learning framework improved the prediction accuracy by integrating the results of multiple prediction models. The integration learning effectively used the advantages of different models and reduced the defects of single ones, because different models may perform better on different sub-data sets. Figure 1 shows a schematic diagram of the dynamic decomposition prediction mechanism.

Data related to graduate career mobility and development trend were first collected, including personal information (e.g., education, major, skills), industry information (e.g., industry development trend, industry salary level), and regional information (e.g., economic development level, job opportunities). Then these data were preprocessed, including data cleansing, missing-value processing, and abnormal-value processing. Let $t_k(k = 1, 2, ..., l)$ be the collected time series data, b be the length of test set t_{TE}, t_{Tr} be the dynamic window being the training set, and $m = l–b$ be its fixed length.

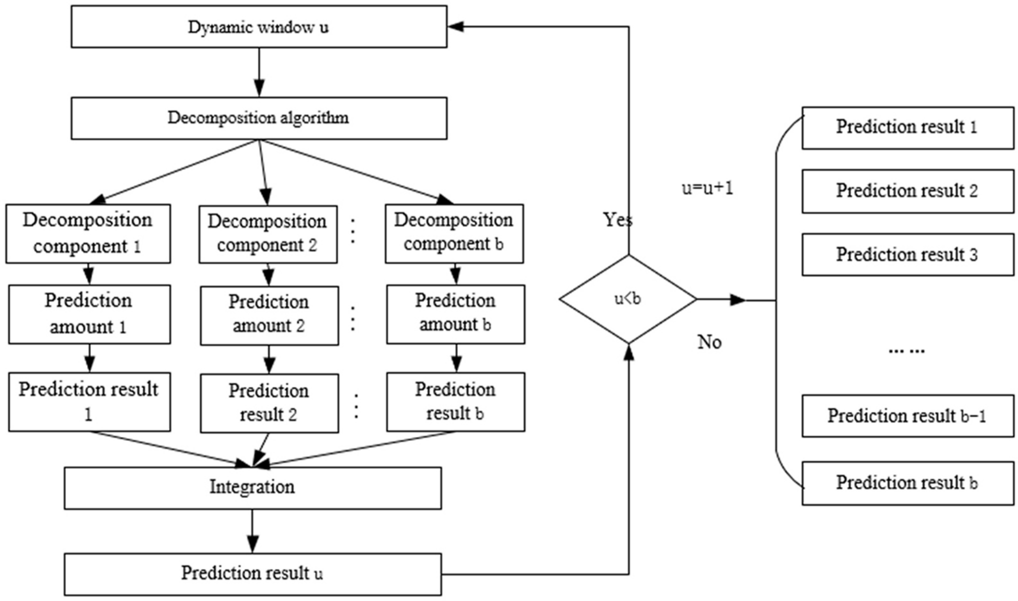

Fig. 1. Schematic diagram of dynamic decomposition prediction mechanism

The dynamic decomposition prediction mechanism was used to decompose the career mobility and development trend of graduates into multiple sub-trends. The career development trend was decomposed into four sub-trends; namely, vocational skill development, career level improvement, career satisfaction, and career stability. Figure 2 shows the schematic diagram of dynamic window decomposition. The decomposition algorithm $d(*)$ was used to decompose the dynamic window u, which obtained w decomposition components V_1, V_2, ..., V_w. Let $\{t_u, t_{u+1} ,..., t_{m+(u-1)+(g-1)-1}, t_{m+(u-1)+(g-1)}\}$ be the training-set sequence in the dynamic window u, then there were:

$$\{V_1, V_2, \cdots V_w\} = d\left(\left\{t_u, t_{u+1}, \cdots t_{m+(u-1)+(g-1)-1}, y_{m+(u-1)+(g-1)}\right\}\right) \tag{9}$$

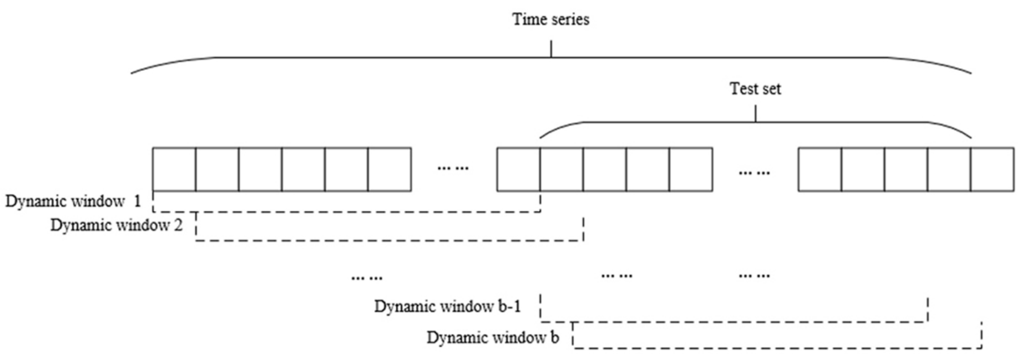

Fig. 2. Schematic diagram of dynamic window decomposition

A direct prediction strategy was used, which obtained the w-th decomposition component V_w. Let f be the input length, then the following gave the calculation formula of the g-step prediction results $\hat{v}_{w,u,g}$ of the u-th numerical value in the test set:

$$\hat{v}_{w,u,g} = g_g\left(\left\{v_{w,u-g}, v_{w,u-g-1}, \cdots, v_{w,u-g-f+1}\right\}\right) \tag{10}$$

The integration learning framework was used to predict each sub-trend. Combined with multiple machine learning models, the framework improved the accuracy and robustness of prediction by voting or weighted averaging. For example, models, such as decision trees, support vector machines, and neural networks, were combined to predict each sub-trend. The prediction results of integrated decomposition components were given by the following formula:

$$t_{TE(u,g)} = r\left(\left\{\hat{v}_{1,u,g}, \hat{v}_{2,u,g}, \cdots, \hat{v}_{w,u,g}\right\}\right) \tag{11}$$

The prediction results of all sub-trends were integrated, which formed an overall prediction of career mobility and development trend of graduates, using simple summation and weighted averaging or more complex optimization algorithms. Whether u met $u<b$ was determined. If it was false, the prediction process ended and the prediction results were output.

3 EXPERIMENTAL RESULTS AND ANALYSIS

Combined with examples, Table 1 shows the employment network density in administrative division of multiple regions (A, B, C, D, and E), respectively, including data, such as maximum and actual number of relationships, employment network density, and regional employment network density, providing a framework for analyzing the density of graduate employment network in various regions. The network density of Region A ranges from 0.263 to 0.412, indicating that the graduate employment network relationships in the region are relatively close, especially Area 1, with the most prominent performance. Region B has data from only one area, and its network density of 0.213 is low, indicating less frequent occupational connections among graduates in the region. The network density of Region C ranges from 0.179 to 0.341, with Area 3 having relatively close employment network relationships. The network density of Region D ranges from 0.057 to 0.107, which is generally low. The graduate employment relationships are relatively weak, but Area 2 performs better compared with other areas. Region E has data from only one city, with a network density of 0.188, which is at a moderate level. There are significant differences in the graduate employment network density in different regions. Overall, the graduate employment network relationships in Region A are the closest, while those in Region D are the loosest, which is related to factors such as industry structure, economic development level, and distribution of job opportunities in the region. For graduate employment guidance, attention should be paid to these factors to adapt to the characteristics of employment environments in different regions.

Table 1. Employment network density of graduates in each region

Region	Administrative Division	Maximum Number of Relationships	Actual Number of Relationships	Employment Network Density	Regional Employment Network Density
Region A	Area 1	1,781	721	0.412	0.342
	Area 2	3,536	1,312	0.372	
	Area 3	4,129	1,424	0.324	
	Area 4	3,539	1,146	0.335	
	Area 5	2,948	922	0.317	
	Area 6	3,254	839	0.263	
Region B	Area 1	7,978	1,712	0.213	0.215
Region C	Area 1	5,112	1,541	0.312	0.271
	Area 2	6,789	1,521	0.235	
	Area 3	3,842	1,284	0.341	
	Area 4	4,731	897	0.179	
Region D	Area 1	11,231	1,189	0.107	0.081
	Area 2	6,189	631	0.100	0.192
	Area 3	8,271	564	0.067	
	Area 4	8,270	493	0.061	
	Area 5	6,489	362	0.057	
Region E	City 1	87,413	16,486	0.188	

Table 2 lists different types of employment mobility of rural and urban graduates, including the number of graduates with continued mobility, mobility of returning, mobility in earlier and later periods, and no mobility, as well as corresponding percentages. In the employment mobility types of rural graduates, the largest one is no mobility, which is 77.5%, indicating that the majority of rural graduates have stable employment positions without mobility. The number of rural graduates in later period is the highest, accounting for 13.7%, because they choose mobility after their first employment in order to obtain better job opportunities. The proportion of continued mobility and mobility in earlier period is 1.1% and 3.5%, respectively, which are relatively small. Similar to rural graduates, the proportion of urban graduates with no mobility is the highest, 76.7%, indicating that most urban graduates also have relatively stable employment positions. The mobility of returning has the highest proportion, 8.1%, indicating that the proportion of urban graduates choosing to return to their original places of work is relatively high. The proportion of continued mobility and mobility in earlier period is 3.2% and 2.89%, respectively, which are relatively small, indicating that most of both rural and urban graduates have stable employment positions after graduation and are less likely to experience mobility. However, the comparison results show that rural graduates have more mobility in the early employment stage in order to seek better job opportunities, while urban graduates are more inclined to return to their original places of work after graduation, because of their differences in factors, such as backgrounds, opportunities, and expectations.

Table 2. Number and percentage of graduates with different types of employment mobility

Types of Employment Mobility	Rural Graduates		Urban Graduates	
	Number of Samples	Frequency of Samples (%)	Number of Samples	Frequency of Samples (%)
Continued mobility	11	1.1	35	3.2
Mobility of returning	39	4.1	88	8.1
Mobility in earlier period	35	3.5	32	2.8
Mobility in later period	138	13.7	103	9.5
No mobility	776	77.5	824	76.7
Total	999	99.9	1082	100.3

Figure 3 lists the salary distribution of graduates and other floating populations in detail. For the floating population of graduates, the majority (53%) of them have a salary expectation of over 4500 yuan, which reflects that they have high employment expectation and require high salaries. However, the proportions of other salary distributions are relatively small, with only the distribution proportions of 2,001–2,500 yuan and 3,001–3,500 yuan exceeding 10%, which are 14% and 10%, respectively. In contrast, the salary expectation distribution of other floating populations is relatively uniform, with no particularly prominent salary range. The salary expectation of 19% of the population is 1,001–1,500 yuan, while that of 24% population is 2,001–2,500 yuan, reflecting relatively low salary expectation of other floating populations. However, salary expectation of over 4,500 yuan still accounts for 18%, indicating that some people in other floating populations also have high salary expectation. There are significant differences in the salary expectation distribution between the floating population of graduates and other floating populations. The former are more inclined to seek high-salary jobs, while the latter have more uniform salary distribution and relatively low salary expectation, which reflects that a college education has positive effects in improving the employment quality and salary expectation of individuals, and floating populations with different educational backgrounds have different positions in the job market.

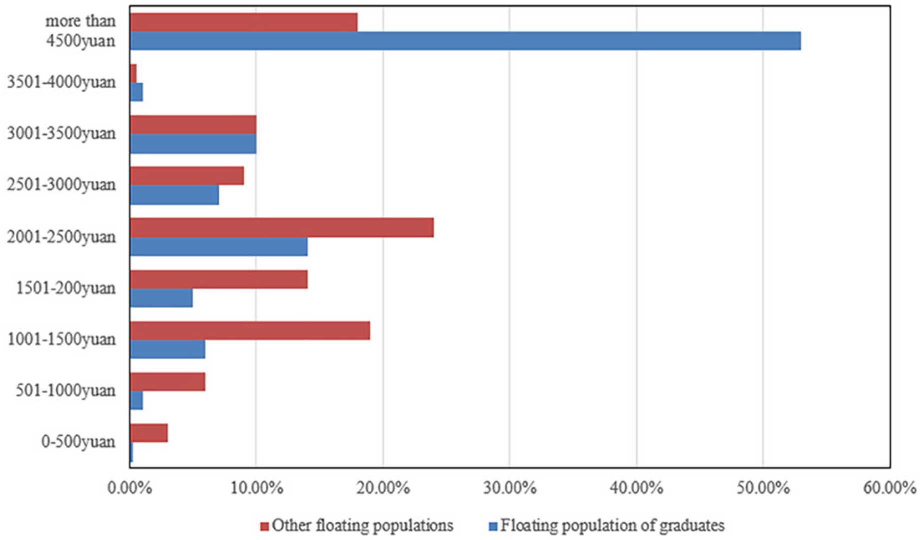

Fig. 3. Salary expectation distribution of different floating populations

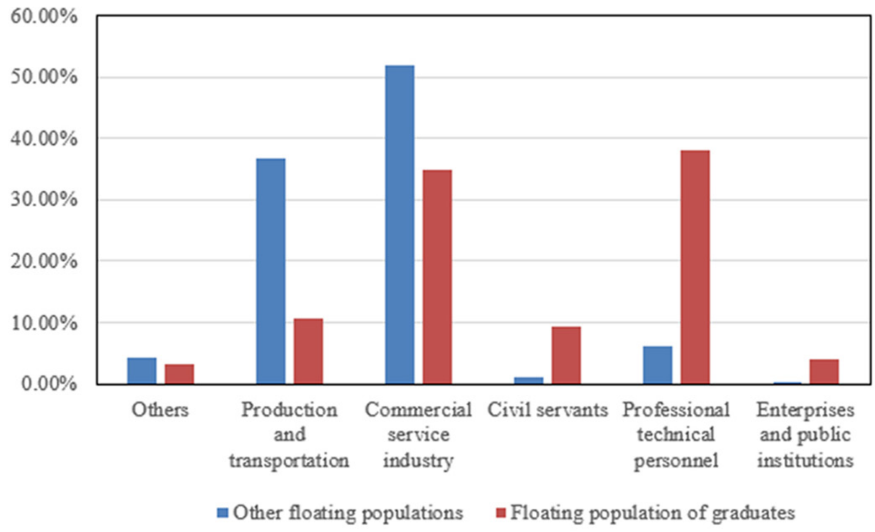

Fig. 4. Industry selection distribution of different floating populations

Figure 4 lists the distribution of graduates and other floating populations in different industries in detail. Other floating populations mainly choose production and transportation, and commercial service industry, which account for 36.61% and 51.89%, respectively, reflecting that other floating populations show an employment trend in industries with relatively low skill and education needs. In addition, the proportions of civil servants, professional technical personnel, enterprises and public institutions are relatively small, which are 0.97%, 6.05%, and 0.27%, respectively, because these industries typically require higher educational backgrounds and professional skills. Professional technical personnel and commercial service industry are main industry choices of the graduate floating population, which account for 37.99% and 34.81%, respectively, reflecting that they tend to choose industries that match their professional skills and knowledge. In addition, the proportions of civil servants and enterprises and public institutions are also relatively high, which are 9.35% and 4.09%, respectively, because these positions typically provide more stable working environments and higher salaries. Therefore, there are significant differences in industry selection between the graduate floating population and other floating populations. The former are more inclined to choose industries requiring higher education backgrounds and professional skills, such as professional technical personnel, commercial service industry, civil servants, and enterprises and public institutions, while the latter are more inclined to choose industries with relatively low skill and education needs, such as production and transportation, and commercial service industry, reflecting the importance of education in determining individual career choices and employment quality.

The career development trend was decomposed into four sub-trends in this study; namely, vocational skill development, career level improvement, career satisfaction, and career stability. The vocational skill development trend was quantified by examining the accumulation of individual continuing-education credits. The career-level improvement trend was represented by changes in individual position levels. The career satisfaction trend of individuals was quantified using standardized questionnaire surveys. The career stability trend was evaluated by observing individual employment history. These indexes were quantified in the process of data collection and analysis, and effectively reflected various aspects of the career development trend.

Figure 5 shows the comparison between predicted and true values of continuing-education credits. It can be observed from the overall trend that both values show a quarterly changing trend, reflecting that education credits change along with the change of semesters. It can be seen from the figure that the differences between both values are relatively small at most time points, indicating that the prediction model has captured the changing trend of continuing-education credits to some extent. However, the predicted values deviate significantly from the true values at some time points, such as Jul. 2021, Oct. 2021, and Oct. 2022, because of certain non-cyclical influencing factors, such as policy changes and sudden changes in educational demand. Overall, although there are some deviations, the prediction model accurately predicts the changing trend of continuing-education credits at most time points.

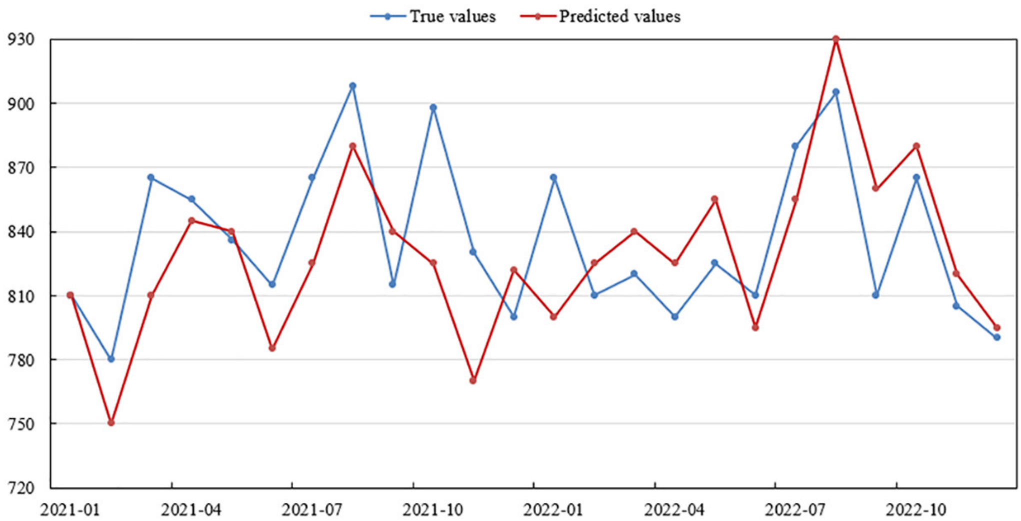

Fig. 5. Comparison between predicted and true values of continuing-education credits

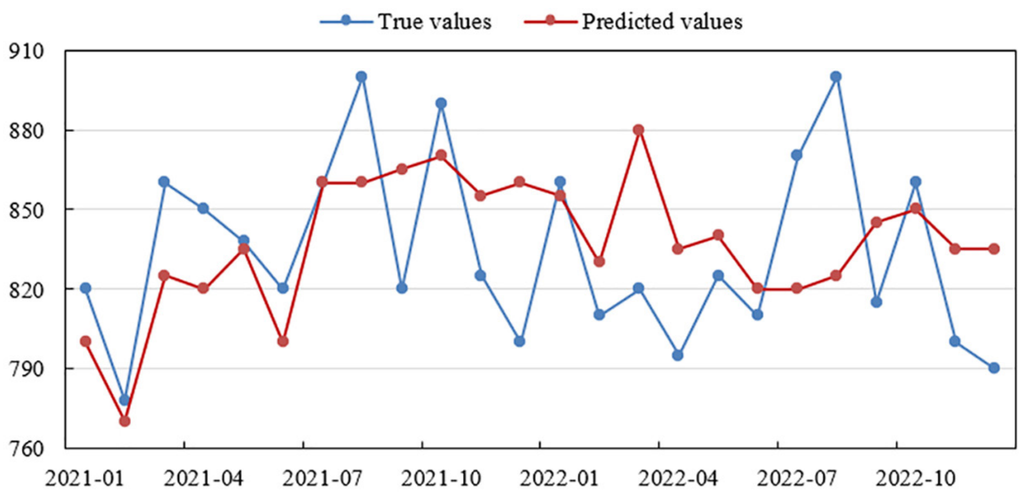

Fig. 6. Comparison between predicted and true values of position-level growth scores

Figure 6 shows the comparison between both values of position-level growth scores. First, it can be noted from the figure that both values exhibit a seasonal trend, reflecting that the position levels of graduates increase over time. Second, both values are very close to each other at most time points, indicating that the prediction model performs well in capturing the changing trend in position-level growth scores. However, there are significant deviations between both values at some time points, such as Oct. 2021 and Jul. 2022, because of special influencing factors, such as seasonal fluctuations in the industry, or certain unexpected events. Although prediction deviations exist at some time points, this prediction model effectively predicts the position-level growth scores at most time points.

Figure 7 shows the comparison between both values of career satisfaction scores. It can be seen from the figure that both values maintain high consistency at most time points, indicating that the prediction model has considerable accuracy in predicting the career satisfaction scores. However, predicted values also deviate from true values at some time points. For example, predicted values are significantly lower than true values in Oct. 2021 and Jul. 2022, while predicted values are higher in Jan. 2022 and Apr. 2022, because some special factors affect career satisfaction at these time points, such as changes in the work environments and in industry dynamics, or specific social events. Overall, although deviations between both values exist at certain time points, the prediction model is relatively accurate in predicting career satisfaction scores on the whole.

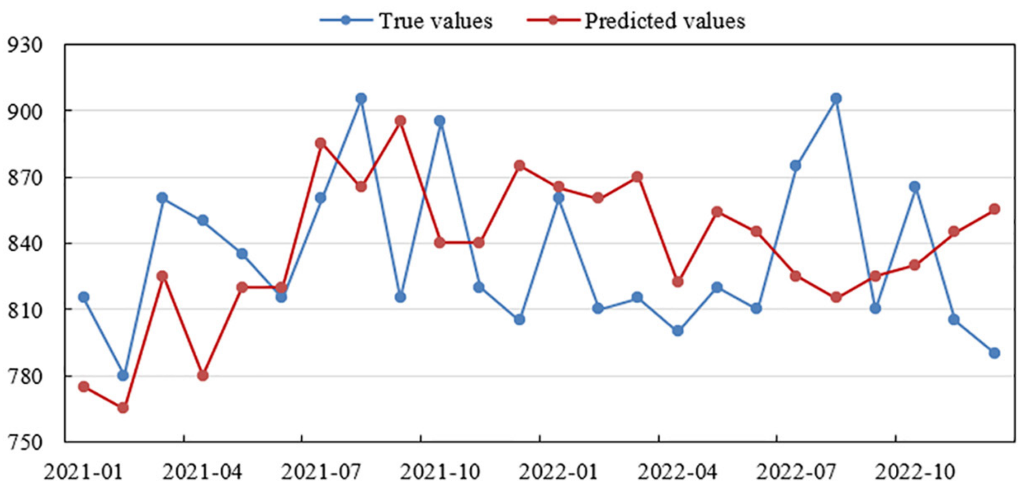

Fig. 7. Comparison between predicted and true values of career satisfaction scores

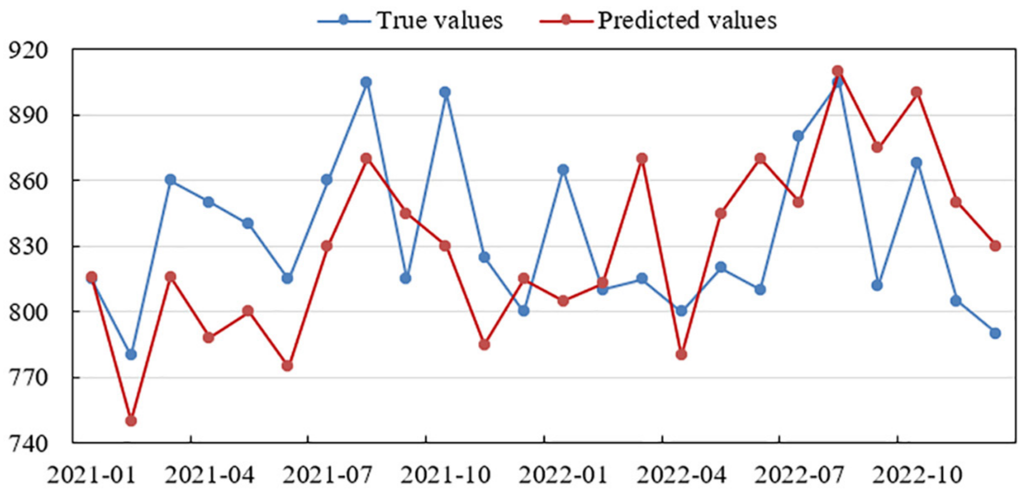

Fig. 8. Comparison between predicted and true values of service continuity-level scores

Figure 8 shows the comparison between both values of service continuity-level scores. It can be seen from the figure that both values are relatively close to each other at most time points, indicating that the prediction model performs well in predicting the service continuity-level scores. However, there are some deviations between both values at some time points. For example, predicted values are lower than true values in Jul. 2021, Jul. 2022 and Oct. 2022, while predicted values are higher in Oct. 2021, Jan. 2022 and Apr. 2022, reflecting the shortcomings of the prediction model in dealing with some abnormal or unique situations. Overall, this prediction model predicts the service continuity-level scores very well. However, to further improve the prediction accuracy, it is necessary to further study and explore the special factors leading to deviations between both values, and to attempt to incorporate these factors into the prediction model, thereby predicting the service continuity-level scores more accurately.

4 CONCLUSION

This study explored the graduate employment mobility characteristics, city-industry integration effect evaluation analysis, and career development prediction from multiple perspectives. Overall, the research results revealed the following key conclusions:

(1) The spatial correlation-measure analysis showed that graduate employment mobility had obvious network characteristics, which was an important reflection of the adjustment of urban spatial and industrial structure. The overall employment mobility characteristics were effectively grasped using indicators, such as network density, correlation, and efficiency. Degree and betweenness centrality further revealed the network node streets' spatial correlation strength of other streets and their control degree of employed population mobility.

(2) In terms of city-industry integration effect evaluation, the Moran's I method effectively identified the spatial agglomeration characteristics of different industries. The research results showed that the matching degree between industrial agglomeration and urban service industry agglomeration was not high, indicating that the urban service industry needs to be improved.

(3) This study established a relatively comprehensive prediction model for graduate career development, by decomposing the career development trend into subtrends; namely, vocational skill development, career level improvement, career satisfaction, and service continuity level, and by using corresponding quantifiable indicators for evaluation. Although certain deviations between predicted and true values existed, the prediction results were relatively accurate on the whole and reflected the effectiveness of the prediction model.

(4) The distribution characteristics of various types of graduates in several aspects were analyzed, such as employment mobility type, salary expectation, and industry selection, providing valuable references for further deepening graduate employment guidance and urban development planning.

In summary, this study not only revealed some key characteristics and dynamics of graduate employment mobility but also provided an empirical basis for urban planning and education policy makers, thereby guiding them in better promoting urban development and improving the graduate employment quality. However, it is worth noting that the results of this study still need further empirical testing and improvement because of sample limitations and model assumptions.

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