The Annals of Regional Science (2025) 74:57
https://doi.org/10.1007/s00168-025-01382-6

ORIGINAL PAPER

Uneven spatial patterns and disparate socioeconomic impacts of intercity labor mobility in China

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Received: 4 September 2024 / Accepted: 15 April 2025

Abstract

Labor migration has become an important factor affecting urban development. Although population mobility has been analyzed from various perspectives, existing research requires a more comprehensive understanding of how uneven socioeconomic characteristics relate to large-scale labor mobility in a country. Hence, this study takes national cities in China as the research objects and explores the dynamic labor mobility patterns from 2021 to 2023. By characterizing the spatial–temporal mobility patterns before and after the New Year, the backflow model is used to capture labor activities and further understand the driving factors of labor mobility. The research results show that large cities in each agglomeration have a huge capacity to absorb incoming labor populations of small- and medium-sized cities with a surrounding distance of about 500–1500. These intercity laborers are more likely to be driven by family and economic pressures, but their salaries may not be high paying. This means that there are still significant uneven socioeconomic disparities between laborers' native city and working city. Taken together, this study contributes to a further in-depth portrayal of the profile of intercity labor mobility on a large scale and reflects on the significance of this spatial mobility for individual and national development.

1 Introduction

In the context of increasingly interconnected urban networks, the mobility of urban populations is becoming more frequent. Population mobility has significantly impacted modern civilization's urban development, livability, and welfare (Bassolas et al. 2019; Mimar et al. 2022; Zhai et al. 2022). =Given that most innovation and technological advancement are now burned in urban centers (Le Néchet 2012),

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Published online: 24 May 2025

cities are attracting more and more population and work there (Shen et al. 2023). As the world becomes more political, economic, and culture-dense, intercity population mobility is bound to increase (Alessandretti et al. 2020), thus leading to the burgeoning focus on relevant topics addressed by this discipline from scholars in the twenty-first century (Marwal & Silva 2023; Shen et al. 2023). Unlike the forced migration of the late 1950s, current population mobility is largely voluntary. In recent years, there has been a marked reduction in the control of intercity mobility within a country, triggering large-scale voluntary rural or small city movements to developed cities (Seeborg et al. 2000).

Previous studies have emphasized the significance of dynamic intercity mobility as an agent of city interaction and relationship (Alessandretti et al. 2020; Aultman-Hall & Ullman 2020; Zhu et al. 2022). More generally, the interaction between cities is complicated in interwoven structures (Caldarelli et al. 2023), affected by various purposes and intentions of mobility. For example, Cui et al. (2020) used millions of Tencent location-based service records to map the spatial network of intercity population movements in the megaregion, Yangtze River Delta, which can be divided into three types of travel purposes—commutes, business trips, and leisure activities. Similarly, Fang et al. (2023) applied mobile data to uncover the driving factors of different intercity mobility patterns in the Pearl River Delta. Among all travel purposes, many studies have proved the close connection between intercity mobility and urban characteristics such as facilities, jobs, and services crucial for better livability and sustainability (Bassolas et al. 2019; Connor & Storper 2020; Mimar et al. 2022).

The uneven development between cities lies behind the purpose of intercity mobility (Gu et al. 2024a, b; Huang and Chen 2022). Uneven development is commonplace in urban and rural areas, with income, wealth, power, and education being the most significant resources shaping social stratification and the core factors of interest in examining urban mobility. A few research studies have proved that pursuing better socioeconomic status results in disparities in intercity mobility and even shapes special patterns of mass mobility, including intercity labor mobility (Hu et al. 2020). Traditionally, labor mobility transfers labor between different locations, from countries or cities to departments or workplaces, to achieve higher labor income (Altenried 2021). On the one hand, mass labor mobility promotes the prosperity and development of large cities. Still, on the other hand, it results in the significant contraction and hollowing out of small cities or rural areas (Wen et al. 2023; Zhai et al. 2022). Existing studies have limited analyses depicting the landscape of large-scale labor mobility and the relationships between labor mobility and unequal socioeconomic behind. Hence, a more comprehensive understanding of intercity labor mobility in the country must be achieved by characterizing it through dynamic population mobility, largely driven by socioeconomic characteristics and the nature of employment today.

To research that, this study takes one of the most striking global labor mobility, the large-scale labor movement back home each year during the Chinese Lunar New Year, as the research scenarios. China has long been the world's most populous country, with its population accounting for approximately 18% of the global total, according to data from 2021. The extensive and frequent population mobility across cities presents a uniquely dynamic landscape that profoundly influences urban development (Lao et al. 2022). The uneven development of Chinese cities leading to unequal population mobility has been an important urban research topic (Ji et al. 2020; Pan and Lai 2019). Research indicates that Chinese cities exhibit distinct spatial patterns of intercity mobility during special holidays, such as a significant increase in the influx of tourists to tourist-oriented cities during the National Day holiday (Lao et al. 2022; Pan and Lai 2019). Similarly, during the Chinese New Year, a different mobility pattern emerges compared to regular days, as many people return from their working cities to their hometowns (Mu et al. 2021; Tan et al. 2021). Therefore, as a lens for demonstrating intercity labor interactions, China is a typical and excellent study area for understanding and excavating the large-scale labor mobility pattern based on migration data.

Overall, this study aims to identify the spatial pattern of labor mobility and explore the uneven spatial patterns and socioeconomic disparities by assessing the large-scale labor mobility pattern among cities. Based on the Baidu Migration Big Data from 2021 to 2023, we calculate the labor mobility network of each city before and after the Chinese New Year to measure the urban hierarchical structure and the intercity mobility network during this special festival. Subsequently, we further employ statistical and regression methods to explore how unequal socioeconomic characteristics affect labor distribution. Taken together, this study can help understand the overall labor mobility pattern and the socioeconomic disparities of labor forces in China. Moreover, it is a pioneering study that analyzes the dynamic labor mobility of 368 cities across China based on urban migration data rather than traditional panel data. By revealing the comprehensive patterns of intercity labor mobility, the study can help inspire better labor mobility management for urban planners and government managers.

2 Research backgrounds

2.1 Intercity labor mobility patterns

As the urbanization rate of global cities continues to increase, high-productivity cities have greatly promoted the opportunities for labor migration to improve productivity, ultimately forming a network of flows between cities (Gu et al. 2024a, b; Seeborg et al. 2000). Unlike the labor migration of the past, contemporary labor mobility is more diverse and cyclical, meaning that the movement is not permanent and often circulates between the place of work and the place of household registration. The sought-after jobs have also become more diversified and are no longer limited to traditional labor-intensive industries (Kelley et al. 2020), resulting in a more complex mobility pattern.

If what we understand is that the population flow in cities is mainly composed of transient populations, the dynamic intercity labor mobility is also hidden within, making it difficult to identify and count (Pan and Lai 2019; Tan et al. 2021). Estimates of the size of the mobile population vary by region, and accurately estimating the exact size of the mobile population has always been a challenging issue (Seeborg et al. 2000). However, there is no doubt that it represents an important force in China's urbanization. As shown in Table 1, the statistical data of China's urban floating population from 2000 to 2020 reveal that, over these 20 years, the proportion of the national Floating Population to the total population increased from 9.55% to 26.63%. From these figures, it is clear that urban mobility is occurring on a large scale, and labor migration to cities is playing an increasingly important role in this process (Altenried 2021).

Although the growth of these numbers is impressive, they are only collected through sociological statistics at the end of each year; hence, some studies have pointed out that they might underestimate the scale of population transfer between cities: Many people who temporarily arrive in urban areas for medium- to long-term work may not be counted due to the lack of a permanent residence (Goldstein 1991; Seeborg et al. 2000). Moreover, as shown in Table 1, the static panel data of Chinese cities can only reflect the overall proportion of population mobility but fail to record the specific flow numbers between cities. Many studies on labor migration reflect the labor transfer from rural to urban areas based on the year-end population numbers of cities and villages, but this data is also static and lagging (Gao et al. 2020).

Data shows that China's urbanization rate increased from 50% in 2010 to 63.9% in 2020, with an average annual growth rate of 1.4%, indicating a high-speed development stage of urbanization. Therefore, as the urbanization rate further increases, the rural population has become a minority, and most of the labor mobility comes from urban residents: mostly moving from smaller cities to developed cities in search of better job opportunities (Huang and Chen 2022; Tang and Hao 2018). Due to the low returns of employment in rural or small cities, many people choose to work in more developed areas, which triggers labor mobility between cities.

Currently, labor migration in our country includes various types such as seasonal migration, circular migration, and permanent migration (Gao et al. 2020). Among them, seasonal migration, represented by "Chunyun," remains an important window for observing intercity labor mobility (McCarthy 2018; Tan et al. 2021). "Chunyun," the most representative of these large-scale movements, is the annual Spring Festival travel rush, a phenomenon characterized by high transportation pressure and congestion around the Lunar New Year (Pan and Lai 2019; Tan et al. 2021). It is difficult to identify and filter out the migrating labor force within the massive floating population of "Chunyun." Fortunately, the prevalence of emerging urban geographic information big data has allowed researchers to attempt to extract the labor mobility component based on the seasonal migration characteristics of the population in intercity flows, to analyze the physical spatial mobility patterns of the new era of

Table 1 Floating population in China (100 million persons) from China Population and Employment Statistics Yearbook

Year	Total Population (year-end)	Population of Residence-Registration Inconsistency	Floating Population
2000	12.6743	1.44	1.21
2010	13.4091	2.61	2.21
2020	14.1212	4.93	3.76

migrant workers. However, such studies are still few and far between, and there is an urgent need to further identify their spatial patterns and analyze the effects of mobility.

2.2 Relationships between labor mobility and socioeconomic status

The mobility of the labor population is closely linked to the speed of regional economic development, job opportunities, natural environment, medical education, and other public services. They hope to obtain a higher sense of identity by seeking better job opportunities, but essentially, it is a pursuit and desire for better socioeconomic status (Lumpe 2019). Many studies have found that the geographic patterns of labor activities that create job opportunities have changed, reshaping the patterns of socioeconomic disparities (Bian 2002; Connor and Storper 2020; Seeborg et al. 2000). It is evident that labor mobility and socioeconomic status are closely related: The long-term patterns of social mobility can be understood through the deep roots of places and the constantly changing economic fortunes of individuals (Connor and Storper 2020).

Classic labor migration theories suggest that migration self-selection can be interpreted through existing individual notions, family pressures, income distribution at the workplace, and the costs of migration (Chiswick 1999; Fehr et al. 2024; Lumpe 2019). For example, Michael Todaro's internal migration model posits that labor migration depends on the expected regional income differences, meaning that potential migrants will consider the likelihood of obtaining employment and the expected wage rates. That is, even if the urban unemployment rate is high, migration will still occur if urban wages are sufficient to overcome the risk of unemployment (Todaro 1969). Moreover, the model also assumes that labor mobility is motivated by the expectation of long-term income streams rather than current income. This means that migration might occur even if the actual income in the city is lower than the actual income of rural people for some time after migration. Labor can be willing to endure a short-term low-income level in exchange for the promise of a higher income in the long term (Seeborg et al. 2000).

A review of the literature reveals that most studies on successful class ascension through job mobility have focused on the twentieth century (Xie et al. 2022), with a particular emphasis on the USA (Connor and Storper 2020). However, whether the findings and conclusions of these studies are still applicable in the twenty-first century and developing countries, such as China, is unknown. Moreover, an increasing number of studies indicate that social classes are becoming more rigid globally, and the chance of mobility is reducing (Kavanagh et al. 2021). Therefore, whether socioeconomic disparities between laborers' native cities and working cities are still large is undoubtedly an important topic worth exploring.

2.3 Research gaps and objectives

The following section aims to explicitly state each innovation and explain how it diverges from or enhances existing work in the field. The first one is the identification and analysis of dynamic labor mobility patterns. Most existing studies rely on static panel data to reflect intercity population movements (as shown in Table 1), which cannot accurately capture specific intercity flow volumes and their dynamic changes. This study uses Baidu Migration Big Data from 2021 to 2023 to calculate the labor mobility network of each city before and after the Chinese New Year, thereby measuring the urban hierarchical structure and intercity mobility network during this special festival. This real-time big data approach provides a new perspective for understanding large-scale labor mobility, surpassing traditional research methods that depend on end-of-year statistical data.

The second objective is to understand the disparate impact of socioeconomics on labor distribution. While the literature has explored the relationship between labor mobility and socioeconomic development, specific mechanisms through which these factors interact remain underexplored. This study not only examines the phenomenon of labor migration from rural to urban areas but also investigates how different cities' socioeconomic characteristics influence labor distribution. By employing statistical and regression analyses, this research aims to reveal how socioeconomic disparities drive labor mobility between cities, providing theoretical support for policymakers to optimize labor management and promote more balanced urban development.

China, with its unique urban–rural dual structure and socioeconomic development model, serves as an ideal case study for examining labor mobility. Particularly during the Spring Festival, the "Chunyun" phenomenon offers a unique window into intercity labor mobility. Unlike previous studies that often focus on developed countries, this research centers on the specific context of developing countries, addressing gaps in non-Western contexts.

In summary, by introducing emerging big data technologies, combining specific Chinese contexts, and deeply analyzing the impact of socioeconomic disparities on labor mobility, this study aims to address existing research gaps. It provides new insights and methodologies for academic discussions and practical applications in the field. Through these innovations, the research contributes to a deeper understanding of labor mobility patterns and socioeconomic inequalities in contemporary urban development.

3 Materials and methods

3.1 Research area and scenarios

As one of the most populous countries in the world, China experiences massive intercity movement every day. In China, the Lunar New Year is the most important event and marks the beginning of a new year. No matter how far people are from their families, they try to reunite with them on New Year's Eve to celebrate it. This migration activity typically occurs 15 days before and 25 days after the Spring Festival. During this period, the number of people returning home and going out increases, and the number of passengers nationwide continues to rise. Due to the overlapping of family visits, the student movement, migrant worker flow, and tourism (Mu et al. 2021), this period presents a "rare global population movement phenomenon," which the media has dubbed "the world's largest human migration" (McCarthy 2018).

In the 40-day Spring Festival travel rush in 2023, the total social personnel flow was about 4.733 billion person-times. Of these, the commercial passenger flow was about 1.595 billion person-times, becoming the largest scale of personnel movement since 2020. Not only that, but many parts of Asia, such as Vietnam, Indonesia (Oktavio and Indrianto 2019), and South Korea (Ahn et al. 2020), which share the same migration as China, also have nationwide phenomena of returning home for the spatial festival.

The "Chunyun" reflects the large-scale movement of human resources caused by the uneven development between different cities in China. Since the reform and opening up, the Chinese government has begun to encourage self-employment and has also started to loosen restrictions on personnel movement. As a result, many people have moved from economically underdeveloped areas to more developed areas for employment, causing a large-scale labor movement. These people who leave home to work in other places return home for the New Year, becoming the main group of people transported during the "Chunyun." Therefore, the long-distance labor migration reflects the gap between the East and the West and the urban–rural disparity, a very important urban research topic for China and even the world, and urgently needs more comprehensive research and depiction.

3.2 Intercity spatial mobility data

Using big data on urban migration to depict intercity population mobility has become mainstream scientific research data (Chen et al. 2023; Mu et al. 2021; Pan and Lai 2019). This study uses big data from Baidu migration to intuitively display the trajectory and characteristics of the massive migration before and after the New Year and characterize the intensity of population mobility between cities. The inflow and outflow volume between each pair of cities can be obtained by calculating the geographic location services owned by Baidu Maps (https://qianxi.baidu.com). We crawled the daily migration data of 368 cities during the research period (as shown in Table 2) from the Baidu migration platform, enabling us to calculate the national cross-city population mobility matrix during the festival.

Table 2 Research Lunar New Year's dates, departure, and return period from 2021 to 2023

Lunar New Year	Departure period	Return period
2021-02-12	2021-01-28 to 2021-02-11	2021-02-13 to 2021-02-27
2022-02-01	2022-01-17 to 2022-01-31	2022-02-02 to 2022-02-16
2023-01-22	2023-01-07 to 2023-01-21	2023-01-22 to 2023-02-06

The 15 days before the holiday is the departure period when the inter-municipal labor force will leave the working city and return to their hometowns on a large scale, while the 15 days after the holiday are the return period when the large-scale resumption of workflows will take place

Notably, recent research suggests that the particular social time of COVID-19 does not affect the pattern of intercity mobility because it and the proliferation of teleworking do not diminish the attractiveness of large cities to the population (Gu et al. 2024a, b; Sharifi and Lee 2024), and thus, the multi-year data of the present study can to a greater extent reflect the pattern of labor mobility.

3.3 Backflow model to detect labor mobility

Due to the difficulty in determining which part of the migrants in the departure and return period are intercity labor force, many studies on the massive migration during the Chinese New Year use daily data for spatial–temporal analysis (Lao et al. 2022; Mu et al. 2021). To fill this research gap and better filter the flows caused by the intercity labor force, this study refers to the backflow model developed by Tan et al. (2021), considering those who leave a certain city during the departure period and return to the same city during the return period as migrant workers. The technical concept of this backflow model is shown in Fig. 1.

For the departure period d, the flow matrix is denoted by A^d, where a_{ij} and a_{ji} are the sum outflow and inflow from the city i to city j during d, respectively. Then, the unidirectional network matrix is denoted by E^d, where $e_{ij} = a_{ij} - a_{ji}$ and $e_{ji} = a_{ji} - a_{ij}$. Hence, a logical xor is applied for the following equation to calculate the L value between two cities:

$$L_{ij}^{dr} = xor(E_i^d, E_j^r) \tag{1}$$

where d and r are the departure and return periods separately. If the $e_{ij} \in E_i^d$ and $e_{ij} \in E_j^r$ have the same signs, the $L_{ij}^{dr} = 0$. Otherwise, $L_{ij}^{dr} = 1$, indicating the opposite variation in total flows between city i to city j during d and r.

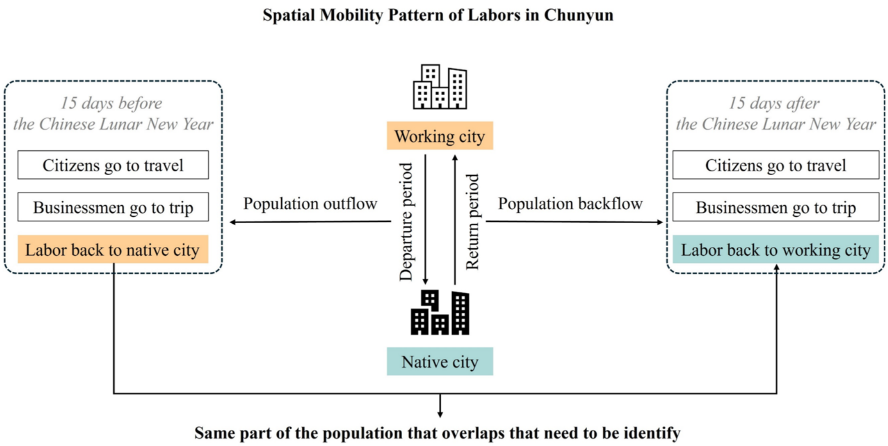

Fig. 1 Technical concept of the backflow model to detect labor mobility

3.4 Relationship between labor mobility pattern and socioeconomic disparities

3.4.1 Statistical analysis

To reflect each city's specific socioeconomic and urban development conditions, this study collected the 2021 statistical yearbooks of various cities in China and the data from the seventh national census. Based on data availability, the 368 municipalities were further cleaned to 290 cities for subsequent analysis of the socioeconomic characteristics. Referring to previous studies on urban development and population mobility (Fang et al. 2023; Gu et al. 2024a, b), we summarize the socioeconomic variables collected from three aspects: socio-environment, economic environment, and urban environment to represent the individual development possibility, as shown in Table 3.

Based on the measured of L value, the study first categorizes it into different levels from low to high using the natural break (Jenks) method. The method divides continuous total L values into five levels and creates a hierarchical system. This approach ensures that data around each breakpoint show high inherent similarity and low differences between categories. As a result, the classification of data is coherent and meaningful, reflecting the data's intrinsic distribution characteristics (Chen et al. 2013; Fang et al. 2023).

Based on this level division, the study utilizes boxplots to visualize the statistical characteristics of selected urban environment variables at each level of L value. Boxplots are a type of graph used to summarize the distribution of a set of data. They show the central tendencies of the data including the median (the line inside the box), the upper quartile (the top boundary of the box), and the lower quartile (the bottom boundary of the box). Additionally, they illustrate the data dispersion (the length of the box) and any outliers (points outside the box). They are particularly useful for comparing variables across different groups or categories to observe variations between them. Hence, they assist us to identify whether there are socioeconomic development inequalities in areas under different levels.

3.4.2 Regression analysis

To further study the relationships between labor mobility and socioeconomic characteristics. The linear ordinary least squares (OLS) model and nonlinear light gradient boosting machine (LightGBM) regression model is constructed with these 18 socioeconomic variables as independent variables and the total L value of each city as the dependent variable.

Previous studies have proved that population mobility is complex, and its relationship with urban development is not linear (Hu et al. 2023; Tan et al. 2021) due to the influence of nonlinear relationships such as the distance decay effect and social network relationships. The analysis of the influencing factors of population mobility needs to be constructed using a nonlinear regression model. We similarly find that the correlation patterns are not well captured using traditional linear OLS models. Therefore, the OLS model is used in this study can not only assess the significance

Table 3 Research variables related to socioeconomic characteristics in this study

Dimensions	Variables	Description
Economic	Gross Domestic Product (GDP)	Represents regional production and the market value of all final products produced by economic activities in a region during a year
	Percentage of Primary Sector	Refers to the production of some agricultural sectors, including forestry, fishery, etc.
	Percentage of Secondary Sector	Comprised of all types of specialized workers and all types of industries or products. Such as manufacturing and construction
	Percentage of Third Sector	Refers to modern services or commerce, mainly including non-material production sectors
	Industrial Enterprises	Reflects the number of industrial working opportunities in a city
	Number of Public Sector Workers	Reflects the number of working opportunities of public sectors in a city
	Number of Patents	Represents the working opportunities in some novel and innovation sector
Social	Extra-city Population	Reflects the number of floating populations without hukou in the city, being a control variable in the study
	Average Wage	Average wage level of all workers in a city
	Education Level	Refers to the average education level of all population in a city
	Dependency Ratio	Children and the elderly in need of support as a proportion of the rest of the population
	First-generation households	Represents single residence settlement in a family
	Second-generation households	Represents two generations in a family
	Third-generation households	Represents three generations in a family including the children and grandparents
Urban	Built-up Area	Includes the area of urban built-up area available for human activities
	Urban Paved Roads	Includes the roads in the city for daily human transportation need
	Hie Mileage of Expressway	Reflects the city's level of external connectivity
	Highway Passenger Traffic	

of each variable but also test the variance inflation factor (VIF) between the variables that are not too high to ensure non-collinearity between the indicators.

Then, this study uses the most advanced nonlinear machine learning regression model, LightGBM, to analyze the influencing factors of migration difference and uses the Python interpretable machine learning library SHapley Additive exPlanations (SHAP) to reveal further the positive and negative effects of the influencing factors (Hu et al. 2023; Li 2022). The equation of LightGBM is as follows:

$$\hat{f} = \underset{f}{\operatorname{argmin}} E_{x,y}\left[L(y,f(x))\right] \tag{2}$$

where the best approximation $\hat{f}$ at each iteration to minimize the loss function $L(y,f(x))$, given a training database $\left\{\left(x_1,y_1\right),\left(x_2,y_2\right),\ldots,\left(x_n,y_n\right)\right\}$.

The equation of SHAP is as follows:

$$y_i = y_{base} + f\left(x_{i1}\right) + f\left(x_{i2}\right) + \cdots + f\left(x_{ij}\right) \tag{3}$$

where $f\left(x_{ij}\right)$ is the SHAP value of x_{ij}. Suppose the i sample is x_i, the j feature of the i sample is x_{ij}, and the predicted value of the model for that sample is y_i, then the mean value of the target variable for all samples is y_{base}.

4 Results

4.1 Contextual patterns of intercity mobility in Chinese new year

The main source of mobility data for migration pattern analysis is Baidu, the largest search engine in China. This dataset records the daily inflow and outflow of each city in China, which allows the study to calculate the daily OD matrix between each pair of cities. Focusing on the intercity labor mobility reflected in large-scale Chinese New Year migration, the departure period (15 days before Chinese New Year) and return period (15 days after Chinese New Year) can be selected to filter the migration data from 2021 to 2023. To understand the features or objectives of each OD record between cities, it is effective to integrate the huge numbers of cities into different scales. According to the scale of permanent residents in urban areas, the 368 Chinese cities are divided into five categories to depict better migration (Ji et al. 2020; Louail et al. 2015), including megacity Behemoth (population of more than 10 million), supercity (population of 500-10 million), big city (population of 100-5 million), medium city (population of 50-1 million) and small city (population of less than 500,000).

Before delving into an analysis of labor mobility, the study first introduces the overall patterns of intercity mobility during the Spring Festival. While this mobility includes all population groups (e.g., students, retirees, tourists), there is a significant amount of labor mobility embedded in it. Subsequent Sects. (4.2–4.3) will focus specifically on labor mobility, a subset of the economically active population. The temporal variation in the migration of different categories of cities used in our analysis for the study period is depicted in Fig. 2A. Migration at all city levels shows

Fig. 2 Intercity mobility network pattern in China for 2021–2023 Chinese Lunar New Year. **A**. Comparing the temporal patterns of five city levels in the departure and return period. **B**. Comparing the migration ratio of cities' OD matrix in the departure and return period

an almost uniform temporal evolution. Even though the number of cities gradually decreases as the size of cities increases, the amount of migration in large-scale cities is much higher than in small- and medium-sized cities. Specifically, a substantial increase can be observed in migration flow between cities during the departure period, while a sharp decrease occurs in the days approaching the Lunar New Year. Then, these intercity mobilities slowly increase and fluctuate from the days after the festival. Many previous studies consider these fluctuations were caused by labor mobility (McCarthy 2018; Tan et al. 2021). When comparing the three-year temporal patterns, the migration population in the departure period showed a significant upward trend from 2021 to 2023, and the migration in 2021 was significantly less than in 2022 and 2023. This indicates that the COVID-19 pandemic especially hit mobility during this important period for people (Jia et al. 2020; Zhu et al. 2022), but this tendency recovered steadily in the following years.

Constructing a city OD matrix effectively describes the mobility interaction between two cities (Hussain et al. 2021). To understand the distribution patterns of migrations between different levels of cities, the study calculates the mean value of O city to D city relative to the mean value of the whole matrix, as shown in the heatmaps (Fig. 2B). The migration ratios between megacities (ratio = 6.99) demonstrate a dominant status compared to the ratios between small cities (ratio = 0.29). Around the Chinese Lunar New Year, the top destinations for all levels of cities are megacities, except for small cities, where the top destinations are medium-sized cities, followed by small cities. This trend has been stable over several years, although there will be a definite change in 2023: The ratio of mobilities between large cities will increase further.

The mobility flows of the 386 cities in China during the departure period and the return period of the Chinese New Year in 2021–2023 are aggregated, as shown in Fig. 3. Since we calculated the total number of migration populations as the weight of the network edges, the darker color means the more flow on this edge. Compared with the migration in 2021, the migration population significantly increased in 2022 and even more in 2023. As for the difference between departure and return periods, the total number of migration populations in departure periods is larger than in return ones. Since the departure periods overlap with the winter holidays for students, there are many intercities travels during this period, causing more migration flows.

Nevertheless, the mobility network is very similar from period to period, all showing a polycentric network structure. It can be found that there are four main central notes of these mobility networks, in descending order, including the Guangdong–Hong Kong–Macau Greater Bay Area, Yangtze River Delta Urban Agglomeration (including Shanghai, Zhejiang, and Jiangsu), and Chengdu–Chongqing Economic Cluster, and Beijing–Tianjin–Hebei Urban Agglomeration (Gu et al. 2024a, b; Zhang and Song 2003). This shows that there are only these four urban agglomerations in the true sense of the word in China. These four urban agglomerations, especially their central cities, have also been attracting a large number of migrant labors (Fang et al. 2024; Gu et al. 2024a, b; Tan et al. 2021). In particular, the Beijing–Tianjin–Hebei Urban Agglomeration does not show a significant central effect in the urban network until 2023. Among these four centers, two coastal megaregions, Guangdong–Hong Kong–Macau Greater Bay Area and Yangtze River Delta Urban Agglomeration, can witness much more population migration than other regions in China.

4.2 Distribution of labor mobility between cities

Since the Chinese Lunar New Year is a temporary relocation over spatial periods, many intercity workers might depart the city they are working in while returning to it when they finish the special event. This part of mobility can be considered intercity labor mobility, which contributes most to the migration of the population in the New Year. These laborers will leave before the Chinese New Year and then return to the same city at the end of the festival, a phenomenon that can be seen as a backflow effect. To quantify this labor backflow effect (L value) between two cities, the study constructs a net flow OD matrix between cities based on net inflow and net outflow values, as described in the Methods section.

As shown in Fig. 4A, the top 50 cities with the strongest backflow effects are measured, most of which are mega- and supercities. Overall, the L values 2023 are generally higher than those in 2021. In particular, it can be seen that some cities named Beijing, Foshan, Hangzhou, Shanghai, Shenzhen, and Zhoukou in 2022 or 2023 have a very high L value near the maximum value of L. These are

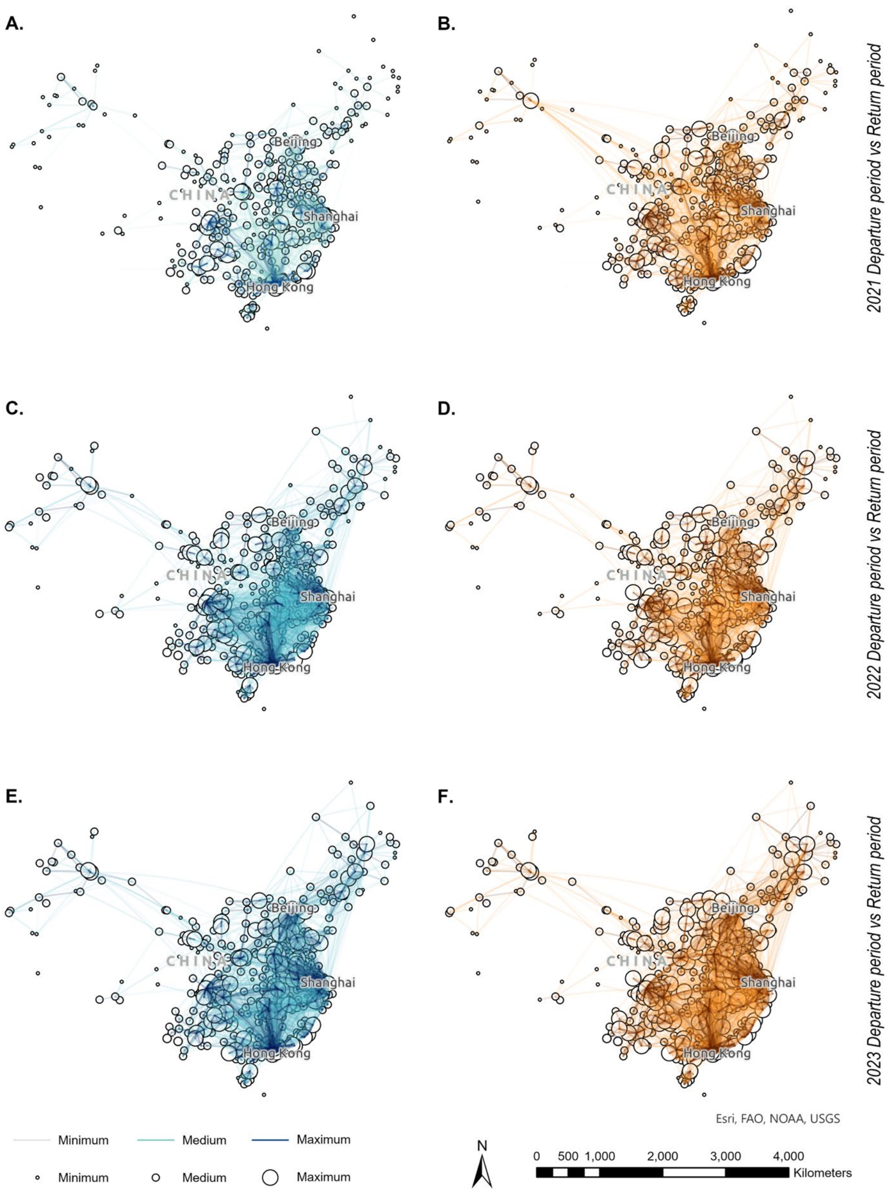

Fig. 3 Mobility networks in China for 2021–2023 Chinese Lunar New Year

all the important cities in their corresponding province or megaregions. Subsequently, labor mobility is analyzed by distance decay to observe whether it complies with the first law of geography (Tobler 1970). This backflow follows the distance decay effect in both departure (Fig. 4B) and return periods (Fig. 4C). This

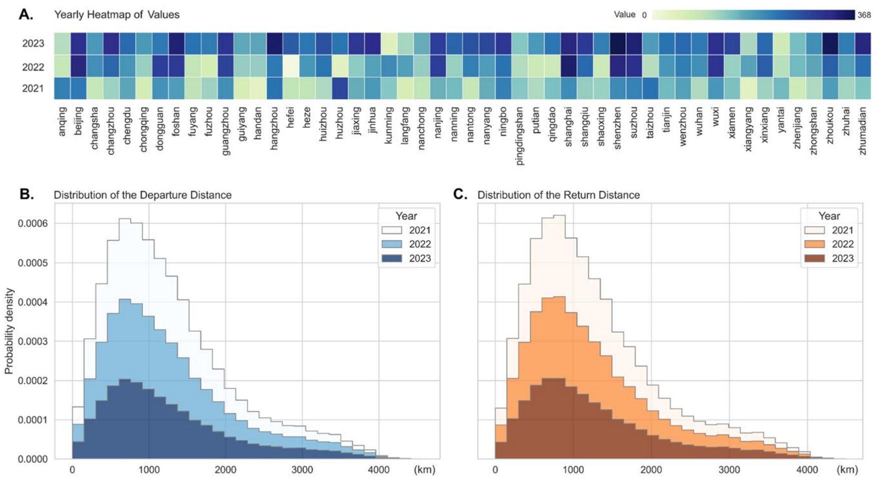

Fig. 4 Intercity labor mobility patterns in China for 2021–2023 Lunar New Year

means that labor mobility across cities is driven by several factors, such as urban development and distance from home (Zhang and Song 2003).

4.3 Impact of socioeconomic disparities on labor mobility

4.3.1 Results of statistical analysis

By segmenting the L value into five levels using the natural break method, Fig. 5 shows the boxplots to elucidate the relationship between these levels and related socioeconomic data.

As for the economic chances in the working cities, it can be seen that the GDP of Level 5 is much higher than other levels. With the exception of the primary sector, the larger the L-value, the relatively greater the variety of economic opportunities, especially working opportunities in the industrial enterprises and the public sectors. However, what can be found is that the average wage seems to not that dominant in the Level 5, around 9500. Instead, its salary is only slightly higher than the other four levels, which are all pretty even. This means that the cities where laborers come to work may have more job opportunities and more decent jobs, but wealth may not be accrued as well.

In the social dimension, what can be seen is that apart from the dependency ratio, the distribution of other social groups is similarly greater in large cities, probably because cities with a high L value are themselves hosting a larger urban population. However, the dependency ratio shows that cities with high L value are relatively younger, as they house a larger number of workers of working age.

Similarly, cities with higher L-values also tend to have better urban development, especially in terms of built-up area and road coverage, which means that these cities have higher building densities and host larger numbers of people and jobs.

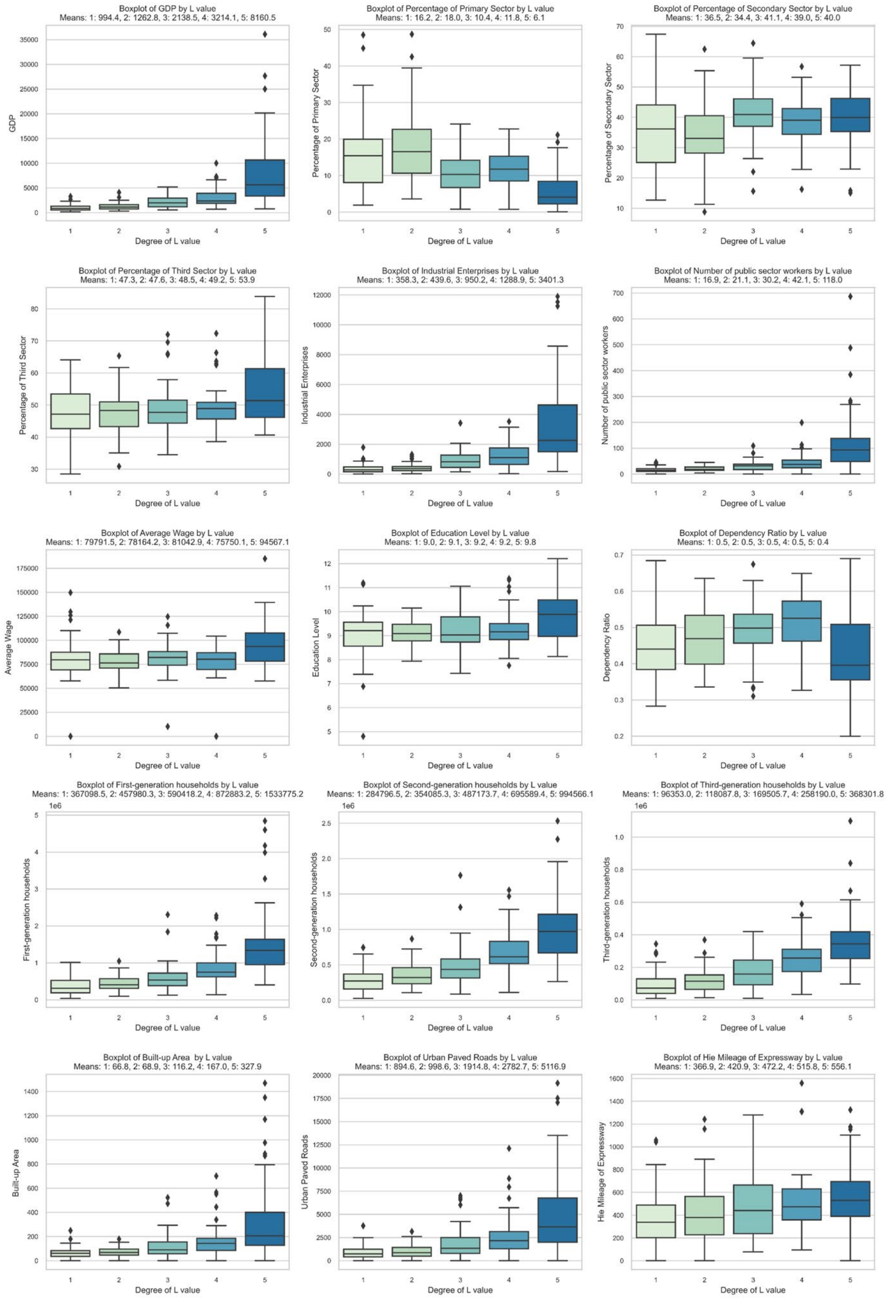

Fig. 5 Statistic distribution of different socioeconomic characteristics in L value

4.3.2 Results of regression analysis

Based on the L value of each city in three years, the mean value of L is calculated to represent the average attraction to extra-city labor, acting as the dependent variable in the regression model. The study first carried out the ordinary least squares (OLS) model to assess the significance of each variable. The overall regression is acceptable, having Adj. R2 of 0.630. The F-statistics are 33.74 with a p-value (Prob (F-statistic): 1.70e-53), indicating that the overall model is significant. Table 4 shows the coefficient and significance of each variable based on the OLS model, the most significant influencing factors are industrial enterprises, education level, dependency ratio, and third-generation households. The OLS confirmed that we can further construct the machine learning regression model.

Based on the covariance test and the hyperparameter tuning, the study employs the optimal parameters learning rate = 0.01, max depth = 4 and estimators = 500 to construct the LightGBM model. The R2 of the training set is 0.85, the RMSE is 21.85, the R2 of the test set is 0.65, and the RMSE is 24.48. The machine learning model is balanced and has a certain degree of interpretability. Then, the LightGBM model is interpreted by SHAP. The regression results are shown in Fig. 6.

From the importance ranking of the 15 variables, it can be witnessed that the economic driving forces show more significant impacts on intercity labor than the other two factors. Specifically, the percentage of the primary sector shows the highest impact on intercity labor mobility. However, Fig. 6B shows that the larger the number of portions of primary industry, the less favorable the promotion of

Table 4 Summary results of the ordinary least squares (OLS) model

	Coef	std err	t	P>|t|*	VIF
GDP	−0.0016	0.002	−0.767	0.444	11.887
Percentage of Primary Sector	−0.0261	0.275	−0.095	0.924	1.588
Percentage of Third Sector	0.3150	0.299	1.053	0.293	1.645
Industrial Enterprises	0.0161	0.002	7.465	0.000	4.087
Number of public sector workers	0.0119	0.086	0.139	0.890	9.646
Average Wage	−0.0002	0.000	−1.271	0.205	1.709
Built-up Area	0.0121	0.024	0.499	0.618	6.508
Urban Paved Roads	−0.0005	0.001	−0.352	0.725	5.146
Hie Mileage of Expressway	−0.0059	0.009	−0.680	0.497	1.581
Highway Passenger Traffic	0.0004	0.000	1.055	0.293	1.245
Education Level	23.4330	3.654	6.413	0.000	2.842
Dependency Ratio	115.7853	34.297	3.376	0.001	3.128
Extra-city Population	−3.542e−06	3.66e−06	−0.967	0.334	10.333
Second-generation households	1.464e−05	1.48e−05	0.991	0.323	9.880
Third-generation households	0.0001	3.25e−05	3.113	0.002	7.037

The variables such as percentage of secondary sectors, number of patents, and first-generation households are excluded in the regression analysis because of their strong multicollinearity

*A *p*-value of less than 0.05 means that the variable has a significant effect on the dependent variable

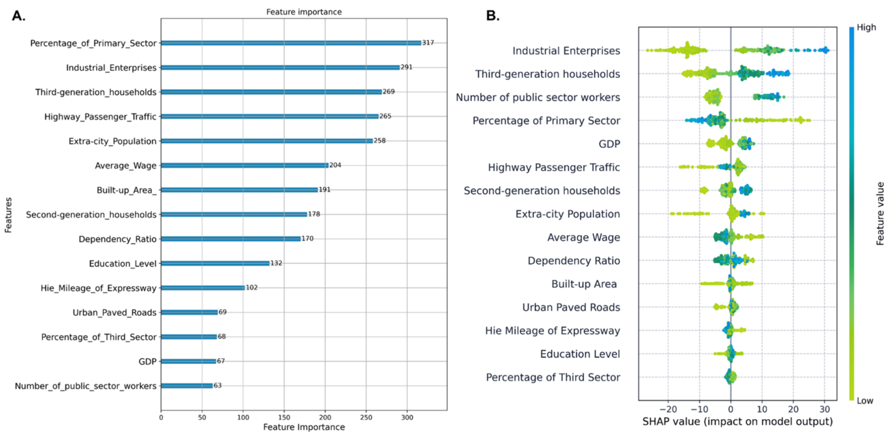

Fig. 6 Importance ranking results of the various forces driving laborers to work in other cities. **A**. The ranking result of the LightGBM model is based on the feature's importance. **B**. The ranking result of the explanatory model is based on the feature SHAP value

mobility (Seeborg et al. 2000). The number of industrial enterprises and highway passenger traffic took second and fourth place, respectively, effectively attracting labor mobility. The third important variables are third-generation households and extra-city population, showing that the impacts of population are also very high. The extra-city population takes fifth place, demonstrating that many laborers choose to work here without transferring their household registration to another city. This implies that most migrant workers do not have a strong sense of identity and integration with the city where they work (Li 2006; Tang and Hao 2018). Close behind is the average wage in the city. While it is interesting that higher salaries do not contribute to larger labor mobility, this is consistent with the results in Fig. 5.

Next, the eighth and ninth important variables are the second-generation households and dependency ratio, ranking medium in Fig. 6B, representing the city's family labor pressure. Together with the third-generation households, this demonstrates that a certain family pressure drives people to big cities to search for job opportunities. Education level, calculated on the city's educated population, takes fourteenth place in rank. As an important representative variable of the urban environment, the city's hie mileage of expressways and urban paved roads rank eleventh and twelfth. And the mileage of expressways negatively impacts increasing labor mobilities (Wang et al. 2019). Then comes the percentage of the third sector and GDP, as one of the most representative features of the city economy, which only ranks thirteenth and fourteenth and shows a certain positive effect on laborers. The final one in the position of Fig. 6A is the number of public sector workers. Notedly, even though it placed the least, its SHAP value is the third highest, meaning that improving the job opportunities of public sector workers may significantly enhance the number of labor mobilities (Seeborg et al. 2000). Combined with the first highest one of SHAP value, the industrial enterprises, most extra-city laborers come to seek jobs mainly in industries and the public sector. Besides, few can obtain the jobs the secondary and third sectors provide, which show little importance and SHAP value in the model.

5 Discussion

This study examines the patterns of intercity mobility, particularly labor migration, during the Chinese New Year period from 2021 to 2023. The findings offer valuable insights into the dynamics of large-scale population movements and the socioeconomic factors influencing these trends. By comparing our results with previous studies and situating them within broader academic contexts, we aim to strengthen our arguments and highlight potential policy implications.

Our findings largely align with those of McCarthy (2018) and Tan et al. (2021), who emphasized the significant role of labor mobility in shaping intercity migration patterns. Specifically, the migration ratios between megacities are notably higher than those involving smaller cities, underscoring the economic centrality of large urban centers (Gu et al. 2024a, b). Additionally, our study reveals a marked recovery in migration volumes post-pandemic, especially from 2021 to 2023, which contrasts with the observations by Jia et al. (2020) and Zhu et al. (2022). While these earlier studies focused on long-term migration impacts due to the pandemic, our data highlights the short-term fluctuations and subsequent stabilization.

The analysis of labor backflow effects (L values) is supported by Tobler (1970)'s distance decay law, but it also shows that despite geographic distances, economic opportunities remain a strong pull factor for returning migrants. Cities such as Beijing, Foshan, Hangzhou, Shanghai, and Shenzhen exhibit high L values, indicating their importance as both employment hubs and return destinations. This finding not only validates existing theories but also extends them by demonstrating the resilience of these cities in attracting laborers even during challenging times (Gu et al. 2024a, b).

From a policy perspective, our findings suggest several avenues for enhancing urban attractiveness through targeted investments in infrastructure and industry. For instance, regression analysis indicates that industrial enterprises and education levels are critical determinants of labor inflows. Local governments could leverage this information by prioritizing investments in manufacturing and educational sectors to attract more workers. Additionally, the relatively younger demographic profile of cities with high L values suggests the need for youth-oriented employment policies.

Drawing on theoretical frameworks proposed by Seeborg et al. (2000) and Li (2006), our study underscores that while wage levels do not significantly drive labor migration, the availability of job opportunities—particularly in industries and the public sector—is crucial. The SHAP analysis further corroborates the importance of industrial enterprises and third-generation households. These findings imply that family pressures, alongside economic incentives, play a pivotal role in motivating individuals to migrate to larger cities in search of better employment prospects.

Moreover, the observation that many migrant workers choose to work in cities without transferring their household registration (hukou) reflects a lack of integration and identity with their new environments (Li 2006; Tang and Hao 2018).

Addressing this issue requires comprehensive social policies aimed at fostering a sense of belonging among migrant populations.

This study also has some limitations in the following aspects: Firstly, the backflow model may mistakenly consider individuals traveling for tourism or other reasons as migrant workers. However, due to the lack of individual information in the dataset, it is difficult to identify the accurate purpose from the complex urban migration data that includes intercity work, business trips, tourism, etc. This study made an attempt based on the unique activity patterns of the labor force during the Chinese Lunar New Year, but how to obtain specific migration numbers of the labor force still needs further exploration. If future studies could access the data with individual migration patterns, they could enhance their analysis by identifying consistent migration patterns across these years. Besides, the current study mainly focuses on the destination cities' factors rather than source cities as the socioeconomic characteristics of destination cities can better reflect the work environment of these migrant laborers. However, a more comprehensive research framework is necessary to capture the full dynamics of intercity labor mobility by considering the relationships between cities. In addition, the study does not specifically address the issue of endogeneity between dependent and independent variables in depth, as we aim to explore relationships rather than strict causation. More accurately causal impacts of socioeconomics on labor mobility can be conducted, which will provide more effective guidance for developing small- and medium-sized cities in the future.

6 Conclusions

Mobility embodies vitality and creates value. Labor mobility, often accompanied by the flow of intelligence, capital, information, services, and culture, has always been an important source of enhancing regional development vitality in our country. In the context of more apparent population mobility trends and further expansion of the mobile population scale, this study innovatively depicts the national landscape of intercity labor mobility during the massive return home and resumption of work activities during the Lunar New Year. It reveals the significant uneven socioeconomic disparities between laborers' native city and working city.

The results show that despite the impact of COVID-19, labor mobility had largely fully recovered by 2023, with short-term large-scale migration activities occurring near the festival and gradually small-scale backflows after the festival. Mega- and supercities are the main areas absorbing migrant labor, mainly from surrounding small- and medium-sized cities with a surrounding distance of about 500-1500. Driven by family and economic pressures, labor forces seek work in other cities, but most job opportunities come from low-end industries or public sectors with low incomes. This study is of great value for both individual workers and different types of urban development.

Author's contribution All authors wrote and reviewed the manuscript. XG prepared data and figures, and XL supervised the work.

Funding Open access funding provided by The Hong Kong Polytechnic University.

Data availability Data could be available on request from the authors.

Declarations

Conflict of interest The authors declare no competing interests.

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