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Intergenerational Occupational Mobility, Labor Migration and Sustained Demographic Dividends

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Abstract: Based on the 1% sample survey of the National Population Census (2015), this paper empirically analyzes the impact of intergenerational occupational mobility levels on labor migration in terms of push and pull factors. We found that increasing the degree of intergenerational occupational mobility has a significant "agglomeration effect" on registered and mobile labor: reducing the emigration willingness of household registered labor and increasing the immigration probability of labor from cities with a lower degree of intergenerational occupational mobility. Labor migration generally occurs from cities with lower intergenerational occupational mobility to cities with a higher degree of intergenerational occupational mobility. The heterogeneity analysis reveals that the agglomeration effect of a city on native labor is insignificant in east, northwest and northeast China. Rural laborers, highly educated laborers and rural laborers with high education levels are more likely to move from their registered cities. The mechanism analysis finds that improving the city's comprehensive economic incremental competitiveness will enhance the city's agglomeration effect on native labor, while increasing the degree of educational returns will strengthen the city's agglomeration effect on mobile labor from cities with a lower degree of intergenerational mobility. Moreover, after using IV-probit, IV-2SLS and heteroscedasticity-based IVs to deal with endogenous problems, the above conclusions are still robust. Our findings may contribute to realizing sustained demographic dividends through internal migration.

Keywords: intergenerational occupational mobility; labor migration; sustained demographic dividend; heteroscedasticity-based IVs; absolute educational returns

JEL Classification: J11; J61; R11

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1. Introduction

Since the reform and opening up in the late 1970s, the remarkable economic achievements in China can be attributed largely to the "demographic dividend"; that is, the economic benefits of the demographic structural transition (an increase in the labor participation ratio and a decline in the dependence ratio). However, as the tendency of population ageing and low birth rates become increasingly severe, most studies have identified the Lewis' turning point in the Chinese labor market [1–3]. According to data from the seventh National Population Census, the total fertility ratio in China decreased to 1.3 (significantly below replacement fertility levels) in 2020, and the annual number of new births also hit a new low of 12 million. In addition, the proportion of the population aged 65 years and older is 13.5%, which is very close to the standard of deep aging (14%). As a result of population ageing and having fewer children, the sustainability of China's "demographic dividend" is facing severe challenges.

A demographic dividend can accrue at two different points over the age structural transition period [4]. The first demographic dividend flows from an increase in the productivity and employment of the labor force during the "window of opportunity". The second dividend accrues alongside an ageing population, which leads to improved health and longevity and smaller family size, making saving easier and more attractive [5–7]. However, under a situation where the first demographic dividend ceases to exist, how can we avoid the vacuum dividend between the two demographic dividends? There is a general agreement that migration is an immediate solution to such demographic problems. Studies based on Europe find that migration is not effective at preventing the age structural transition and demographic deficit, but it is useful to alleviate it [8–13], and can at very high levels, avert a future decline in the total population (United Nations 2000). Similarly, Chinese scholars believe that if the government takes measures to enhance its capacity to change industries and move rural workers from the first baby boom generation between different regions, the labor shortage would be alleviated to some extent. Reducing labor mobility between rural–urban regions and industries may hinder the reallocation of production resources, which leads to low productivity growth and high labor costs. If the free movement of labor between industries and regions can be achieved, it is possible to continue to utilize the surplus labor in urban and rural areas, thus extending the first "demographic dividend" to ensure the successful transition to the second "demographic dividend"—achieving the sustainability of the demographic dividend. Simply put, guiding the free flow of labor is crucial to the sustainability of China's demographic dividend and economic development. Given that some institutional obstacles hindering the social mobility of labor and talents are removed, beneath the appearance of "disorder" such as "localization" and "reflow" of population mobility, what are the determinants of internal migration?

Studying the determinants of labor migration has always been of interest to scholars. [14,15]. During the development period of labor migration theory, there emerged two important theories: the "push–pull theory" and the "human capital investment theory". The "push–pull theory" was first proposed by Ravenstein [3] in his article "The Law of Migration" and was systematized and applied by Bogue [16]. The core idea is that the migration decision is influenced by both the push factors of the original area and the pull factors of the migratory destination. Many scholars have partially modified or supplemented the "push–pull theory" since then. For instance, Lee [17] took the lead in incorporating migration barriers, such as migration distance, physical barriers, linguistic and cultural differences, and migrants' value judgments on these barriers, into the influencing factor set of migration decision-making, which gave birth to the "multi-factor push–pull theory". In addition, with the emergence and popularization of "human capital investment theory", the individual factors of migrants have been paid more attention during the procedure of migration decision making. Based on the concept of human capital investment, the direct motivation of migration is to reallocate individual skills in different places to maximize net economic returns. These factors, such as migrants' identity characteristics, their position in the life cycle, post-migration employment status, age, family and migration networks, all have impacts on the migration decision of potential migrants [18–24]. In addition, factors such as migrant fertility status, the age of their children, and whether or not their children move with them, can also affect the migration decision [25–27]. In addition to the wage gap between urban and rural areas, the investment in human capital for children, especially education investment, is the main driver of migration for parents [28].

Parents will invest in their children to ensure that their children have a better income and livelihood level in the future and will seek to maximize their economic utility. Therefore, the regional factors that affect children's future income will inevitably influence the migration decisions made by their parents or families [29]. In other words, while seeking to maximize their own direct economic benefits, factors that affect the expected income of families and future generations can also directly influence the migration decisions of migrants, especially those with children.

Therefore, given the national condition whereby few children are being born, cities with more employment opportunities, particularly those with a high degree of upward intergenerational mobility, would be more attractive for migrants. The level of intergenerational mobility reveals the degree of connection between children and their parents in political, economic, and social terms, which directly influences parents' migration decision. Numerous studies have confirmed the "two-way" effect between intergenerational mobility and migration [30,31]. In general, parental migration increases intergenerational mobility, including upward intergenerational mobility [27,30,32–35]. That is, parents' investment in human capital for their children through migration directly affects their children's expected income and intergenerational mobility in adulthood [36], and then influences the regional intergenerational mobility level of the migration destination. Conversely, the spatial heterogeneity of regional intergenerational mobility levels [37] can also contribute to labor migration, reducing the willingness of labor to migrate out from cities with a high level of intergenerational mobility and enhancing the crowding-out effect on labor in cities with low levels of intergenerational mobility.

The spatial heterogeneity of intergenerational mobility implies spatial inequality in development opportunities for children, thus encouraging parents who focus on their children's human capital investment and future income to migrate to cities with higher levels of upward intergenerational mobility [29]. The heterogeneity in the level of intergenerational mobility between the origin residence and migration destination creates both the push factor and the pull factor in the migration process; that is, a high level of intergenerational mobility is a pull factor for inflow, while a low degree of intergenerational mobility is a push factor for emigration. The spatial heterogeneity of intergenerational mobility levels is an effective unification of the "push–pull theory" and the "human capital investment theory" and reflects the considerations of potential migrants based on their own and their family's permanent benefits. Combing the domestic and foreign studies that are most relevant to this paper, the existing literature can be broadly divided into three branches: (1) Based on individual or household income data from developed countries to construct a regional intergenerational mobility index and analyze its impacts on labor migration. (2) Based on household samples from developed countries to analyze the impacts of parent's migration direction on children's expected income. (3) Based on analyzing the impacts of regional intergenerational mobility level on emigration in developing countries. Compared with previous studies, the innovation points of this paper are described as follows: (1) We used the education attainment information of individuals in the 1% sample survey of the National Population Census (2015) to calculate the occupational educational intensity index to rank occupations and construct a regional intergenerational occupational mobility index, which is an effective solution to the data shortage in developing countries. (2) We combined the push factor, pull factor, and "emotional factor" from the perspectives of immigration and emigration to analyze the general law of migration, thus correcting the bias in the existing literature that is incurred by conflating or separating push factors and pull factors [29,38,39]. (3) We adopt various regression approaches, such as Logit, IV-probit, IV-2SLS and heteroskedasticity based IV, to empirically analyze the motivations and influencing factors of migration decision-making, which may contribute to research on migration in developing countries. Our principal finding is that increasing the degree of intergenerational occupational mobility has a significant "agglomeration effect" on registered and mobile labors; that is, reducing the emigration willingness of household registered labor and increasing the immigration probability of labor from cities with lower degrees of intergenerational occupational mobility.

2. Theoretical Hypotheses

This paper refers to the theoretical model of Borjas [40] to analyze the impacts of regional intergenerational occupational mobility level on labor migration. The key conclusion of this model is that the heterogeneity among the levels of regional intergenerational skill transmission can influence the migration decision of parents. It is assumed that the transfer of skills from generation $t-1$ to generation t ($t > 1$) follows Equations (1) and (2).

$$s_{at} = \alpha_{at} + \theta_a s_{a,t-1} + \varepsilon_{at} \tag{1}$$

$$s_{bt} = \alpha_{bt} + \theta_b s_{b,t-1} + \varepsilon_{bt} \tag{2}$$

where s_{jt} represents the skill level of the tth generation of migrants in country j ($j = a$ or b); the parameter θ_j is the level of intergenerational skill transmission in country j, which takes values between 0 and 1; ε_{jt} represents the unobservable factors in country j, which affect the skill level of the tth generation of migrants. The random variable ε_{jt} has zero mean and finite variance, is distributed independently of skills, and is uncorrelated over time. If $\theta_a = \theta_b$, it means that there is no heterogeneity in the levels of intergenerational skill transmission between two countries, and the migration does not occur. If $\theta_a \neq \theta_b$, the potential migrants who are concerned about the incomes of future generations and the cumulative incomes of the family will migrate between the two countries; that is, the heterogeneity in the levels of intergenerational skill transmission between two countries creates the pull factor and push factor simultaneously. Skilled workers prefer to migrate to a destination country with a higher level of intergenerational skill transmission, while unskilled labor is willing to migrate to countries with lower levels of intergenerational skill transmission, as this decision will not result in a large welfare loss.

The impact of spatial heterogeneity in the levels of intergenerational skill transmission on labor migration behavior lies in the spatial heterogeneity of the expected economic benefits. Thus, skilled workers prefer to move to a location where skills are easily transferred to their children to safeguard the income of their children in the future. The influence of spatial heterogeneity on regional intergenerational skill transfer levels on migration behaviors at different skill levels confirms that labor migration decisions are influenced by regional non-economic factors. Based on the above analysis, this paper proposes the first hypothesis: spatial heterogeneity in regional occupational intergenerational mobility levels affects the migration decisions of migrants, especially those who are concerned with children and the family's cumulative generational gains.

In this paper, the definition of regional intergenerational occupational mobility level is absolute regional intergenerational occupational mobility level, i.e., the average occupational percentile that children whose parents have an occupational rank below 50% of the occupational distribution can obtain. A higher level of regional intergenerational occupational mobility means a greater scope for career advancement and more employment opportunities for immigrants' children, allowing them to achieve an even higher occupational position than that of their parents, thus maximizing the sustained or cumulative intergenerational earnings of the family. Therefore, this paper proposes a second hypothesis: migrants follow a general migration law and move from cities with lower intergenerational occupational mobility levels to cities with higher ones.

3. Data and Methods

3.1. Data and Statistical Analysis

3.1.1. Data Sources

Constrained by the availability of long-term high-quality income panel data for developing countries [41], this paper empirically analyses the interrelationship between regional intergenerational occupational mobility level and migration in cities using the occupational and educational data of workers. The data used in this paper include the 1% sample survey of the National Population Census (2015), the 1999 and 2004 WITS tariff data, the China Statistical Yearbook (2015), the Blue Book of Urban Competitiveness (2015), and the District and Urban–Rural Division Codes for Statistical Purposes, all of which can be download from the China National Bureau of Statistics.

3.1.2. Statistical Characteristics

After data cleaning and matching, the core data covers 29 provinces (municipalities) and 248 cities in China, with 76,067 samples in total. Given the diversity of migration patterns due to China's household registration system, this paper defines migration as the movement of mobile workers that work outside their registered cities for at least half the year. The dependent variable Migrate is an indicator of migration. This variable takes the value of one if migration has happened and, zero otherwise. The mean value of the dependent variable is 0.2448, which implies approximately 25% of the individuals have migration experience (Table 1). The independent variable ab_occ_mobility is an indicator of absolute regional intergenerational occupational mobility in the birth city of children. This variable measures the average percentile rank of a child in his age cohort whose father's occupation ranks below the median at the national occupational percentile ranking. Its mean value is 38.17%, which reveals upward intergenerational occupational mobility; that is, the average occupational percentile rank of children is 38.17 when their father's occupation is 25th in the national occupational distribution. This result implies that the economic structure of the region is open and that children from below-median families have a greater possibility of improving their intergenerational occupational ranks.

Table 1. Statistical analysis.

Name and Explanation	Mean	Std. Dev	Min	Max
Dependent and independent variable				
Migrate: Migration status (1: Migrate, 0: Otherwise)	0.2448	0.43	0	1
ab_occ_mobility: Absolute regional intergenerational occupational mobility (%)	38.1693	0.675	34.52	41.17
Individual, paternal and family variables (Individual)				
age_i: Age of individual	27.8728	6.2669	15	60
sqage_i: Age square of individual	816.1687	388.1984	225	3600
edu_i: Education attainment of individual	3.724	1.262	1	8
married_i: Marital status of individual (1: Married, 0: Otherwise)	0.5405	0.4984	0	1
age_f: Age of father	54.2651	7.5242	32	104
sqage_f: Age square of father	3001.3117	855.5347	1024	10.816
edu_f: Education attainment of father	2.8149	0.8836	1	8
nation_f: Nationality of father (1: Han, 0: Minorities)	0.9479	0.2222	0	1
lnhouse_size: Log (housing area)	4.8116	0.5396	0	6.9068
house_member: Number of family members	4.7964	1.6233	2	18
Variables about city population, land and industry scale (city01)				
lnave_population: Log (average population at year end)	6.2536	0.6111	3.6778	8.1237
popu_density: Population density (person/sq.km)	515.3641	317.3962	5.77	2501.14
area: Total land area of administrative region (sq.km)	16.6717	17.7786	1.201	252.777
area_urban: Area of land used for urban construction	182.3216	245.6218	17	1597
area_living: Area of land used for living	55.2187	71.2322	3	417
secondary_indus_ratio: Share of employees in the secondary industry	48.0947	12.6566	10.32	82.6
tertiary_indus_ratio: Share of employees in the tertiary industry	50.6359	12.047	17.38	86.37
num_foreignfunded: Number of foreign-invested enterprises	115.9819	288.7244	1	3063
num_gangaotai: Number of enterprises funded by HK, Macao and Taiwan	87.0337	203.1228	1	1990
Variables of city economics (city02)				
lnoutput_foreignfunded: Log (gross industrial output value of foreign funded enterprises)	14.1054	1.8873	6.9994	18.7883
lnoutput_gangaotai: Log (gross industrial output value of enterprises funded by HK, Macao and Taiwan)	13.8734	1.807	7.789	18.0995
lnGDP: Log (GDP)	16.9214	0.8178	14.8789	19.2542
lnave_wage: Log (average wage of employed staff and workers)	10.8767	0.1832	10.4696	11.6358

Table 1. *Cont.*

Name and Explanation	Mean	Std. Dev	Min	Max
Variables of social expenditure and welfare (city03)				
lnpub_finance_exp: Log (public finance expenditure)	15.1843	0.707	13.5762	17.8652
lnedu_exp: Log (expenditure for education)	10.7405	1.2456	7.6492	14.8726
lnsci_exp: Log (expenditure for science and technology)	13.4603	0.71	11.7038	15.9622
lnnum_higheredu: Log (number of regular institutions of higher education)	1.7052	1.125	0	4.4998
lnnum_regularedu: Log (number of regular secondary schools)	4.2818	0.8549	1.0986	5.2781
lnnum_primaryedu: Log (number of primary schools)	6.4002	0.8589	3.2189	8.3357
per_collections: Collections of public libraries per 100 persons (copy, piece)	59.0953	79.1008	5.68	924.57
lnnum_hospital: Log (number of hospitals and health centers (unit))	5.4137	0.6355	2.1972	7.3576
lnnum_bed: Log (number of beds of hospitals and health centers (bed))	10.0564	0.6536	7.355	12.0099
Observations		76,067		

There are four categories of controlled variables: individual related factors, city economics, social culture, welfare and covariates at the city level. The individual related factors include the age and age quadratic terms of children and their fathers, which are controlled to address life-cycle bias [42,43]. All children in the sample are non-students and have stable occupations, and the age difference between the father and child is 15 years or more. The average age of the children is approximately 27.87 years and that of the fathers is approximately 54.27 years, which obeys the multiple conditions of "father–son co-residence", "adult children" and being active in the labor market at the same time [44]. Referring to the articles of Chetty et al. [37] and Kim and Lee [29], the city-level control variables include economic indicators, socio-cultural welfare indicators and city-level size covariates (Table 1).

3.2. Index Construction Methods

3.2.1. Occupational Educational Intensity

A key challenge in quantifying regional intergenerational occupational mobility is to rank the socioeconomic status of occupations. Referring to the method of Ahsan and Chatterjee's [45], this paper uses the individual's educational attainment to construct an occupational educational intensity index and uses it to rank the occupations. The 1% sample survey of the National Population Survey provides 437 refined occupational categories that are denoted by five-digit codes, and eight different education categories that include no schooling, primary school, graduate etc. To construct the occupational educational intensity index, we first reclassify the five-digit occupation codes into occupational categories that are represented by three-digit codes and then we calculate the weighted average education attainment of employees within the same three-digit occupational category, i.e., occupational educational intensity. This paper defines the educational intensity of occupation o, ED_O, as:

$$ED_O = \sum_{i=1}^{n_o} \left(\frac{\omega_i}{\sum_i^{n_o} \omega_i} \right) * E_i \tag{3}$$

where ED_O is the educational intensity of occupation O, n_o represents the total number of employees with occupation o, E_i denotes an individual i's education category and ω_i is an individual's sampling weight. This paper is based on 73 occupations that are denoted by three-digit codes, Equation (3) is repeated for each occupation in our sample, thus calculating an occupational educational intensity index for every occupation. In addition, we accord the values of occupational educational intensity to rank the occupations.

3.2.2. Regional Intergenerational Mobility Index

Given the superiority of using occupational data to estimate permanent income [46], this paper refers to the approach of Chetty et al. [37] and uses the occupational data to estimate the absolute regional upward intergenerational occupational mobility index (regional intergenerational occupational mobility). Unlike the occupation ranking methods of Duncan [47], Beller and Hout [48], this paper uses three different occupation ranking methods based on the values of occupational educational intensity to prove the feasibility of measuring the intergenerational occupational mobility index; the father's percentile rank at the national occupational distribution, highly linearly correlates with their children's average percentile rank of occupation within the same birth cohort. (1) Based on the magnitudes of occupational educational intensity indices, we sort the 73 occupations from 1 to 73 sequentially and define upward occupational mobility as the change from a lower occupational rank to a higher one. (2) We treat the magnitudes of the occupational educational intensity index as occupation ranks in the occupational distribution with 73 occupations. (3) Based on ranking method (1), this paper refers to the computing approach of Elsworth and Osborne [49] to measure the fathers' and children's occupational percentile ranks. What needs to be emphasized is that fathers' occupational percentile ranks are their positions in the distribution of the fathers' occupations in the core sample, while the occupational percentile ranks of children are the average positions in the distribution of child occupations within their birth cohorts. Using the three approaches, we can obtain the relationships between father's occupational percentile ranks and the children's average occupational percentile positions, which are depicted in Figure 1a–c. The regression coefficients and R^2 reported in Figure 1 are estimated for the underlying micro-data using OLS regressions. Figure 1a–c all show a significantly linear relationship between the father's occupational percentile ranks and the occupational percentile positions of their child, and the magnitudes of regression coefficients and R^2 do not change significantly. To test the robustness of the relationship between the occupational percentile positions of father–child pairs, we deleted the individual samples where the father's occupational positions ranked below the 50th percentile in the occupational distribution. The slope in Figure 1d is higher than the slopes in the other pictures within Figure 1, which means that children have more opportunities to achieve upward intergenerational occupational mobility. To maintain generality, this paper constructs an indicator of regional occupational intergenerational upward mobility based on the relationship between the fathers' and their children's occupational percentile ranks in the core sample.

Referring to the measuring method of Chetty et al. [37], this paper uses the occupational percentile ranks of father–child pairs to replace the income percentile ranks to compute the regional occupational intergenerational mobility. We begin by examining the rank–rank relationships in selected cities and summarizing the conditional expectation of a child's rank given his father's occupational percentile position in each city using two parameters: a slope and an intercept. The measuring models are set as follows:

$$R_{sic} = a_c + \beta_c R_{fic} + \varepsilon_{ic} \tag{4}$$

$$\overline{r_{P,c}} = a_c + \beta_c * R \tag{5}$$

where s, f, i, c and P are the indexed child, father, individual, city and percentile rank of occupation, respectively. In Equation (4), R_{sic} denote the national occupational rank (among children in his birth cohort) of child i who grew up in city c. R_{fic} represents child $i's$ father's national occupational rank in the core sample. The parameter β_c is the slope of rank–rank relationship, which indicates the degree of relative regional intergenerational occupational mobility in city c. a_c represents the intercept and ε_{ic} is the random disturbance term.

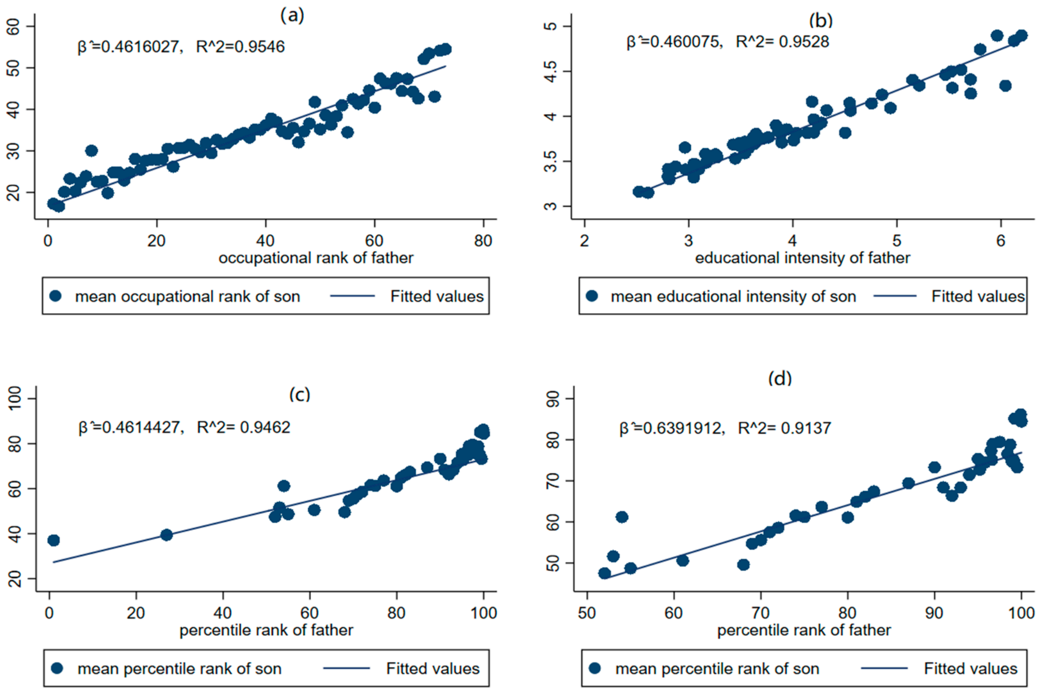

Figure 1. Fathers' occupations vs. children's occupations under different occupational rankings. (**a**–**d**) present scatter plots of the relationship between child and parent occupational ranks with different ranking methods. (**a**), Based on the magnitudes of occupational educational intensity indices to rank the 73 occupations; (**b**) used the values of the occupational educational intensity index as the positions of related occupations in the occupational distribution. (**c**) referred to the computing approach of Elsworth and Osborne [49] to measure the fathers' and children's occupational percentile ranks. (**d**) deleted the individual samples where the father's occupational positions ranked below the 50th percentile in the occupational distribution.

To measure the degree of absolute regional intergenerational occupational mobility, we constructed Equation (5). $r_{P,c}$ represents the average expected occupational rank of a child among children in his/her birth cohort when his/her father's occupation is at the Pth percentile in the father's national occupational distribution. Because of the significant rank–rank relationship between a child's occupation and his/her father's, this paper refers to the method of Chetty et al. [37] to define the absolute regional intergenerational occupational mobility index as the average absolute regional intergenerational occupational mobility for children from families with below-median parent occupational ranks in the national distribution ($E[R_{sic} \mid R_{fic} < 50]$). Given the perfect linear rank–rank relationship between father–child pairs, this paper redefines the absolute regional intergenerational occupational mobility index as: $\overline{r_{25,c}} = a_c + \beta_c * 25$. The higher the magnitude of $\overline{r_{25,c}}$, the greater the probability of children achieving intergenerational occupational upward mobility and the less their employment opportunities and quality are influenced by their parents' occupations.

3.3. Empirical Method

Labor migration is not a blind or random behavior, but a subjective action after rationally considering the trade-offs between the migration costs and the family benefits. It is also a process of optimizing the spatial allocation of resources. The migration decision is influenced by multiple factors and the most intuitive affecting factors include an individual's age, educational attainment, migration experience, migration networks and so on [29]. Therefore, this paper, based on the multi-factor "pull and push theory" and "the concept of human resource investment", sets the empirical model from the intergenerational perspective as follows:

$$Migrate_{ic} = a_c + \beta_1 ab\_up\_mobility_c + \beta_2 I_{ic} + \beta_3 M_{fc} + \beta_4 H_{hc} + \gamma_1 city01_c + \gamma_2 city02_c + \gamma_3 city03_c + \theta_P + \varepsilon_{ifc} \quad (6)$$

where i is potential migrant, f represents his/her father, h denotes his/her household or family and c is the city where i was registered. Dependent variable $Migrate_{ic}$ represents the migration status of i. It takes the value of 1 when individuals move out from his/her registered city and takes the value of 0 otherwise. Independent variable $ab\_up\_mobility_c$ denotes the degree of absolute regional intergenerational occupational mobility of city c. I_{ic} controls the factors that influence the emigration decision of migrants, including age, age square, educational attainment and marital status. M_{fc} controls the parental factors that affect the emigration decision of a child, such as the father's age, age square, educational attainment and nationality. H_{hc} controls for household factors that interfere with the decision-making of migration (the housing area and the number of families). City01, City02 and City03 are three categories of factors that influence the migration decision-making processes of migrants from the perspective of their registered city (pull factor), including city size covariates, economic variables and sociocultural welfare variables. θ_P represents province-level fixed effects while controlling for province-level factors, such as floating population policy and geographical distance, that influence labor migration behavior across provinces and regions. ε_{ifc} is a random disturbance term that controls the effect of unobservable factors on labor migration behavior.

4. Empirical Results

4.1. Logit Regression

4.1.1. The Impact of Regional Absolute Intergenerational Occupational Mobility on Emigration

As we mentioned above, the spatial heterogeneity of the intergenerational occupational mobility level constitutes the pull factor of destination cities and the push factor of registered cities over the migration procedure. This paper focuses on the pull factors, using the logit regression method to empirically analyze the impacts of regional intergeneration occupational mobility levels on emigration behavior. After controlling for variables such as individual variables, city size covariates, economic variables and sociocultural welfare variables, the empirical results are shown in Table 2.

Table 2. Benchmark regression results.

Migrate	(1)	(2)	(3)
ab_occ_mobility	−0.1179 **	−0.1162 **	−0.1320 ***
	(0.0549)	(0.0534)	(0.0505)
Individual	YES	YES	YES
City01	YES	YES	YES
City02	NO	YES	YES
City03	NO	NO	YES
FE (Province)	YES	YES	YES
N	76,067	76,067	76,067
Pseudo R^2	0.0694	0.0676	0.0698

** and *** indicate 5% and 1% levels of significance, respectively; the detailed information of control variable categories (Individual, City01, City02, City03) can be found in Table 1; FE is the fixed effect of provincial level; standard errors are in parentheses, and all regression cluster standard errors are at the city level.

In Table 2, the coefficients of regressions (1)–(3) are significantly negative at the 5% or 1% significance levels. These results reveal a negative relationship between the degree of regional intergenerational occupational mobility and the emigration probability of registered residents. In other words, a city with a higher degree of intergenerational occupational mobility has a significant "agglomeration effect" on local mobile labor, i.e., it reduces the willingness of local people to leave. From regressions (1) to (3), by gradually adding more control variables to partially revise the endogenous problem that is caused by omitted variables, we find significant growth both in significant levels and absolute values of regression coefficients. This phenomenon leads to two conclusions: (1) the negative impact of regional intergenerational occupational mobility on emigration is robust; (2) the endogenous problem of the model reduces the "agglomeration effect" of cities with a high degree of intergenerational occupational mobility, on household registered labor.

4.1.2. Heterogeneity Analysis

As we analyzed above, parents may be more activated to migrate to improve the expected income of their children in the future, but how about those without children? To answer this question, we first look at those potential migrants who may not have a baby (born after 1980s). The coefficient of regression (1) in Table 3 is significantly negative at the 1% significance level, indicating that as the level of intergenerational occupational mobility increases in household registered cities, young native laborers are more likely to prefer to work in their home cities. In other words, increasing cities' intergenerational occupational mobility level would decrease the emigration probability of household registered laborers. In addition, based on the theoretical hypothesis 2 in part 2, we match "the 1% sample survey data of National Population Survey (2015)" with "the statistical use of district codes and urban–rural division codes (2014)" to determine the urban–rural attributes of individuals, thus constructing two dummy variables: Dum_hukou and Dum_edu. Dum_hukou takes the value of 1 if an individual was born in a rural area; it takes the value of 0 otherwise. Dum_edu takes the value of 1 if an individual's education attainment is higher than the mean educational attainment of the core sample; it takes the value of 0 otherwise. We use these two dummy variables and explanatory variables to create three interaction terms to perform regressions (Table 3). The coefficient of mobility_hukou in regression (2) indicates that labor from a rural area are more willing to move out from their registered city as the degree of intergenerational occupational mobility increases. The coefficient of mobility_edu in regression (3) implies that laborers with higher-than-mean educational attainment also prefers to move from their native city. Simply put, both laborers from rural areas and laborers with higher-than-mean educational attainment are potential emigrants. However, what about rural laborers with high educational attainment? The coefficient of the interaction term in regression (4) is positive at the 1% level of significance, which indicates that rural laborers with higher-than-mean educational attainment have a higher willingness to move out. From regressions (2)–(4), we can conclude that rural labor, labor with higher-than-mean education attainment and rural labor with high educational attainment, in particular, constitute the majority of the mobile population in China. This conclusion is consistent with the basic national conditions of China's mobile population.

The heterogeneity of the industrial agglomeration and migration costs due to economic geographical location is an important source of heterogeneity in the impact of regional intergenerational occupational mobility levels on labor migration behavior. Therefore, this paper divides the core samples into eight categories according to their geographic locations, namely, individuals from North China, Central China, South China, East China, Beijing–Tianjin, Northwest China, Southwest China and Northeast China (Table 4). In regressions (1)–(5), the regional intergenerational occupational mobility level increases by one percentile, the emigration probability of household residents in the Beijing–Tianjin area decreases by 684%, while the probability of emigration of labor in the Southwest region decreases only by 7.67%. These results imply that the agglomeration effect of city on potential migrants is stronger in cites that enjoy a higher level of economic development, which to some extent explains the causes of China's "northwest–southeast coast" migration and the "big city disease" in cities such as Beijing.

Table 3. Heterogeneity analysis of age, household register and education level.

Migrate	(1)	(2)	(3)	(4)
	Age < 35	**Dum_hukou**	**Dum_edu**	**Dum_hukou × Dum_edu**
ab_occ_mobility	−0.1343 *** (0.0506)			
mobility_hukou		0.0060 *** (0.0012)		
mobility_edu			0.0093 *** (0.0011)	
rural_high_mobility				0.0145 *** (0.0014)
Individual	YES	YES	YES	YES
City01	YES	YES	YES	YES
City02	YES	YES	YES	YES
City03	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES
N	67,038	76,067	76,067	76,067
Pseudo R^2	0.0679	0.0710	0.0679	0.0692

*** indicates 1% levels of significance; FE is the fixed effect of provincial level;standard errors are in parentheses, and all regression cluster standard errors are at the city level; mobilty_hukou = ab_occ_mobility × Dum_hukou; mobility_edu = ab_occ_mobility × Dum_edu; rural_high_mobility = mobility_hukou × Dum_edu × Dum_hukou.

Table 4. Analysis of heterogeneity in terms of geographic location.

Migrate	(1)	(2)	(3)	(4)	(5)
	North China	**Beijing–Tianjin**	**Central China**	**South China**	**Southwest China**
ab_occ_mobility	−0.1884 ** (0.0854)	−6.8409 ** (3.0626)	−0.4363 *** (0.1339)	–0.3846 *** (0.0911)	–0.0767 * (0.0397)
Individual	YES	YES	YES	YES	YES
City01	YES	YES	YES	YES	YES
City02	YES	YES	YES	YES	YES
City03	YES	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES	YES
N	9002	1216	18,714	8889	9156
Pseudo R^2	0.0754	0.0975	0.0587	0.0714	0.0898

*, ** and *** indicate 10%, 5% and 1% levels of significance, respectively; standard errors are in parentheses, and all regressions cluster standard errors are at the city level; only the results of the statistically significant regional heterogeneity analysis are shown in the table.

4.1.3. The Impact of Regional Absolute Intergenerational Occupational Mobility on Emigration and Immigration

The baseline regression results confirm the "agglomeration effect" of cities with a high degree of intergenerational occupational mobility on household registered residents. However, these cities also have a significant "crowding-out effect" on specific populations–those who come from rural areas, those with high educational attainment, and those who come from rural areas and have high education attainment. Naturally, where will those migrants who move out from their household registered cities go? When taking both the immigration and the emigration behaviors into account and connecting the pull and push factors, we will find the potential answer. According to an individual's household registered city, current residence, and surveyed city in the 1% sample survey of the National Population Census (2015), we can correctly identify immigration and emigration behavior, thus making it feasible to analyze the impact of regional intergenerational occupational mobility levels on labor migration by combining the push and pull factors of the surveyed city. (1) We analyze the impact of intergenerational occupational mobility level on labor migration behavior by treating the surveyed city as the migration destination. (2) We analyze the impact of intergenerational occupational mobility level on an individual's migration behavior using the surveyed city as the place of origin (Table 5). Regressions (1) and (2) are performed from the perspective of immigration, and the results indicate that as the level of intergenerational occupational mobility in the surveyed city increases, the willingness to move in from cities with lower levels of intergenerational occupational mobility is higher, while the probability of moving in from cities with higher levels of intergenerational occupational mobility is lower. In other words, the spatial heterogeneity of intergenerational occupational mobility levels encourage the labor force to move from cities with lower intergenerational occupational mobility levels to cities with higher intergenerational mobility levels.

Table 5. Regional intergenerational occupational mobility vs. emigration and immigration.

Migrate	**(1)**	**(2)**	**(3)**	**(4)**
	Migrate_in_high	**Migrate_in_low**	**Migrate_out_high**	**Migrate_out_low**
ab_occ_mobility	0.7506 ***	−0.9425 ***	0.2989 *	−0.0231
	(0.1104)	(0.1283)	(0.1784)	(0.0500)
Individual	YES	YES	YES	YES
City01	YES	YES	YES	YES
City02	YES	YES	YES	YES
City03	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES
N	58,500	40,683	4049	68,848
Pseudo R^2	0.0939	0.3036	0.1137	0.0658

* and *** indicate 10% and 1% levels of significance, respectively; standard errors are in parentheses, and all regression cluster standard errors are at the city level; Migrate_in_high and Migrate_in_low indicates migration from cities with higher and lower levels of intergenerational occupational mobility to the surveyed city, respectively; Migrate_out_high and Migrate_out_low represents migration from the surveyed city to cities with higher and lower levels of intergenerational occupational mobility, respectively.

In addition, this paper also performs an empirical analysis from the perspective of emigration. The results are shown as regressions (3) and (4) in Table 5. The regression coefficients of ab_occ_mobility are positive and significant, which indicates that as the level of intergenerational occupational mobility increases in registered cities, those who move out of their registered cities are more likely to move to destinations with higher levels of intergenerational occupational mobility. The relative regression coefficient in regression (4) is insignificantly negative, which suggests that the migration from cities with high intergenerational occupational mobility to cities with low intergenerational occupational mobility is insignificant. In conclusion, the regressions (1)–(4) confirm that cities with high levels of intergenerational occupational mobility have a significant "agglomeration effect" on mobile labor by both reducing the emigration of natives and increasing the immigration of labor from cities with lower levels of intergenerational occupational mobility. Spatial heterogeneity in the level of intergenerational occupational mobility leads to difference in the level of intergenerational occupational mobility between two cities, which constitute a "pull" factor for one city and a "push" factor for the other if the migration behavior occurs between the two cities.

4.1.4. Heterogeneity Analysis (Combining Pull Factor and Push Factor)

The empirical results in Table 3 show that rural laborers, highly educated laborers, and highly educated rural laborers are the groups that are more likely to move out of their registered cities. However, where are their migration destinations? This section focuses on finding the motivation behind the emigration behavior based on the information of surveyed cities. The regression coefficients of ab_occ_mobility in Table 6 are significantly positive at the 1% level of significance, and the regression coefficients with rural samples are bigger than those with city samples. However, the regression coefficients with highly educated samples are only greater than the coefficient uses urban samples with below-mean education attainment. The coefficient in regression (3) implies that as the intergenerational occupational mobility level increases by one percentile unit at surveyed cities, the probability of the moving in of rural labor with below-mean educational attainment rises by over 130%. This conclusion explains the phenomenon of "Seasonal Migration of Peasants" in China to a certain extent. Table 6 reveals that the direction of labor migration from cities with low intergenerational occupational mobility levels to cities with high intergenerational mobility levels is general, and the urban–rural attributes or educational attainment do not have a significant effect on it. Combining these with the results in Table 3, we can understand how regional intergenerational occupational mobility affects labor migration behavior: an increase in the level of intergenerational occupational mobility in cities will first reduce the willingness of natives to move out and attract mobile labor force through the "agglomeration effect"; secondly, it will squeeze out part of the labor through the "crowding-out effect", but those who are crowded out or who move out voluntarily will migrate to cities with higher levels of intergenerational occupational mobility.

Table 6. Heterogeneity analysis.

Migrate	(1)	(2)	(3)	(4)
	Rural_edu_high	**City_edu_high**	**Rural_edu_low**	**City_edu_low**
ab_occ_mobility	0.9142 ***	0.7941 ***	1.3329 ***	0.4648 ***
	(0.2025)	(0.1928)	(0.2091)	(0.1748)
Individual	YES	YES	YES	YES
City01	YES	YES	YES	YES
City02	YES	YES	YES	YES
City03	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES
N	58,500	11,311	25,938	11,350
Pseudo R^2	0.2667	0.0825	0.3082	0.1158

*** indicate 1% levels of significance; standard errors are in parentheses, and all regression cluster standard errors are at the city level; Rural_edu_high, Rural_edu_low, City_edu_high and City_edu_low indicate rural highly educated labor, rural labor with below-mean education attainment, urban highly educated labor and urban labor with below-mean education attainment, respectively.

4.2. Endogeneity Analysis

4.2.1. IV-Probit Regression

The level of regional intergenerational occupational mobility is a result of long-term adjustments to the socioeconomic structure, and regional tariff changes can significantly influence intergenerational occupational mobility [45]. Tariff changes before and after China's WTO accession play an important role in the formation of spatial heterogeneity in intergenerational occupational mobility levels in China but do not affect current labor migration behavior directly. In addition, the intergenerational occupational mobility level measures the average occupational rank of a child whose father's occupation ranks below the national median. Thus, the ratio of children whose occupation ranks above the 50th percentile (within his/her age cohort) can directly influence the regional intergenerational occupational mobility level, but would not impact the migration decision directly. Therefore, this paper selects the regional tariff changes between 2000 and 2005 [1,41] and the ratio of children whose occupational percentile is above the 50th of their occupational distribution as the instrumental variables. After using the IV-probit approach to deal with the endogeneity, the results are shown in Table 7. Compared with the results of the baseline regression, the absolute value of the coefficient of ab_occ_mobility is significantly higher, indicating that the existence of the endogeneity causes the regression result to underestimate the effect of regional intergenerational occupational mobility level on migration behavior. Meanwhile, the *p*-value of the Wald test of exogeneity is 0.0005, which rejects the original hypothesis that the explanatory variable is exogenous at the 1% level of significance.

Table 7. IV regression.

Migrate	(1)	(2)	(3)	(4)
	IV-Probit	**Std-IV**	**GenInst**	**GenExtInst**
ab_occ_mobility	−0.6236 *** (0.1649)	−0.1778 *** (0.4967)	−0.0150 *** (0.0054)	−0.0148 *** (0.0054)
Individual	YES	YES	YES	YES
City01	YES	YES	YES	YES
City02	YES	YES	YES	YES
City03	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES
N	75,767	75,767	75,767	75,767
Wald test of exogeneity (p value)	0.0005			
Kleibergen-Paap rk LM statistic (p value)		0.0003	0.0000	0.0000
Cragg-Donald Wald F statistic (f value)		3180.495	5875.148	5819.285
Kleibergen-Paap rk Wald F statistic (f value)		10.413	106.895	105.237
Hansen J statistic (p value)		0.1713	0.1048	0.1098
C statistic (p value)				0.3769

*** indicate 1% levels of significance; standard errors are in parentheses, and all regression cluster standard errors are at the city level; IV-probit: instrumental variable regression for discrete choice models; StdIV: two-stage least squares instrumental variable regression; GenInst: regression based on model's heteroskedasticity; GenExtInst: internal instrumental variables constructed based on all sets of exogenous variables and two external instrumental variables.

In addition, we use the IV-2SLS method to deal with exogeneity and the result of regression (2) shows that the coefficient of the explanatory variable is significantly negative at the 1% significance level. Compared to the coefficient in regression (1), the sign and significance level of the coefficient does not change, except for the absolute value of the coefficient. This means that the regression results using the IV-probit method are robust. The p-value of the Underidentification test is 0.0003, the f-value of the Weak identification test is significantly greater than 10, and the Hansen J statistic is 0.1713. These suggest that the instrumental variables are not unidentifiable, weakly identified or over-identified and that the selected instrumental variables have strong explanatory power.

4.2.2. Using Heteroscedasticity to Estimate Endogenous Regression Models

Although our use of IV-probit and the IV-2SLS method rules out potential bias in our empirical estimation because of the reverse causality, there may still exists a few identification threats. For instance, the measurement of regional intergenerational occupational mobility may have some potential errors, thus causing an endogeneity problem. To address this concern, we follow a new identification strategy proposed by Lewbel [50], which utilizes a heteroskedastic covariance restriction to construct internal IVs. This is a feasible method to test the robustness of results using traditional IV regression, but it also has some shortcomings. (1) Estimates based on internal IVs (heteroskedasticity-based IVs) are potentially sensitive to the choice of instrument. (2) Lewbel's [50] method relies on higher moments: the covariance between the regressors and the product of heteroskedastic errors is 0. Therefore, we use two methods to select IVs in the process of constructing internal instrumental variables based on model heteroskedasticity. (1) Construct IVs using all sets of exogenous variables for different specifications to test the robustness of our results. (2) Add two external instrumental variables based on method (1) to correct it. The regression results are shown in regressions (3) and (4) in Table 7.

Both methods of constructing internal instrumental variables pass the Breusch–Pagan test, i.e., the exogenous variables chosen by both methods satisfy the precondition of model heteroskedasticity. The heteroskedasticity-based IV and conventional IV-2SLS are applicable to linear regression models, while the IV-probit method is applicable to discrete choice models. Therefore, the absolute values of the regression coefficients using these three methods are not compared in this paper. However, according to the results in (1) to (3), the regression results using heteroscedasticity-based IVs fully confirm the robustness of the "agglomeration effect" of regional intergenerational occupational mobility level on migrants. In regression (3), the p value of the Underidentification test is 0.0000, the F statistical value of the Weak identification test is 106.895, and the p value of the Hansen J statistic is 0.1048. It shows that the heteroscedasticity-based IVs do not have the problems of unrecognizability, weak recognition, or over-recognition. Meanwhile, the regression results of using the second instrumental variable selection method to construct internal IVs (Table 7(4)) further confirm the robustness of the regression results of regression (3). Overall, the "agglomeration effect" of cities with high levels of intergenerational occupational mobility on mobile labor is robust.

4.3. Mechanism Analysis

4.3.1. Urban Comprehensive Incremental Competitiveness

Labor migration is a process of the spatially optimal reallocation of resources in order to maximize an individual's socioeconomic value or to pursue the maximization of future generations' income and the cumulative income of families. The heterogeneity of a city's ability to create current value and sustainable future value is an important pull factor influencing the migration decision of mobile labor. The ability of cities to create value is the specific connotation of urban competitiveness, and there is a positive cyclical accumulation relationship between it and talent agglomeration. Based on the factor endowment and environment, cities form a strong comprehensive incremental competitiveness through the agglomeration of talents, enterprises, and other economic agents and create greater value more efficiently and more quickly than other cities, which in turn affects the competitiveness input of cities and the agglomeration process of talents and enterprises. Cities with high comprehensive incremental competitiveness may provide more value creating opportunities for local labor, which mean they are more likely to achieve upward intergenerational occupational mobility, thus reducing the willingness of the household registered people to move out. In this paper, we take the city's comprehensive incremental competitiveness index as the mediating variable, and use the traditional "three-step" method to analyze the mediating effect of the city's comprehensive incremental competitiveness based on the mediating effect analysis framework proposed by Baron and Kenny [51]. The regression results are shown in regressions (1)–(3) in Table 8.

Table 8. Mechanism analysis.

	(1)	(2)	(3)	(4)
	Migrate	**Growth_compe**	**Migrate**	**Ab_edu_return**
ab_occ_mobility	−0.1229 *** (0.0209)	0.0062 *** (0.0003)	−0.1201 *** (0.0210)	0.0683 *** (0.0043)
Growth_compe			−0.5787 ** (0.2787)	
Individual	YES	NO	YES	NO
City01	YES	YES	YES	YES
City02	YES	YES	YES	YES
City03	YES	YES	YES	YES
FE (Province)	YES	YES	YES	YES
N	74,451	74,451	74,451	74,451
Pseudo R^2	0.0699	0.9711	0.0699	0.8449

** and *** indicate 5% and 1% levels of significance, respectively; standard errors are in parentheses, and all regression cluster standard errors are at the city level; regressions (1)–(3) use the OLS method. Growth_compe indicates a city's comprehensive incremental competitiveness index, while Ab_edu_return represents city's absolute educational returns level.

Regression (1) is a baseline regression analysis using the OLS method, and the regression coefficient of ab_occ_mobility is significantly negative at the 1% level of significance, compared with the baseline result of *Logit*, both of which only change in the numerical magnitude of the absolute value of the coefficients. This conclusion confirms the robustness of the effect of intergenerational occupational mobility on migration. The regression coefficient of regression (2) with the city's comprehensive incremental competitiveness index as the explanatory variable is significantly positive at the 1% level of significance, i.e., the relationship between a city's intergenerational occupational mobility level and comprehensive incremental competitiveness index is positive. In regression (3), we add the mediating variable to regression (1) to perform an empirical analysis. The coefficients of the explanatory variable and the mediating variable are significantly negative at the 1% and 5% levels of significance, respectively. This implies that the "agglomeration effect" of the intergenerational occupational mobility level on mobile labor is partly achieved by enhancing the comprehensive incremental competitiveness of the cities.

4.3.2. Degree of Absolute Educational Returns

From the previous sections, we find that highly educated laborers and rural laborers with high educational attainment are more likely to migrate from their registered cities and move to cities with a higher degree of intergenerational occupational mobility. What is the incentive behind their migration behavior? Based on the multi-factor "pull–push theory" and the "human capital investment theory", the spatial heterogeneity of incomes is the dominant driving factor of migration. This means that improving education attainment would be an effective way to help mobile labor pursue the maximization of economic benefits; that is, highly educated labor is more willing to migrate. To measure the impacts of educational factors on labor migration, this paper adopts Chetty et al.'s [37] method of accounting for the absolute regional intergenerational occupational mobility index to construct the index of regional absolute educational returns and the expected occupational percentile rank of labor with an education level above the 50th percentile at the education attainment distribution of the core sample for mediating effects analysis.

The coefficient of regression (4) in Table 8 is significantly positive at the 1% significance level, which means that cities with high levels of intergenerational occupational mobility also have a high degree of absolute educational returns. Following the traditional "three-step" test [51], we add the absolute educational returns index into the control variable sets of regression (1) to perform a regression. Unfortunately, the regression results are statistically insignificant. Therefore, this paper conducts a bootstrap mediating effect test with absolute educational returns as the mediating variable, and the results are shown in Table 9: the indirect effect is 0.0007 and the direct effect is 0.0216, which means that cities with high levels of absolute educational returns will increase the probability of emigration. These results explain the migration of highly educated laborers to some extent, regardless of whether their migration behavior is voluntary or "forced". Given the general law of migration from cites with low intergenerational occupational mobility levels to those with higher levels, the effect of absolute educational returns on migration is "two-way"; a high level of absolute educational returns in origin cities incentivizes native labor to migrate out by reducing relative migration costs. A high level of absolute educational returns in destination cities attracts mobile labor from cities with lower levels of absolute educational returns to immigrate by increasing expected incomes.

Table 9. Bootstrap intermediary effect test.

Intermediate Variable: Index of Absolute Educational Returns (Ab_edu_return)					
	Observed Coef.	**BootstrapStd. Err.**	**[95% Conf. Interval]**		
indirect_effect	0.0007239	0.00019901	[0.0003326 [0.0003368	0.0011213] 0.0011269]	(P) (BC)
direct_effect	−0.02162232	0.0039026	[−0.0295396 [−0.029494	−0.147455] −0.014739]	(P) (BC)

5. Discussion

Among the existing literature, the articles most related to this paper can be broadly divided into three branches: (1) Constructing regional intergenerational mobility based on individual or household income data in developed countries. Some scholars have calculated the intergenerational elasticity (IGE) between father and son based on American household income data as an indicator of regional relative intergenerational mobility [52,53], which is made into a coefficient by regressing the log child income with the log parent income. Others have determined the income percentile rank of children (in their age cohorts) and their fathers' income percentile rank in the national income distribution and indicated intergenerational mobility as the slope of the rank–rank relationship [29,37,42]. (2) Population migration vs. occupational mobility. Differences in employment opportunities and career restrictions between regions usually force individuals to develop their careers through migration [30]. The results of a lagged regression model based on the 1970 occupation access data show that groups that have recently migrated are more likely to realize the upward occupational mobility than non-migrants [35]. In addition, Blau and Duncan [30] found that migrant workers would achieve higher occupational ranks and experience higher upward mobility relative to non-migrants. (3) Migration and intergenerational occupational mobility. Long and Ferrie [32] investigated rural–urban migration in Britain in the 19th century and found that the intergenerational occupational mobility of migrants in 1881 increased compared with that of their fathers in 1851. In addition, parents' migration improves intergenerational mobility and even upward intergenerational mobility [30,32–34]. This is because parental migration affects human capital investment in offspring and directly influences offspring's income and intergenerational mobility in adulthood [36]. As far as we know, studies measuring the level of intergenerational mobility in developing countries and its impact on population migration are few and far between, and our study is an important complement and innovation to such studies.

1. A major challenge in studying population migration and intergenerational mobility in developing countries lies in obtaining accurate income data. In China, for example, in the absence of income data, some scholars have used the survey information of respondents' own social status and their family social status at age 14 to construct data on the social status of fathers and sons based on data from the China Labor Dynamics Survey and have used this as a benchmark for measuring regional intergenerational mobility [26]. Due to the strong subjectivity of family social status information, the regional intergenerational mobility index measured by this method needs to be further tested, given that intergenerational occupational change has also been used as a measure of mobility and is superior to income change in some respects [32]. In addition, the occupation's weighted average educational attainment is a better proxy for a person's stable economic status and is closely linked to other socioeconomic characteristics that better explain the phenomenon of intergenerational occupational mobility over time than income [54]. Therefore, this paper constructs an occupational education intensity index based on individual education information instead of income, and ranks occupations based on this index to measure the intergenerational occupational mobility, which can more truly reflect the intergenerational mobility level in cities.

2. By connecting "push factors", "pull factors" and "third factors", we analyze the general law of migration from the "two-way" mobility behavior of immigration and emigration and correct the bias of existing studies that equate or separate push and pull factors [29,38,39]. Based on Chinese data, studies that equate or separate pull and push factors find that high levels of intergenerational mobility reduce the probability of individuals emigrating; conversely, low levels of intergenerational mobility have a crowding-out effect on people [24]. However, the regression results of this paper find that there are three effects of increasing the level of intergenerational occupational mobility on migration: (1) It significantly reduces the likelihood of the emigration of local laborers. (2) It enhances the immigration attractiveness of cities for mobile laborers, especially those from cities with lower levels of intergenerational occupational mobility. (3) It has a crowding out effect on some laborers, such as rural laborers, high educated laborers, and rural highly educated laborers. Labor migration follows the general law of moving from cities with a low degree of intergenerational occupational mobility to cities with high intergenerational occupational mobility levels. The results of this paper reveal the crowding out effect of high intergenerational mobility on some specific local labor, which has not been found in previous articles. It thus has stronger explanatory power for some phenomena that exist in the development of China's mobile population, such as "inland–coastal migration", "reflow", "tide of migrant workers" and so on.
3. Using logit, IV-probit, traditional IV, heteroscedasticity IV and other regression methods, this paper analyzes the influencing factors of individual migration from a microscopic perspective and provides new methods for the study of labor migration decision factors in developing countries. The empirical methods of existing studies mainly include the semiparametric maximum score estimation method [29], multinomial logit regression method [55], and OLS regression method [26]. In this paper, we establish the dummy variable of individual willingness to migrate and analyze the impact of regional intergenerational occupational mobility on population migration using the logit regression method. In the treatment of the model endogeneity problem, traditional IV and IV based on heteroskedasticity produce similar results in empirical analyses [50]. We further use the approach of Lewbel [50], heteroskedasticity-based IVs, to test the robustness of the regression results of the traditional IV.
4. The findings of this paper fill a gap in the research field of demographic migration factors, highlighting the significant impact of non-economic factors on population mobility. The analysis of the feasibility of using a mobile labor force to compensate for the lack of demographic dividend during the demographic dividend transition from the perspective of city-level intergenerational occupational mobility has positive implications for guiding the achievement of both SDGs 3 (ensuring healthy lifestyles and promoting the well-being of people of all ages) and 8 (promoting sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all). However, the article does not have further in-depth theoretical discussions. Future research direction should focus on exploring the mechanisms that guide the free movement of labor to achieve a sustainable demographic dividend.

Mechanistic analyses have found that improving a city's comprehensive incremental economic competitiveness, i.e., its ability to create current and future benefits, can effectively increase the "agglomeration effect" of a city on local labor. In contradiction to existing research, however, it is generally accepted that enhanced investment in education and health is critical for fully reaping the benefits of a demographic window of opportunity [5]. However, the findings of this paper show that increasing the absolute education returns in cities increases to some extent the probability of individuals moving out, i.e., accelerating the disappearance of the demographic dividend. However, following the migration law, laborers' migration to cities with higher absolute education returns instead increases the overall welfare of society, i.e., the demographic dividend is more fully unleashed. The government played an important role in the process of cultivating and utilizing the first demographic dividend by promoting high-quality economic development and increasing spending on education to improve the comprehensive skills of the labor force.

Over the period of transition from the first demographic dividend to the second demographic dividend, looking through the disordered migration phenomenon to discover migration patterns and to guide the orderly flow of migrants is an effective solution to create a sustained demographic dividend and realize balanced and stable economic growth. To avoid the vacuum between two demographic dividends, policymakers should first break down the institutional barriers that prevent the free flow of labor, and guide the flow of labor from rural to urban areas, from coastal to inland areas, from agriculture to manufacturing industries, and from low value-added industries to high value-added industries, so as to further release the first demographic dividend. Secondly, policy makers should improve the human capital of all age groups, especially that of the elderly population, by developing education and training; improving the medical security system to extend the life expectancy of the elderly population; and appropriately delaying the retirement time to increase the labor force participation rate of the elderly population based on China's current "aging" population. In this way, the first demographic dividend and the second demographic dividend can be successfully bridged.

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