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Does labor mobility follow the inter-regional transfer of labor-intensive manufacturing? The spatial choices of China's migrant workers

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ABSTRACT

There is a close interactive relationship between industrial transfer and labor mobility. Previous studies on China roughly determined whether industrial transfer and labor mobility are evolved in the same direction according to macro data, paying less attention to the analysis of mechanisms and heterogeneity. Based on the Chinese Industrial Enterprise Database and China Migrants Dynamic Survey, this study is the first to match data on the individual spatial selection of migrant workers with those on urban labor-intensive manufacturing transfer, use a logistic model to discuss the effects of industrial transfer on labor mobility, and reveal the heterogeneity of cities with different economic locations, as well as the heterogeneity of migrants with different educational backgrounds. The regression results show that overall, with the increase in industrial transfer-outs, the inflow probability of migrant workers increases, and decreases with the increase in industrial transfer-ins. Nevertheless, there is a significant difference in the impact of labor-intensive manufacturing transfer on the choice of labor inflows between the central and the peripheral cities of urban agglomerations, as well as other cities outside an urban agglomeration. Highly educated migrant workers are not significantly affected by labor-intensive manufacturing transfer-ins. These findings are helpful for the relevant decision making.

1. Introduction

Despite its continued contraction, labor-intensive manufacturing plays an important role in China's economic growth and job provision; in particular, it is of great significance for addressing the employment of the rural surplus labor force and supporting the internal economic cycle in China. In the early days of reform and opening-up of the country, driven by the transfer of overseas industries, the industries dominated by labor-intensive manufacturing rapidly gathered in the eastern coastal areas, attracting labor from all over the country. Later, due to industrial restructuring, the industries with low added value and low labor productivity were gradually transferred from the coast to other regions.

In 2010, the State Council of China promulgated the 'Guidance on undertaking industrial transfer in central and western regions', which aims accelerate the transfer of industry from the eastern to the central and western regions, thus speeding up the process of new industrialization and urbanization in inland areas, so that people can find jobs easier and have a better life in their hometowns (Zhu et al., 2021). Such a policy initiative is in sharp contrast to the dominant urbanization pattern in China since the late 1990s, marked by the rapid growth of large cities in the coastal areas due to rural-urban migration (Zhu, 2017). Generally, labor-intensive manufacturing is characterized by a small amount of capital per unit of labor and a large demand for labor; therefore, theoretically, there may be a decline in the demand for the quantity of the labor force in industrial transfer-out areas and an increase in the demand for the quantity of labor force in industrial transfer-in areas. Currently, encouraging return migration from the eastern to the central and western regions, or the *in situ* transfer of the surplus labor force from agriculture to non-agricultural industries in central and western China, are in line with the change in labor demand due to the transfer of labor-intensive manufacturing. However, over the past few decades, the population has continued to move from developing to developed regions and, in this process, the question is whether the labor-intensive manufacturing industry can attract the labor force to follow.

As one of the industries with a significant inter-regional transfer trend that is also closely related to the labor supply, whether the transfer of labor-intensive manufacturing drives the corresponding spatial flow of the labor force has an important impact on industrial development, regional economic growth, and employment. Such an analysis can also

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serve as reference for other developing countries. There are some studies on industrial transfer and labor mobility in China, but most of them use qualitative methods (Fan & Jiang, 2014). More importantly, many studies analyse the spatial relationship between industrial transfer and labor mobility according to the distribution and change of industry and population over large ranges (Li & Zhu, 2014; Cai, 2009; Fan, 2015; Wang & Li, 2019). The differences in the data and spatial scales used in these studies lead to inconsistent conclusions (Fan & Jiang, 2014). Meanwhile, very few studies have carried out a comprehensive analysis of the current driving mechanism and the relationship between industrial transfer and labor mobility, and heterogeneity has also been ignored.

This study contributes to the literature on the impact of the regional transfer of labor-intensive manufacturing on the mobility of manufacturing workers from the perspective of individual choice by matching labor-intensive manufacturing transfer data on 275 cities nationwide with individual spatial selection data on manufacturing migrant workers. This approach provides a relatively clear and accurate answer. Another contribution of this paper is to putting forward the hypotheses of urban heterogeneity and individual heterogeneity based on theoretical and factual analyses and testing them using the empirical results.

The remainder of this paper is organized as follows. To provide the foundation for the analysis, in section 2, we review the relevant theories and studies on industrial transfer and labor mobility and describe the evolution and characteristics of labor-intensive manufacturing and labor mobility in China. This is followed by the research hypotheses in Section 3. Then Sections 4 and 5 describe the model, variables, and empirical analysis. Finally, the conclusions and a discussion of the policy implications of the study are provided in Section 6.

2. Labor-intensive manufacturing transfer and labor mobility in China

Industrial transfer is an important method for industrial restructuring and the rational allocation of regional resources. Some classical theories have been proposed around this concept, for example, Akamatsu (1930s) proposes the 'flying geese' model, which explains the rapid economic growth in East Asia. Economies at different stages form an industrial chain, which leads to an industrial upgrading echelon, similar to the flying geese paradigm (Akamatsu, 1962). Lewis (1978) analyses the transfer mechanism of labor-intensive industries between developed and developing countries, considering that the insufficient supply of unskilled labor and rising costs makes developed countries lose their comparative advantages, and then transfer some labor-intensive industries to developing countries. Labor-intensive industries transfer more easily or earlier than other industries (Pennings & Sleuwaegen, 2000). The new economic geography theory also discusses the relationship between industrial agglomeration and labor mobility, pointing out that, due to the increasing returns to scale within enterprises, transportation costs, and knowledge spillover and externalities, the manufacturing industry continues to gather to the 'centre', resulting in the labor force migrating from the 'periphery' to the 'centre'. When the industry is concentrated in developed areas to a certain extent, it will be transferred to other areas in time, while the technology and capital brought about by industrial restructuring repel the labor force (Audretsch & Feldman, 1996; Krugman, 1998, 2009; Overman et al., 2010). Many theories and studies imply that labor mobility is synchronized with industrial agglomeration and transfer and there must be a co-directional relationship between them (Fan et al., 2004).

Since the late 1970s, by turning its latent comparative advantage into a competitive advantage in the global market, China has created a miracle of economic growth (Lin, 2012). Beginning in the 2000s, labor-intensive manufacturing enterprises in eastern China have been facing issues, and most of them chose to transfer rather than upgrade (Wang et al., 2020). Compared to the original flying geese model of tiered production in Asia, China's industrial transfer mainly occurred domestically (Ang, 2018), causing labor-intensive industries to move from eastern coastal areas to low-cost inland areas (Bobek, 2020; Qu et al., 2013; Wang et al., 2020). Both the central and local governments support inter-regional industrial transfer. Following the State Council's 2010 Circular, a host of concrete ministerial level policies promoted industrial transfer, and the central government established several 'recipient of industrial transfer model zones'. Many developed regions implement forceful policies to expel low-end, polluting industries from their jurisdictions, meanwhile the new opportunities brought about by industrial transfer caused local governments in developing regions to be interested to attract domestic investment (Ang, 2018).

When the dual structure theory discussed labor mobility, it did not consider migration cost, which also holds that the restructuring of industry and employment are synchronized (Chen & Chen, 2007). Ravenstein (1885, 1889) proposes the law of migration in the 1880s and considered that improving the economic situation was the main incentive for population mobility. In the initial development stage, the labor-intensive manufacturing industry in an advantaged nation (or region) makes it easier to attract low-cost labor inflows, the two maintaining the same direction, which has been confirmed by the development process including the eastern coastal areas of China. In the decades after the reform and opening-up, the agglomeration and development of industries in coastal areas attracted large-scale migration from the underdeveloped central and western regions. With the economic and societal development, the determinants of migration are becoming diversified, from wages and job opportunities to risk aversion, personal preference, agglomeration effect, family factors, and so on (Chan, 2001; Chen et al., 2017; Crozet, 2004; Poncet, 2006; Qin & Zhu, 2018; Rabe & Taylor, 2012). Some studies consider that, at present, migration can be analysed as a process rather than a single event (Kou & Bailey, 2014) and the factors affecting it are dynamic and can vary (Bobek, 2020). In the study of international mobility, migration can be understood as a cultural event involving individuals, families, communities, and nations (Fielding, 1992; McHugh, 2000), and the complexity of motivations not only includes employment and career, but also factors such as the quality of life and lifestyle (Bobek, 2020). The pursuit of a better quality of life has also been confirmed for China's inter-regional migrants. Migrants are prone to move to larger cities with more job opportunities, higher wages, and better public services (Zhu & Chen & Chen, 2007).

In this context, when labor-intensive manufacturing transfers from developed regions to developing regions in China, does labor mobility follow? Based on the analysis of China's national and regional data, some studies conclude that the manufacturing industrial transfer can be matched with labor mobility, because the manufacturing industry transfers from the eastern region to the central and western regions, and some individuals are also returning to the central and western regions (Li & Zhu, 2014). Some studies consider that there may be a mismatch between industrial transfer and labor mobility, because the industry has a significant tendency to transfer from the eastern to the central and western regions, while there is still a population flow to the eastern regions (Cai et al., 2009; Fan, 2015). Moreover, some studies point out that two are becoming increasingly coordinated (Wang & Li, 2019). These studies judge the spatial relationship between industrial transfer and labor mobility according to their direction. A recent study points out that industrial transfer is driven by local governments attracting investment, while labor returns have a spatial selection effect; therefore, there is a mismatch between the two (Wang, 2021), however there is a lack of rigorous empirical analysis and in-depth discussion.

3. Follow or not when labor-intensive manufacturing transfers

With the change in the spatial direction of industrial transfer and the diversification of labor mobility determinants, labor-intensive manufacturing transfer affect labor mobility; however, in addition to employment, they may also lead to changes in other regional characteristics through the adjustment of the industrial structure, which will affect the spatial choices of the labor force.

Transfer-outs leads to the reduction of related jobs, and the resulting industrial restructuring may strengthen the substitution of technological capital for labor; as a result, some less competitive workers will be eliminated. However, more competitive migrants can move to other manufacturing industries, while industrial restructuring has increased the attractiveness of the region for those who pursue a higher quality of life, which may be conducive to the labor inflow. Moreover, extant studies have revealed that, at present, China's migrant workers are more likely to supplement the employment of the local labor force than replace it (Combes et al., 2015; Wu et al., 2019), and the local labor force benefits more from industrial restructuring. This means that, in transfer-out areas, many local workers employed in labor-intensive manufacturing move to other sectors, while migrants can cope with the employment shock caused by the contraction of labor-intensive industries by filling the positions vacated by the locals. As a result, labor mobility may not be accompanied by industrial transfer to backward areas. Moreover, the transfer-in of labor-intensive manufacturing in a region can create job opportunities, which may promote the labor inflow. Nevertheless, if the development of the region lags behind, it is difficult to attract the labor force. In short, labor-intensive manufacturing transfer pursues lower cost while labor strives for a better quality of life, which may lead to a spatial mismatch between the two.

In reality, it can be observed that the labor-intensive manufacturing mainly moves from coastal areas to inland areas in China. For example, at and above the prefectural level, nearly 80% of transfer-in cities are in the central, western, and northeast areas. Meanwhile, although the return of the labor force has been observed in recent years, more than 70% of migrants still flow to the eastern areas. Accordingly, we posit:

Hypothesis 1. Currently, the labor mobility in China may not follow the inter-regional transfer of labor-intensive manufacturing. That is, the transfer-out of labor-intensive manufacturing does not necessarily lead to a decrease in labor inflow, and the transfer-in of labor-intensive manufacturing does not necessarily lead to an increase in labor inflow.

Global population migration is characterized by populations moving to metropolitan areas in the middle and later stages of urbanization, which is also true in China. City clusters with highly integrated characteristics have become an important form of the evolution of regional spatial patterns (Hall & Pain, 2006). However, the distribution patterns of the elements in urban agglomerations at different stages is not the same. On the one hand, urban agglomeration in developed regions is in the stage of diffusion. The crowding-out effects caused by the population policy, industrial upgrading, and the rise of living cost are obvious, promoting economic activities and the population constantly moving from central cities to periphery. As a result, for central cities, the transfer-out of labor-intensive manufacturing may lead to a reduction in the probability of labor inflows. However, the peripheral cities in developed agglomerations have more opportunities and integrate more rapidly, which makes them more attractive to the labor force. To some extent, the transfer-out of labor-intensive manufacturing represents a more optimised industrial structure, which further enhances attractiveness to the labor force, and industrial relocation may be conducive to promoting further labor force inflows.

On the other hand, urban agglomeration in developing areas is still clustered. The central city has outstanding advantages and obvious polarisation in regional development, resulting in a strong attraction for the labor force. Once the attraction is further reinforced by the employment growth brought about by the transfer-in of labor-intensive manufacturing, an increasing amount of labor would inflow. However, peripheral and other cities outside urban agglomerations have no advantage in wage and living conditions, which is not conducive to labor inflows, especially when migrant workers consider the quality of life. Therefore, the employment growth brought about by the transfer-in of labor-intensive manufacturing may not be able to drive the influx of labor.

Data show that, in recent years, the overall trend of labor mobility in eastern China has not changed, but the distribution among main inflow areas has become increasingly balanced (Duan et al., 2019), with many people in the eastern provinces moving from large cities to the surrounding areas. Meanwhile, backflow to the central and western areas began to appear. Since 2009, the growth rate in the number of migrant workers working in the central and western provinces has been significantly higher than that in the overall number of migrant workers (Sun & Wang, 2016). However, the returning labor force is mainly concentrated in central cities (National Health Commission of the People's Republic of China, 2018; Wang, 2021). According to a survey on the dynamic monitoring of migrant-sending areas in 2015, 41.2% return migrant workers who are willing to go out to work again would choose the provincial capital cities as their destinations (Wang, 2021). According to census data, Chengdu, Zhengzhou, and Xi'an ranked third to fifth in China's average annual growth in China from to 2010–2020, all being central cities in the central and western regions. The labor shortage in small- and medium-sized cities in the western region is more serious (Fang & Han, 2013). Based on this, we propose:

Hypothesis 2. Affected by the spatial agglomeration and diffusion of regional economic and social activities and the level of urban development, the impact of labor-intensive manufacturing transfer on labor mobility among cities may differ.

It is an obvious trend that migrants prefer to pursue a better quality of life; however, some migrant workers are unable to choose where to go freely because of their limited employment competitiveness. The education level is one of the most important factors affecting the spatial and industrial choices of migrant workers (Liu et al., 2021). Generally, labor-intensive manufacturing enterprises do not have high requirements for workers' skills, meaning migrants with low education levels tend to follow the spatial choice of these enterprises, while high-educated migrants are likely to choose regions where the level of public service, ecological quality, and liveability is higher (Sun et al., 2019; Xia & Lu, 2015). In modern China, the main reason for the transfer-out of labor-intensive manufacturing is industrial restructuring, which may have a more significant crowding-out effect on migrant workers with low education and be more conducive to attracting highly educated migrant workers. Therefore, we posit:

Hypothesis 3. Migrant workers with different education levels may be affected differently by the transfer of labor-intensive manufacturing. Relatively highly educated migrant workers should be less affected by industrial moving-in, while the industrial moving out from areas with better prospects may help improve their entry probability.

Based on the above analysis, the logical framework of this study is shown in Fig. 1.

4. Methodology

4.1. Data source and sample

Based on the two digital industrial data of the Chinese Industrial Enterprise Database, this study calculates the transfer of labor-intensive manufacturing in 275 cities at prefecture-level and above, further divides them into transfer-out areas and transfer-in areas. The data on labor mobility are derived from the Migrant Population Service Centre, National Health Commission, P. R. China. The data include migrant workers who have lived in the place of entry for more than 1 month and are not registered in the district (county or city) as survey subjects. The survey adopted PPS sampling using stratification, multistage, and proportional to the scale. As there is a lag in the effect of industrial transfer on labor mobility, this study considers the migrant workers employed in manufacturing in 2014 and uses the processed data from 2015 to test the

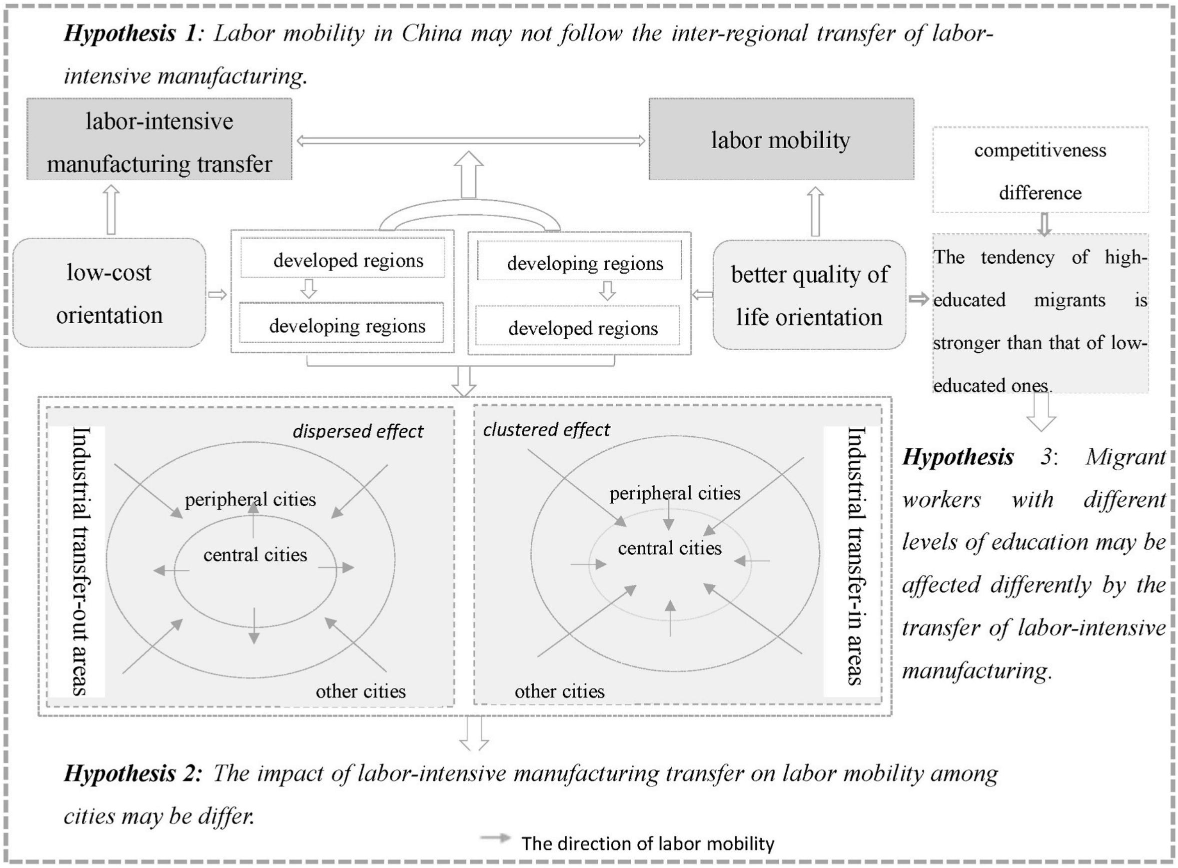

Fig. 1. Analysis framework.

relationships. The sample number of migrant workers studied in this paper is 31790, of which 60% are male and 40% are female. Other data on cities are derived from the 2014 China City Statistical Yearbook and provincial and municipal statistical yearbooks.

Additionally, to study urban heterogeneity, 275 cities in China are divided into the central cities of urban agglomerations (referred to as central cities), peripheral cities of urban agglomerations (referred to as peripheral cities), and other cities. Among them, the central cities are municipalities directly under the Central Government, provincial capitals, and sub-provincial cities; the peripheral cities are outsides the central cities within the spatial scope of each urban agglomeration according to the 'National New Urbanization Planning'; other cities are cities other than the above two types. To study individual heterogeneity, manufacturing migrant workers are divided into two groups: a high-educated group, with undergraduate education or above, and a low-educated group.

The specific sample distributions are shown in Table 1.

Table 1
Statistical information of cities and migrant workers.

	Migrant workers (%)				
	Central cities	Peripheral cities	Other cities	Low-educated	High-educated
Transfer-out areas	36.1	52.4	11.5	96.8	3.2
Transfer-in areas	49.1	38.1	12.8	96.3	3.7
	Cities (%)				
	Central cities	Peripheral cities	Other cities	Eastern coastal cities	Inland cities
Transfer-out areas	15.4	70.8	13.8	40.8	59.2
Transfer-in areas	10.4	65.5	24.1	21.4	78.6

Data source: National New urbanization Planning; http://www.chinaldrk.org.cn; Chinese Industrial Enterprise Database.

4.2. Variables

The core explanatory variable of the model is the transfer of labor-intensive manufacturing. The location quotient is typically used to judge whether an industry constitutes a regional specialized sector, and also reflects the relative concentration of the industry in a particular region, so the change index of the location quotient (ΔLQ) is often used to measure relative industrial transfer (Fan, 2004; Li et al., 2018). This study calculates the labor productivity of all two digital manufacturing industries and identifies the labor-intensive manufacturing industries whose labor productivity is below average (Table 2). Considering the starting time of large-scale regional transfer of labor-intensive manufacturing in China and data availability, the ΔLQ of the labor-intensive manufacturing industry from 2007 to 2013 is calculated to reflect industrial transfer.

$$LQ_{kj} = \frac{q_{kj}/q_j}{q_k/q}, \tag{1}$$

Where LQ_{kj} is the location quotient of labor-intensive manufacturing k in city j, q_{kj} is the total value of industry k in city j, q_j is the total value of all industries in the city, q_k is the total value of industry k in the country, and q is the total value of all industries in the country.

According to the results, the cities with positive ΔLQ values are the transfer-in areas of labor-intensive manufacturing, and transfer-out

Table 2
The identification of labor-intensive manufacturing.

Sectors	Labor productivity	Logarithm of labor productivity	Average of labor productivity
Manufacture of Textile, Wearing Apparel, and Accessories	1113.246	7.015	−1.606
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	1209.412	7.098	−1.524
Printing and Reproduction of Recording Media	1307.053	7.176	−1.446
Other Manufacture	1695.178	7.436	−1.186
Manufacture of Leather, Fur, Feather and Related Products, and Footwear	1877.396	7.538	−1.084
Manufacture of Textile	2481.807	7.817	−0.805
Manufacture of General-Purpose Machinery	2630.860	7.875	−0.746
Manufacture of Metal Products	2784.750	7.932	−0.689
Manufacture of Special Purpose Machinery	2981.061	8.000	−0.621
Manufacture of Rubber and Plastics Products	3023.501	8.014	−0.607
Manufacture of Measuring Instruments and Machinery	3075.725	8.031	−0.590
Repair Service of Metal Products, Machinery, and Equipment	3636.667	8.199	−0.423
Manufacture of Furniture	3639.451	8.200	−0.422
Manufacture of Railway, Ship, Aerospace, and Other Transport Equipment	3884.350	8.265	−0.357
Manufacture of Medicines	3937.422	8.278	−0.343
Utilization of Waste Resources	4018.718	8.299	−0.323
Processing of Food form Agricultural Products	4134.741	8.327	−0.294
Manufacture of Foods	4734.881	8.463	−0.19
Manufacture of Articles for Culture, Education, Arts and Crafts, Sport, and Entertainment Activities	5015.598	8.520	−0.101

Data source: The database of Chinese Industrial Enterprises, 2013.

areas otherwise.

Based on the results in the literature, we add wage (*wage*), population size (*pop*), per capita GDP (*pgdp*), medical service (*heal*), basic education (*edu*), and house price (*hp*) as control variables in the regression to control for other influencing factors. The calculation methods and descriptive statistics of the variables are presented in Table 3.

4.3. Model

Since the late 19th century, scholars have presented many theories on population mobility, considering that the basis of individual mobility decision-making is the judgement of expected utility (Harris & Todaro, 1970). Therefore, this study assumes that the labor force decides where to go according to utility maximisation and the utility function depends on industrial transfer, as well as other urban and individual characteristics. The utility function is given by Equation (2):

$$U_{ij} = \alpha \Delta LQ_j + \beta Z_j + \varepsilon_{ij} \quad (i = 1, 2, \ldots, N)(j = 1, 2, \ldots, J) \tag{2}$$

In Equation (2), i represents the individual migrant worker and j indicates the city that migrant workers can choose. ΔLQ_j is the transfer of labor-intensive manufacturing in city j, indicating a change in job opportunities. Z_j represents the other feature vectors of industry j; α, β are coefficients; ε_{ij} indicates unobserved factors. If migrant worker i chooses city j, the following conditions should be met:

$$choice_{ij} = \begin{cases} 1, \ \forall j \neq k \ U_{ij} > U_{ik} \\ 0, \exists j \neq k \ U_{ij} \leq U_{ik} \end{cases}, \tag{3}$$

where, only when $U_{ij} > U_{ik}$, migrant worker i chooses to flow into city j, with a value of 1; otherwise, the value is 0. Therefore, the occurrence probability of migrant worker i choosing to flow into city j is:

$$probit(choice = 1) = \frac{exp(\alpha \Delta LQ_j + \beta Z_j)}{\sum_{j=1}^{J} exp(\alpha \Delta LQ_j + \beta Z_j)}. \tag{4}$$

The conditional logistic model (McFadden, 1974, pp. 105–142) was used to estimate Equation (4), where α indicates the effect of the transfer of labor-intensive manufacturing on labor mobility; that is, the larger the parameter value is, the greater is the probability of the city being selected, and vice versa.

As the transfer-out and transfer-in of labor-intensive manufacturing have different directions and effects on labor mobility, we study transfer-in and transfer-out areas respectively. In the regression, variable Δ *LQ* is taken at the absolute value.

5. Results

5.1. Basic regression analysis

In Table 4, Models 1 and 3 show the results of the effect of industrial transfer on labor entry probability in transfer-out and transfer-in areas, respectively, and Models 2 and 4 are standardized results. The results show that, in the transfer-out areas of labor-intensive manufacturing, there is a significant positive correlation between the probability of labor inflows and industrial transfer-outs at the 1% level. In other words, in such areas, the greater is the amount of labor-intensive manufacturing transfer-outs, the higher is the probability of labor choice to enter. Specifically, for every 1% increase in industrial transfer-out, the probability of labor inflows increases by approximately 0.703%. In the

Table 3
Descriptive statistical information of urban variables.

Variables	Measuring method	Observed quantity	Mean value	Standard deviation	Minimum value	Maximum value
Δ *LQ*	The change of location quotient	275	0.029	0.244	−1.200	0.788
Wage	Average wage of staff and workers in manufacturing (10,000 yuan)	275	4.152	0.922	1.980	7.651
Pop	Total population (million persons)	275	4.496	3.387	0.236	29.700
Heal	Number of tertiary A-level hospital/total population (million persons)	275	0.515	0.567	0.000	3.527
Edu	Number of experimental and leading model school/total population (million persons)	275	2.600	1.461	0.000	8.475
Hp	Total scale of commercial buildings (thousand yuan)/floor space of commercial buildings sold (square meters)	275	5.013	2.732	2.436	24.402
Pgdp	GDP (100 million yuan)/total population (million persons)	275	4.693	2.826	0.910	19.603

Data source: Chinese Industrial Enterprise Database; 2014 China City Statistical Yearbook; provincial Statistical Yearbooks.

Table 4
Basic regression results.

Variabilities	Transfer-out areas		Transfer-in areas	
	Model 1	Model 2 (standardized)	Model 3	Model 4 (standardized)
Δ LQ	0.703***	0.105***	−1.506***	−0.262***
	(0.047)	(0.007)	(0.108)	(0.019)
Wage	0.0336***	0.0314***	−0.167***	−0.151***
	(0.009)	(0.009)	(0.020)	(0.018)
Pop	0.104***	0.406***	0.248***	0.678***
	(0.001)	(0.004)	(0.005)	(0.013)
Heal	−0.604***	−0.340***	0.528***	0.300***
	(0.016)	(0.009)	(0.023)	(0.013)
Edu	0.229***	0.320***	0.006	0.00854
	(0.005)	(0.006)	(0.011)	(0.017)
Hp	0.0790***	0.261***	−0.131***	−0.251***
	(0.001)	(0.005)	(0.007)	(0.013)
Pgdp	0.139***	0.423***	0.245***	0.629***
	(0.002)	(0.008)	(0.004)	(0.011)
Chi^2	31516.23	31516.23	14392.94	14392.94
Pseudo R^2	0.138	0.138	0.188	0.188
Observations	3045510	3045510	1118095	1118095
City samples	130	130	145	145
Labor samples	23427	23427	7711	7711

Notes: Standard errors are between parentheses; ***p < 0.01, **p < 0.05, and * p < 0.1.

transfer-in area of labor-intensive manufacturing, the overall probability of labor inflow is significantly negatively correlated with industrial transfer-in at the 1% level. That is, in such areas, the probability of labor inflow decreases with an increase in the scale of labor-intensive manufacturing transfer-ins. Specifically, for every 1% increase in industrial transfer-in, the choice probability of labor inflow decreases by 1.506%. This result is consistent with Hypothesis 1.

5.2. Robustness tests

The basic regression examines the relationship between the transfer intensity of urban labor-intensive manufacturing and the entry possibility of migrant workers. Whether the sample is representative needs to be further tested.

First, the robustness of the model is tested by replacing the sample of migrant workers in manufacturing with survey data in 2015. The data from the China Migrants Dynamic Survey are resampled every year; therefore, the change in the sample data can be used to test result robustness. This study examines the impact of the corresponding industrial transfer cycle on labor spatial choice in 2014, while the 2015 database contains spatial selection information on migrant workers in 2014; therefore, 5687 observation which inflowed in 2015 were deleted and 27,138 individuals were observed. The results of Models 5 and 6 in Table 5 are consistent with the results of the basic regression. For the different samples, the industrial transfer of labor-intensive manufacturing still has a significant impact on labor mobility and the symbolic direction of regression coefficients does not change; therefore, the results are robust and credible.

Second, the robustness is tested by screening individual samples of migrant workers. Some manufacturing workers move among different regions for marriage, relocation, and other reasons, but most move for a job. That is, not all labor mobility is directly caused by industrial transfer. Therefore, only the manufacturing workers whose cause of mobility is working and doing business are retained in the sample and re-tested. The results of Models 7 and 8 in Table 5 are consistent with the ones of the basic regression, which shows that, after excluding the interference of other factors of labor mobility, the impact of industrial transfer on the spatial choice of migrant workers still exists.

Additionally, in the long run, there is an interaction between industrial transfer and labor mobility, that is, there is endogeneity between the two variables, and labor mobility also affects industrial transfer. However, because cross-sectional individual data are used in this study, they mainly reflect the changes in the spatial choice of individual labor after the transfer of labor-intensive manufacturing industries. In fact, whether industrial transfer affect labor spatial mobility or labor mobility affects industrial transfer, there is a certain lag. In this study, the impact of industrial transfer on labor mobility was considered when selecting the data. However, during the study period, labor mobility cannot affect previous industrial transfer; therefore, there is no reverse causality.

Table 5
Robustness test.

Variabilities	Transfer-out areas	Transfer-in areas	Transfer-out areas	Transfer-in areas
	Model 5	Model 6	Model 7	Model 8
Δ LQ	0.706***	−1.739***	0.714***	−1.485***
	(0.048)	(0.108)	(0.047)	(0.110)
Control variabilities	Yes	Yes	yes	yes
Chi^2	21567.85	13223.78	30406.43	13978.57
Pseudo R^2	0.114	0.171	0.137	0.189
Observations	2518750	1125635	2961010	1078800
Number of cities	130	145	130	145
Number of individuals	19375	7763	22777	7440

Notes: Standard errors are between parentheses; ***p < 0.01, **p < 0.05, and * p < 0.1.

5.3. Heterogeneity analysis

The basic regression is an overall analysis of the transfer-out and transfer-in areas of labor-intensive manufacturing, without considering the differences between cities and individuals. Next, we will further analyse urban and individual heterogeneity.

5.3.1. Heterogeneity in transfer-out areas

(1) Urban heterogeneity

There is a significant positive correlation between industrial transfer-outs and the labor inflow probability in peripheral cities (Table 6), which is consistent with the regression results for transfer-out areas. This indicates that, with the increase in the transfer-outs of urban-intensive manufacturing, the probability of labor inflow increases, which is also consistent with the previous hypothesis. It can be predicted that this trend will be further intensified by industrial restructuring and population dispersal in central cities.

However, in central and other cities, the impact of industrial transfer on labor mobility is significantly negative, which is consistent with Hypothesis 2. Although the regression coefficient symbol of the central city and other cities are the same, the influence mechanism is different. As analysed, the decline in the probability of labor inflow into central

Table 6
Urban heterogeneity in transfer-out areas.

Variabilities	Central cities	Peripheral cities	Other cities
Δ LQ	−0.516***	3.034***	−6.387***
	(0.147)	(0.106)	(0.208)
Control variabilities	yes	yes	yes
Chi^2	7423.88	18189.43	7346.18
Pseudo R^2	0.144	0.186	0.341
Observations	177576	663444	147675
Number of cities	21	54	55
Observed sample	8456	12286	2685

Note: Standard errors are in parentheses; ***p < 0.01, **p < 0.05, and * p < 0.1.

cities accompanied by labor-intensive manufacturing transfer-out is the result of the crowding outs caused by industrial restructuring, the rise in living costs, and the tightening of population policies, while in other cities, it is mainly caused by the reduction of job opportunities.

(2) Labor heterogeneity

Table 7 shows that, regardless of the education level, the probability of choosing to enter decreases with the increase in industrial transfer-outs in central cities and other cities, while in the peripheral cities, with the increase in industrial transfer-outs, the inflow probability of migrant workers is on the rise, which is consistent with Table 6. Generally, migrant workers with different education levels do not show significant differences in the three types of cities in transfer-out areas. The reason why the probability of labor mobility does not decline with industrial transfer in peripheral cities may be due to the opportunities caused by industrial restructuring for highly educated workers, while for low-educated workers, it may be to supplement the vacancy of local workers to some extent offset the crowding-out effect of industrial transfer on them. Moreover, the industrial decentralization policy and high cost of living in central cities, as well as the reduction of jobs in other cities both have significant impact on migrant workers with different academic qualifications.

5.3.2. Heterogeneity in transfer-in areas

(1) Urban heterogeneity

Similarly, in transfer-in areas, only the regression coefficient symbols of the peripheral cities are consistent with the overall regression. Specifically, the labor-intensive mobility transfer-in in peripheral cities leads to a decrease in the labor inflow probability, while in central cities, it promotes an increase in the labor inflow probability. In other cities, although industrial transfer-ins can cause an increase in the probability of labor inflows, it is not significant (see Table 8). Overall, the regression results are still in line with Hypothesis 2.

Table 9 shows significant differences in the impact of industrial inflows on the spatial choices of migrant workers with different education levels. Whether in central cities, peripheral cities or other cities, the relationship between the entry probability of high-educated migrant workers and industrial transfer-ins is not significant, that is, the spatial choice of this group is nearly not affected by transfer-ins in the labor-intensive manufacturing industry. However, the relationship between industrial transfer-ins and the entry probability of low-educated migrant workers is significantly positive in central cities, showing a significant negative correlation in peripheral cities, and being insignificant in other cities. The reason for these differences is that the high-educated labor force has a lower proportion of employment in labor-intensive manufacturing, they have more initiative in terms of spatial choice, and are more inclined to pursue better living conditions and have better prospects for personal development. Relatively, the transfer-ins in the labor-intensive manufacturing industry may have a significant effect on low-educated migrant workers. Hypothesis 3 is thus further confirmed.

Table 7
Heterogeneity of labor force in transfer-out areas.

	Variabilities	Central cities	Peripheral cities	Other cities
Low-educated	Δ *LQ*	−0.4442***	3.0331***	−6.3925***
		(0.1513)	(0.1070)	(0.2122)
	Control variabilities	yes	yes	yes
	Chi^2	6932.47	17784.50	7256.61
	Pseudo R^2	0.1417	0.1851	0.3454
	Observations	168693	650376	144155
High-educated	Δ *LQ*	−1.954***	3.270***	−5.877***
		(0.659)	(0.809)	(1.172)
	Control variabilities	yes	yes	yes
	Chi^2	601.95	480.45	125.97
	Pseudo R^2	0.234	0.249	0.246
	Observations	8883	13068	3520

Note: Standard errors are between parentheses; ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

Table 8
Urban heterogeneity in transfer-in areas.

Variabilities	Central cities	Peripheral cities	Other cities
Δ *LQ*	4.733***	−2.414***	0.198
	(0.378)	(0.199)	(0.191)
Control variabilities	yes	yes	yes
Chi^2	4488.17	3849.06	481.00
Pseudo R^2	0.219	0.165	0.056
Observations	56760	155555	76384
Number of cities	15	53	77
Observed sample	3784	2935	992

Notes: Standard errors are between parentheses; ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

(2) Labor heterogeneity

Table 9
Heterogeneity of the labor force in transfer-out areas.

	Variabilities	Central cities	Peripheral cities	Other cities
Low-educated	Δ *LQ*	4.9421***	−2.5462***	0.1713
		(0.3851)	(0.2055)	(0.1945)
	Control variabilities	yes	yes	yes
	Chi^2	4303.46	3865.51	448.74
	Pseudo R^2	0.2197	0.1710	0.0539
	Observations	54255	150891	73766
High-educated	Δ *LQ*	0.244	0.0207	1.122
		(2.035)	(0.758)	(1.073)
	Control variabilities	yes	yes	yes
	Chi^2	229.73	37.40	40.07
	Pseudo R^2	0.254	0.054	0.136
	Observations	2505	4664	2618

Note: Standard errors are between parentheses; ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

6. Discussion and conclusions

Based on detailed micro data, this study provides a clear answer to the research question. The main conclusions are as follows.

During the study period, the transfer of labor-intensive manufacturing does have a significant impact on the spatial choice of the labor force, but the two directions are inconsistent in space; that is, in industrial transfer-out areas, with the increase in urban industrial transfer, the probability of the labor choice entering increases, while in industrial transfer-in areas, with the increase in industrial transfer, the probability of entry decreases. Further analysis shows that among the three types of cities, only the peripheral cities of urban agglomerations follow this law, while the others do not. Furthermore, in transfer-out areas, there is little difference in the impact of migrant workers with high or low academic qualifications, but the highly educated migrant workers in transfer-in areas are not significantly affected by industrial inflow, which is obviously different from low-educated ones. In the early stages of industrialization and urbanization, the agglomeration and transfer of labor-intensive manufacturing in China mainly drove labor mobility by providing employment opportunities; however, at present, although there is still a significant relationship between the two, the influence path is more complex, as well as the influence direction is different. After superimposing the urban characteristics, the transfer of labor-intensive manufacturing has a more diversified impact on labor mobility, and the difference of migrant workers in the pursuit of life also plays a certain role.

The results show that the assumption presented by some theories that labor mobility is synchronized with industrial transfer is not entirely in line with reality. Moreover, the viewpoint put forward by some literature that China's migrants is bound to return to undeveloped areas following the inter-regional industrial transfer is worthy of discussion. From the perspective of individual choice of labor force, this paper further confirms the view that there is a "reverse" relationship between labor mobility and industrial transfer in present China, and deeply reveals urban differences and group differences.

In China, 'Guidance on undertaking industrial transfer in central and western regions' in 2010 and 'Guidance on promoting orderly transfer of manufacturing' in 2022 accelerated labor-intensive industries to move to the central and western regions where the labor force is enough, additionally, multiple policies encourage people return to the central and western regions, which is in line with the law of comparative advantage and the target of in-situ urbanization. However, the results of this paper show that the labor mobility brought by industrial transfer mainly occurs in the central cities. From this point of view, the target of promoting the transfer of labor-intensive industries and population to the central and western regions may not be fully realized. In the current period, the transfer-in areas of labor-intensive manufacturing are often the main migrant-sending areas, for most of them it is difficult to attract new migrants and return migrants, especially in non-central cities. There is a large demand for labor in labor-intensive manufacturing, if the labor supply was insufficient, it would directly affect the industrial development, and further hinder the process of inter-regional transfer. Moreover, in the peripheral cities in transfer-out areas, artificial intelligence will further replace the low-skilled workers in labor-intensive industries in the future. The excessive mismatch between industrial transfer and labor mobility may aggravate the risk of structural imbalance of the labor force. In the policy decision process, the choice of migrant workers should be considered. It is necessary to implement industrial gradient transfer among the central cities and peripheral areas based on the law of agglomeration and diffusion, as well as strengthen their coordinated development, enhancing the ability of the periphery in transfer-in areas to attract and absorb the manufacturing workers. It is more important for these cities to recruit labor force that meets the needs of local industrial development rather than those with high academic qualifications. Moreover, in the peripheral cities of transfer-out areas, it is also important to improve skills training for migrant workers, to deal with the industrial restructuring and to avoid the aggravation of the structural imbalance of the manufacturing workers.

This paper reveals the impact of labor-intensive manufacturing transfer on the spatial choice of manufacturing labor force based on micro-individual data for the first time. The results and policy implications can be used as reference for China and other developing countries. As the influence mechanism of industrial transfer on labor mobility is becoming increasingly complex, we plan to conduct a follow-up study and intermediary effect analysis in future studies if possible.

CRediT author statement

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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