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Dynamic Effects of Prefecture-Level Industrial Structure on Labor Migration: Evidence from Chinese Census Data

Xiaolan Yang

yangxiaolan@cufe.edu.cn

Central University of Finance and Economics

Xingzhi Yao

Fudan University

Xuankai Zhao

Central University of Finance and Economics

Xinyue Zhu

Chinese Academy of Science and Technology for Development

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Abstract

Cross-regional labor migration, driven by regional disparities in development, has been a defining feature of China's economic transformation. Using census data, this study employs a conditional logit model to examine how prefecture-level industrial structure shapes migrants' destination choices. The results show that prefectures with larger nonagricultural sectors are more likely to be selected than those with larger agricultural sectors. Moreover, the effect of prefecture-level industrial structure follows an inverted-U pattern over 1996–2015, strengthening before 2010 and weakening thereafter. The mechanism analyses identify wage income and employment opportunities as two important channels. After 2010, however, diminishing marginal wage gains and rising living costs associated with industrial agglomeration appear to have reduced the attractiveness of the nonagricultural sector. The heterogeneity analyses show that the pull effect of the nonagricultural sector is stronger among workers engaged in industrial production and production-support tasks, as well as among women, younger workers, and more highly educated workers.

1 Introduction

One of the most salient features of China's demographic landscape is the redistribution of population across space, which has generated large-scale migration. By 2015, the migrant population had exceeded 240 million, accounting for roughly one-sixth of the national population[1]. Over the same period, China's industrial structure changed rapidly. Between 1995 and 2015, the agricultural sector's share declined from 19.6% to 8.9%, whereas the nonagricultural share rose from 80.5% to 91.1% (China Statistical Yearbook 2016)[2]. Against this backdrop, the relationship between industrial structure and population migration has attracted considerable scholarly attention (Gerritse, Wang, and Oort 2026). Building on this literature, the present study examines how industrial structure shapes the destination choices of workers migrating across Chinese prefectures, with potential implications for other countries in the Global South facing similar challenges.

Existing studies have examined how regional industrial structure attracts migrant workers by shaping expected economic returns (Li, Shen, and Gu 2025; Wang and Chen 2024; Wu et al. 2018). Because structural transformation is a prolonged process in China, its effects are unlikely to remain constant over time. In contrast to studies that focus on a specific time window or estimate an average effect over the entire study period (Zhao et al. 2025), this paper investigates the long-run evolution of the effect of industrial structure between 1996 and 2015. Given the challenges posed by an expanding migrant population and continuing structural transformation, the dynamic analysis provides a more comprehensive account of how industrial structure affects labor migration and how this effect evolves over time.

The literature has also paid insufficient attention to the role of individual characteristics in labor migration, particularly workers' occupations. Occupations capture the tasks that workers actually perform and therefore offer a more nuanced perspective than broad industry classifications (Ma, Qiu, and Son 2024)[3]. Analyzing individual migration choices solely through industry classifications may produce incomplete or even misleading conclusions. For example, regions with well-developed industrial sectors may be more likely to attract machine operators than purchasing staff employed by industrial firms, even though both groups work in the same sector. A detailed examination of occupational heterogeneity is therefore warranted because it can provide a clearer explanation of the pull mechanisms underlying labor migration.

Using sample data from the 2000 and 2010 China Population Censuses and the 2005 and 2015 China Population Mini-Censuses, this paper employs a conditional logit model to estimate the effect of prefecture-level industrial structure. Industrial structure is measured by the ratio of the agricultural sector to the nonagricultural sector. The coefficient on this ratio is significantly negative for migrants' destination choices throughout 1996–2015. Specifically, the nonagricultural sector is positively correlated with the probability that a prefecture is chosen, whereas the agricultural sector is negatively correlated with that probability. The magnitude of the effect follows an inverted-U pattern, increasing initially and declining after 2010. The empirical results further indicate that prefecture-level industrial structure affects labor migration through the wage-income and employment-opportunity channels. More specifically, the nonagricultural sector offers higher wages and more jobs, thereby attracting migrant workers. Nevertheless, diminishing marginal wage gains and rising living costs may weaken the pull effect of prefectures' nonagricultural sectors, accounting for the declining phase after 2010.

To assess the robustness of the baseline results, the paper conducts a series of sensitivity analyses addressing concerns about the identification strategy. First, an interaction term is used to test the inverted-U pattern in the dynamic effect of industrial structure. Second, the analysis distinguishes between the secondary and tertiary industries within the nonagricultural sector and finds that the tertiary industry exerts a stronger pull effect on migrant workers. Third, the total number of sent-down youths in each province is used as an instrumental variable to mitigate endogeneity concerns. Fourth, additional sensitivity checks vary the scope of the choice set. Specifically, the set of candidate prefectures is either held constant across census waves or restricted to prefectures in the destination province and adjacent provinces. These results also provide support for the independence of irrelevant alternatives assumption. Taken together, the tests confirm the robustness of the baseline estimates of the effect of prefecture-level industrial structure on labor migration.

The heterogeneity analyses reveal substantial variation in the effects of prefecture-level industrial structure. Agricultural production workers are less responsive to industrial structure, whereas production and transportation equipment operators, clerical workers, and professional technicians are more responsive. Commercial and service workers, by contrast, exhibit no significant heterogeneous effects. These findings suggest that the effect of industrial structure is closely linked to the occupational task composition of local labor demand. The results also show that women, younger workers, and more highly educated workers are more responsive to prefecture-level industrial structure. In other words, the nonagricultural sector exerts a stronger pull effect on these groups. Their greater compatibility with the labor demand of the nonagricultural sector may also make them more responsive to the wage income and employment opportunities available at the destination.

This paper contributes to three strands of literature. The first concerns structural transformation, a long-standing and important topic in development economics. During this process, the center of economic activity gradually shifts from the primary industry toward the secondary and tertiary industries (Caselli and Coleman II 2001; Storesletten, Zhao, and Zilibotti 2026), while capital and labor are reallocated across industries and regions (Bustos, Garber, and Ponticelli 2020; Duarte and Restuccia 2010). Because structural transformation is a long-run process, estimates of its average effect over a specific period cannot capture its full implications. The changing effect of structural transformation on labor migration therefore warrants greater attention. Whereas Wu et al. (2018) examine the effect of the tertiary industry on interprovincial population migration from 1995 to 2015, this paper investigates the dynamic effects of the agricultural and nonagricultural sectors at the prefecture level over the same period. The dynamic analysis provides more comprehensive evidence on the long-run effects of structural transformation in China.

The second strand is the migration literature. As a key driver of population reallocation, labor migration has received extensive scholarly attention. Workers migrate across industries and regions in pursuit of higher wages (Amior 2024; Ranis and Fei 1961), more employment opportunities (Foschi et al. 2025), better public services (Wang, Lin, and Tang 2024), lower living costs (Murphy, Muellbauer, and Cameron 2006), higher environmental quality (Cao et al. 2026; Zhan et al. 2025), and stronger human-capital externalities (Adda, Dustmann, and Görlach 2022; Moretti 2004). Although the literature acknowledges migrant heterogeneity, it typically treats the issue only briefly (Wang, Lin, and Tang 2024; Zhou, Zou, and He 2026). By demonstrating how industrial structure affects labor migration in China and examining heterogeneity across occupations in depth, this paper adds more detailed evidence to the migration literature.

Finally, the paper relates to the literature on labor-supply responses to economic returns. Migrant labor supply is commonly understood as a response to expected economic returns (Borjas 1987; Zhao, Harris, and Gao 2026). In particular, the nonagricultural sector attracts migrant workers by raising wages and expanding employment, a pattern that also operates at the regional level (Cociuba and MacGee 2026; Ding et al. 2026). Accordingly, this paper examines the effect of prefecture-level industrial structure through the wage-income and employment-opportunity channels and provides empirical evidence from China. Because individual characteristics differ, labor-supply responsiveness to economic returns also varies across groups. Women, younger workers, and more highly educated workers exhibit greater labor-supply elasticities with respect to economic returns (Eckstein, Keane, and Lifshitz 2025; Keane 2022; Herkenhoff, Phillips, and Cohen-Cole 2024; Wozniak 2010). This evidence offers an additional perspective from which to interpret the heterogeneous results.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 describes the data, samples, variables, and identification strategy. Section 4 examines the effect of prefecture-level industrial structure on migrants' destination choices and presents the robustness checks. Section 5 investigates the underlying mechanisms and heterogeneous effects across migrant groups. Section 6 concludes.

2 Conceptual Framework

Migration is strongly associated with regional economic growth (Greenwood 1981), and regional industrial structure is an important driver of labor mobility. In the classical accounts of Petty (1690) and Clark (1940), the shift in economic activity from the agricultural sector toward the nonagricultural sector is accompanied by a corresponding reallocation of labor across sectors. The relative sizes of the agricultural and nonagricultural sectors vary considerably across Chinese prefectures[4]. These differences in industrial structure translate into spatial differences in labor demand and, in turn, drive cross-prefectural labor migration.

Building on Lee's (1966) push-pull framework, this paper examines the effect of prefecture-level industrial structure on migrants' destination choices from the perspective of destination-specific pull factors. Migrant workers select destination prefectures according to the economic returns available to them (Ma, Li, and Wu 2024; Sjaastad 1962). First, the productivity gap between the agricultural and nonagricultural sectors generates a wage premium in the latter (Gollin, Lagakos, and Waugh 2014), which in turn affects prefectural wage levels. Higher expected income at the destination exerts a pull effect on migrant workers (Harris and Todaro 1970; Shen 2012). Second, economies of scale allow the nonagricultural sector to generate larger and more concentrated labor demand than the agricultural sector (Krugman 1991; Moretti 2010). Prefectures with larger nonagricultural sectors therefore exhibit stronger labor demand and attract more migrant workers. In sum, the wages and employment prospects offered by prefectures shape migrants' destination choices (Gries, Kraft, and Simon 2016). At the same

time, structural transformation and industrial agglomeration can generate adverse consequences, including diminishing marginal economic returns and rising living costs (Chen et al. 2025; Ji and Zheng 2025). By reducing economic returns, these forces may lower the probability that migrants choose a given prefecture.

Lee's (1966) framework also emphasizes the role of individual characteristics in migration decisions. Prefecture-level industrial structure is likely to affect migrant groups differently because sectors differ in their demand for labor (Lewis 1954). Compared with the agricultural sector, the nonagricultural sector demands different types of workers because its occupational tasks differ (Gollin, Lagakos, and Waugh 2014). The two sectors also differ in their demand for women, younger workers, and more highly educated workers (Autor and Dorn 2013; Lee 2024; Porzio, Rossi, and Santangelo 2022). These cross-sectoral differences in labor demand generate corresponding differences across prefectures, leading migrant groups to respond heterogeneously to industrial structure. Because destination choice is driven primarily by expected economic returns, women, younger workers, and more highly educated workers may also respond more strongly to cross-prefectural differences in industrial structure.

3 Empirical Strategy

3.1 Data, Samples, and Variables

The main analysis uses two types of data. Individual information on labor migration and personal characteristics is drawn from the 2000 and 2010 China Population Censuses and the 2005 and 2015 China Population Mini-Censuses. Prefecture-level characteristics are obtained from the China City Statistical Yearbooks.

The cross-prefectural migrant sample is constructed using the following criteria: (i) the individual does not reside in the prefecture of household registration at the census reference date and moved within the preceding five years; (ii) the individual migrated for employment or business purposes; (iii) the individual is 16–64 years old; (iv) the individual is employed and is not a student living at school; and (v) migrants whose destinations are the four centrally administered municipalities of Beijing, Tianjin, Shanghai, and Chongqing are excluded.

Because the census reference date falls in November of each survey year, the migrant samples are matched to predetermined characteristics of the candidate prefectures. Candidate prefectures are those recorded in the census samples for which the required prefecture-level characteristics are available. The predetermined characteristics are measured as averages over the five years preceding the census reference date. For example, the analysis uses average prefecture-level characteristics for 1995–1999 to explain the destination choices of migrants observed in the 2000 census.

The dependent variable indicates whether an individual chooses a given candidate prefecture. It equals one if the prefecture in which the individual resides at the census reference date matches the candidate prefecture and zero otherwise. The key independent variable measures the industrial structure of the candidate prefecture using the ratio of the agricultural sector to the nonagricultural sector (A/N-A). It is defined as the value added of the primary industry divided by the combined value added of the secondary and tertiary industries. Section 4.2 also examines the relative pull effects within the nonagricultural sector using the ratio of secondary-industry value added to tertiary-industry value added.

The models include a set of predetermined characteristics of the candidate prefectures as controls. The first group comprises the natural logarithms of prefectural GDP [ln(GDP)], population [ln(Population)], and fiscal expenditure [ln(Fiscal expenditure)], which measure economic development, population size, and government

capacity, respectively. The second control is fixed-asset investment (FA), measured as total fixed-asset investment relative to GDP, which captures the overall level of industrial development. The third group comprises medical services (MS; the logarithm of hospital beds), secondary education services (SES; the logarithm of teachers per secondary-school student), primary education services (PES; the logarithm of teachers per primary-school student), and transportation services (TS; the logarithm of total passenger traffic). These variables control for differences in public-service provision and living costs across candidate prefectures.

3.2 Identification Strategy

To estimate the effect of industrial structure on labor migration, the paper employs a conditional logit model of migrants' choices among candidate prefectures. Following McFadden (1974), the probability that migrant i chooses candidate prefecture j is expressed as follows:

(1) $$Prob(Choice_{ij} = 1) = \frac{exp(\beta\ X_{ij} + \theta_{\ ij})}{\sum_{j=1}^{J} exp(\beta\ X_{ij} + \theta_{\ ij})}$$

where $Choice_{ij}$ indicates whether migrant i chooses candidate prefecture j (yes = 1; no = 0). X_{ij} denotes the industrial structure of candidate prefecture j for migrant i, measured as the ratio of the agricultural sector to the nonagricultural sector. $\theta_{\ ij}$ is a vector of prefecture-level controls, including the logarithms of GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. The coefficient β measures the effect of prefecture-level industrial structure on destination choice, and its absolute value captures the magnitude of this effect. A significantly negative β indicates that a prefecture becomes more attractive to migrant workers as the agricultural share decreases and the nonagricultural share increases. Table D1 reports summary statistics for the prefecture-level characteristics.

In addition to estimating the overall effect of prefecture-level industrial structure, the paper examines whether this effect varies with individual characteristics. Following Greene (2008), heterogeneous effects are estimated by adding interactions between prefecture-level industrial structure and individual characteristics to the conditional logit model:

(2) $$Prob(Choice_{ij} = 1) = \frac{exp(\beta\ X_{ij} + \rho\ X_{ij}Z_i + \theta_{\ ij})}{\sum_{j=1}^{J} exp(\beta\ X_{ij} + \rho\ X_{ij}Z_i + \theta_{\ ij})}$$

where Z_i represents an individual characteristic of migrant i. The remaining variables are defined as in Eq. (1). The coefficient ρ captures heterogeneity associated with the individual characteristic. When β is negative, a significantly negative ρ implies that the effect of industrial structure on migration becomes stronger as Z_i increases. Equivalently, the nonagricultural sector exerts a stronger pull effect on migrants with higher values of the characteristic than does the agricultural sector. Summary statistics for the individual characteristics are also presented in Table D1.

4 Main Results

4.1 Baseline Analysis

Table 1 presents the estimates of Eq. (1). Columns 1–4 examine migration during 1996–2000, 2001–2005, 2006–2010, and 2011–2015, respectively. Across the two-decade period, prefecture-level industrial structure has a

significant negative effect on migrants' destination choices. Specifically, the nonagricultural sector in a candidate prefecture positively affects the probability that migrants choose that prefecture, whereas the agricultural sector has a negative effect.

Table 1
Dynamic Effects of Industrial Structure on Labor Migration

	(1)	(2)	(3)	(4)
	Choice	***Choice***	***Choice***	***Choice***
A/N-A	-2.947***	-3.190***	-5.793***	-2.638***
	(0.101)	(0.089)	(0.078)	(0.204)
ln(GDP)	1.458***	1.043***	0.734***	0.781***
	(0.033)	(0.022)	(0.012)	(0.035)
ln(Population)	-1.573***	-0.495***	-0.191***	-0.253***
	(0.029)	(0.016)	(0.012)	(0.030)
ln(Fiscal expenditure)	-0.203***	0.705***	0.261***	-0.054*
	(0.024)	(0.019)	(0.010)	(0.029)
FA	0.039	0.013	0.146***	-1.083***
	(0.101)	(0.064)	(0.023)	(0.052)
MS	0.264***	-0.893***	-0.200***	-0.061*
	(0.027)	(0.023)	(0.016)	(0.034)
SES	-4.054***	-2.017***	0.964***	-0.532***
	(0.128)	(0.073)	(0.030)	(0.056)
PES	0.485***	-1.092***	-2.339***	-1.145***
	(0.097)	(0.047)	(0.025)	(0.054)
TS	0.784***	0.435***	0.508***	0.422***
	(0.015)	(0.008)	(0.006)	(0.014)
Individuals	22,666	61,185	152,159	24,871
Prefectures	227	279	280	285
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.280	0.308	0.251	0.177

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. *** p < 0.01, ** p < 0.05, * p < 0.10.

Appendix A estimates the effects of the agricultural and nonagricultural sectors separately. Table A1 shows that, relative to the agricultural sector, the nonagricultural sector has a positive effect on labor migration, consistent with the baseline results. Table 1 also provides preliminary evidence that the magnitude of the effect of prefecture-level industrial structure first increases and then decreases over time, forming an inverted-U pattern.

The inverted-U pattern may, however, be driven by differences across census samples. To address this concern, the paper conducts a dynamic-effect analysis. It pools adjacent census samples and defines a period indicator (Year), coded zero for the earlier sample and one for the later sample. The model then includes an interaction between prefecture-level industrial structure and the period indicator. For example, the 2000 and 2005 samples are pooled, and Year equals one for migrants drawn from the 2005 sample and zero for those drawn from the 2000 sample. The same procedure is applied to the pooled 2005–2010 and 2010–2015 samples. In Eq. (2), the interaction coefficients reveal changes in effect magnitude. The coefficients in columns 1 and 2 of Table 2 are negative, indicating that the effect strengthened between 1996 and 2010. The positive interaction coefficient in column 3 indicates that the effect weakened after 2010. These results confirm the inverted-U pattern in the effect of industrial structure on labor migration.

Table 2
Dynamic-Effect Analysis

	(1)	(2)	(3)
	Choice	***Choice***	***Choice***
A/N-A	-2.465***	-3.024***	-6.349***
	(0.064)	(0.057)	(0.073)
A/N-A × *Year*	-1.576***	-4.340***	1.786***
	(0.068)	(0.055)	(0.110)
Controls	Yes	Yes	Yes
N	22,215,797	59,675,135	49,692,755
$PseudoR^2$	0.290	0.252	0.235

Note: Columns 1–3 examine changes in the effect of prefecture-level industrial structure across the 2000–2005, 2005–2010, and 2010–2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

4.2 Analysis of the Nonagricultural Sector

The baseline results identify a positive pull effect of the nonagricultural sector relative to the agricultural sector. Because the nonagricultural sector comprises the secondary and tertiary industries, it is useful to compare their relative attractiveness. The key independent variable is therefore replaced by the ratio of secondary-industry value added to tertiary-industry value added (SI/TI). Columns 1–4 of Table 3 estimate the relative effect using Eq. (1). The results indicate that prefectures with larger tertiary industries exert a significantly stronger pull effect on migrants' destination choices than prefectures with larger secondary industries. Columns 5–7 examine changes

in effect magnitude over time. Relative to the tertiary industry, the pull effect of the secondary industry has declined over time. This sustained decline partly explains the attenuation of the dynamic effect of prefecture-level industrial structure during the later phase of the inverted-U pattern.

Table 3
Nonagricultural-Sector Analysis

	Baseline Analysis				**Dynamic-Effect Analysis**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Choice	*Choice*	*Choice*	*Choice*	*Choice*	*Choice*	*Choice*
SI/TI	-0.009	-0.357***	-0.295***	-0.394***	0.115***	0.144***	-0.227***
	(0.013)	(0.013)	(0.008)	(0.018)	(0.006)	(0.004)	(0.007)
SI/TI × *Year*					-0.655***	-0.704***	-0.487***
					(0.009)	(0.004)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235	22,215,797	59,675,135	49,692,755
$PseudoR^2$	0.276	0.307	0.247	0.178	0.291	0.253	0.232

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively, to estimate the effect of the secondary-to-tertiary value-added ratio on labor migration. Columns 5–7 examine changes in this effect over time. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

4.3 Endogeneity and Instrumental-Variable Analysis

Prefecture-level industrial structure affects labor migration, but migrant labor supply may also shape local industrial structure, creating a potential endogeneity problem. The paper uses an instrumental variable to mitigate this concern. Because prefecture-level data are unavailable, the instrument is the total number of sent-down youths (SDYs) in each province between 1968 and 1977[5] (Chen et al. 2020). The relevance argument is that sent-down youths were primarily resettled in areas with large agricultural sectors and were mainly engaged in agricultural production; the number of sent-down youths is therefore correlated with regional industrial structure. The exclusion argument is that, as the outcome of a historical political movement, the number of sent-down youths is unlikely to affect labor migration during 1996–2015 through other channels. Table 4 reports the instrumental-variable estimates, which support the robustness of the main findings: prefecture-level industrial structure has a significant negative effect on migrants' destination choices, and the magnitude of the effect follows an inverted-U pattern. The IV coefficients are generally larger in absolute value, indicating that endogeneity may lead to an underestimation of the effect of industrial structure.

Table 4
Instrumental-Variable Analysis

	(1)	(2)	(3)	(4)
	Choice	***Choice***	***Choice***	***Choice***
A/N-A	-3.270***	-38.562***	-13.448***	-9.276***
	(0.719)	(1.150)	(0.168)	(0.504)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.280	0.310	0.252	0.177

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. The instrument passes the weak-instrument and underidentification tests. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

4.4 Additional Robustness Analyses

The paper conducts additional robustness analyses by varying the scope of the candidate prefectures.

A. Using a Consistent Set of Candidate Prefectures

Because of missing census observations and prefecture-level characteristics, the 2000, 2005, 2010, and 2015 samples contain different sets of candidate prefectures. To control for these differences, this section restricts the analysis to a consistent set of 219 prefectures, none of which has missing observations in any census sample. Columns 1–4 of Table 5 replicate the regressions in Table 1, and columns 5–7 replicate those in Table 2. The results confirm that prefecture-level industrial structure has a significant negative effect on migrants' destination choices and that the magnitude of the effect follows an inverted-U pattern. The results also suggest that the independence of irrelevant alternatives (IIA) assumption is credible, as the coefficients exhibit no systematic change after candidate prefectures are excluded.

Table 5
Results Using a Consistent Set of Candidate Prefectures

	Baseline Analysis				**Dynamic-Effect Analysis**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Choice	*Choice*	*Choice*	*Choice*	*Choice*	*Choice*	*Choice*
A/N-A	-3.106***	-3.194***	-6.641***	-3.991***	-2.640***	-3.335***	-7.286***
	(0.104)	(0.099)	(0.089)	(0.256)	(0.067)	(0.065)	(0.084)
A/N-A × *Year*					-1.500***	-4.761***	2.182***
					(0.074)	(0.064)	(0.132)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,943,925	13,121,385	32,140,221	5,089,341	18,065,310	45,261,606	37,229,562
$PseudoR^2$	0.280	0.298	0.245	0.179	0.282	0.245	0.232

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively, and replicate the baseline regressions. Columns 5–7 replicate the dynamic-effect analysis. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

B. Restricting the Set of Candidate Prefectures

Geographical constraints make it impossible for migrants to obtain information about every prefecture in China. The set of destinations realistically available to them may therefore be narrower than the choice set used in the baseline specification. The paper assumes that migrants possess the same level of information about the observed destination prefecture and its surrounding areas. Panel A of Table 6 restricts the candidate prefectures to those in the same province as the observed destination. Panel B further includes prefectures in provinces adjacent to the destination province. The main findings remain robust under both restrictions and continue to support the IIA assumption[6].

Table 6
Results with a Restricted Set of Candidate Prefectures

	Panel A. Candidate Prefectures in the Destination Province			
	(1)	**(2)**	**(3)**	**(4)**
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-3.830***	-2.457***	-3.906***	-1.101***
	(0.124)	(0.086)	(0.087)	(0.210)
Controls	Yes	Yes	Yes	Yes
N	358,162	1,054,299	2,246,892	375,092
$PseudoR^2$	0.295	0.264	0.313	0.198
	Panel B. Candidate Prefectures in the Destination and Adjacent Provinces			
	(1)	(2)	(3)	(4)
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-3.333***	-3.288***	-5.410***	-1.714***
	(0.108)	(0.083)	(0.080)	(0.217)
Controls	Yes	Yes	Yes	Yes
N	1,225,917	3,998,606	9,720,087	1,641,171
$PseudoR^2$	0.302	0.313	0.292	0.192

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

5 Mechanisms and Heterogeneity

This section further examines the effect of prefecture-level industrial structure on labor migration. It first investigates the mechanisms underlying the dynamic effect and then uses the specification in Eq. (2) to examine heterogeneous effects across migrant groups.

5.1 Mechanism Analysis

Section 5.1 examines the channels through which prefecture-level industrial structure affects labor migration and explores why its effect weakens in the later period. Building on the conceptual framework in Section 2, the analysis tests two principal channels: wage income and employment opportunities. Together, these channels explain the consistently negative effect of the agricultural-to-nonagricultural ratio on labor migration during 1996–2015.

Table 7
Mechanism Analysis: Wage-Income Channel

	Panel A. Wage Income as the Dependent Variable			
	(1)	**(2)**	**(3)**	**(4)**
	ln(Wage)	*ln(Wage)*	*ln(Wage)*	*ln(Wage)*
A/N-A	-0.137***	-0.040***	-0.529***	-0.596***
	(0.000)	(0.000)	(0.000)	(0.001)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$AdjustR^2$	0.804	0.700	0.612	0.590
	Panel B. Destination Choice with Wage Income			
	(1)	(2)	(3)	(4)
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-2.505***	-2.821***	-5.574***	-0.523**
	(0.102)	(0.088)	(0.082)	(0.212)
ln(Wage)	2.354***	0.945***	0.257***	2.042***
	(0.100)	(0.034)	(0.021)	(0.063)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.284	0.309	0.251	0.180

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

First, the paper examines wage income in the candidate prefectures. Wage income is proxied by the natural logarithm of the average prefectural wage [ln(Wage)] and is added to Eq. (1). The relationship between prefecture-level industrial structure and wage income is estimated using ordinary least squares. Panel A of Table 7 shows that prefecture-level industrial structure has a significant negative effect on prefectural wage income, implying that prefectures with larger nonagricultural sectors have higher wages. Panel B shows that wage income has a significant positive effect on migrants' destination choices, thereby supporting the wage-income channel.

Table 8
Mechanism Analysis: Employment-Opportunity Channel

	Panel A. Employment Opportunities as the Dependent Variable			
	(1)	**(2)**	**(3)**	**(4)**
	ln(Unit employees)	*ln(Unit employees)*	*ln(Unit employees)*	*ln(Unit employees)*
A/N-A	-0.216***	-0.078***	-0.080***	0.138***
	(0.001)	(0.001)	(0.000)	(0.001)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$AdjustR^2$	0.880	0.735	0.863	0.878
	Panel B. Destination Choice with Employment Opportunities			
	(1)	(2)	(3)	(4)
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-2.951***	-3.150***	-5.420***	-2.084***
	(0.105)	(0.087)	(0.079)	(0.202)
ln(Unit employees)	0.006	0.292***	0.166***	0.354***
	(0.038)	(0.019)	(0.009)	(0.030)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.280	0.309	0.251	0.177

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

Second, the paper examines whether prefecture-level industrial structure affects labor migration through employment opportunities. The natural logarithm of the number of employees in prefectural work units [ln(Unit employees)] is used as a proxy for employment opportunities in Eq. (1). The relationship between industrial structure and employment opportunities is also estimated using ordinary least squares. Panel A of Table 8 shows that prefecture-level industrial structure generally has a significant negative effect on employment opportunities, implying that prefectures with larger nonagricultural sectors generate greater demand for labor. Panel B supports the employment-opportunity channel by showing that the nonagricultural sector attracts migrants by expanding employment. A potential concern is that the work-unit measure excludes private-sector employees, which may reduce its validity as a measure of local employment opportunities. Appendix Table B1 therefore uses the number of private employees as an alternative measure and obtains similar results. A comparison of the coefficients in Tables 7 and 8 further suggests that wage income has a stronger effect on labor migration than employment

opportunities. Raising wages may therefore be more effective than expanding employment in attracting workers and skilled labor.

The mechanism analysis indicates that the nonagricultural sector provides higher wage income and more employment opportunities than the agricultural sector, thereby affecting cross-prefectural labor migration. The paper next examines the mechanisms underlying the inverted-U pattern, particularly the attenuation of the effect in the later period. Following the dynamic-effect analysis, it pools adjacent samples, defines a period indicator, and uses interaction terms to estimate changes in the effects of prefecture-level industrial structure on wage income and employment opportunities.

As the nonagricultural sector expanded, higher wages and more employment opportunities initially strengthened the effect of prefecture-level industrial structure. The interaction coefficients in Table 9, however, show that the effect on wage income weakened after 2010. Because the preceding analysis suggests that wage income has a stronger influence on destination choice than employment opportunities, diminishing marginal wage gains associated with nonagricultural agglomeration may have weakened the pull effect of prefectures in the later period. Figure C1 also shows rapid growth in housing prices in prefectures with larger nonagricultural sectors. After 2010, the widening gap in living costs further reduced the relative attractiveness of these prefectures. Because appropriate instruments are unavailable to causally identify the mechanisms behind the inverted-U pattern, this section provides suggestive evidence on the factors that may drive the changing effect of prefecture-level industrial structure.

Table 9
Dynamic Effects on Wage Income and Employment Opportunities

	Wage Income			**Employment Opportunities**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ln(Wage)	*ln(Wage)*	*ln(Wage)*	*ln(Unit employees)*	*ln(Unit employees)*	*ln(Unit employees)*
A/N-A	-0.127***	-0.199***	-0.546***	0.659***	0.053***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Year	0.318***	0.391***	0.377***	-1.259***	-0.380***	-0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A/N-A × *Year*	0.063***	-0.240***	0.082***	-1.024***	-0.220***	-0.470***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	22,215,797	59,675,135	49,692,755	22,215,797	59,675,135	49,692,755
$AdjustR^2$	0.846	0.856	0.796	0.849	0.826	0.864

Note: Columns 1–3 examine changes in the effect of prefecture-level industrial structure across the 2000–2005, 2005–2010, and 2010–2015 samples, respectively; columns 4–6 follow the same sequence. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

5.2 Heterogeneity Analysis

Unlike studies of population migration in China that rely on city-level panel data, the conditional logit model uses individual-level data and therefore allows the effect of industrial structure to vary across individuals. Section 5.2 examines heterogeneous effects across migrant groups.

The analysis first considers occupation, an important yet understudied dimension of migration (Sjaastad 1962). Because occupations involve different tasks within industries, distinguishing among them can deepen our understanding of how prefecture-level industrial structure affects migration. Based on the Classification and Codes of Occupations used in the census data[7], all occupations are grouped into eight broad categories: (i) leaders (LEA; for example, chief executives); (ii) professional technicians (PT; for example, engineering technicians); (iii) clerical workers (CP); (iv) commercial and service workers (CSP; for example, purchasing staff); (v) agricultural production workers (APP); (vi) production and transportation equipment operators (PTEO; for example, machine operators); (vii) military personnel (MP); and (viii) unclassifiable personnel (NCP). Three categories are excluded: leaders, because they are few in number and face complex migration determinants; military personnel, because they are excluded from all census samples; and unclassifiable personnel, because they cannot be matched to specific tasks. For each of the remaining five categories, the paper defines an indicator equal to one when an individual belongs to that occupation and zero otherwise. For example, PT equals one for a

professional technician, while all other occupational indicators equal zero. The occupational indicators are interacted with prefecture-level industrial structure, and the results are reported in Table 10.

The interaction coefficients indicate that agricultural production workers are less responsive to prefecture-level industrial structure, reflecting their weaker match with the nonagricultural sector. Production and transportation equipment operators, by contrast, are more responsive because they are more closely matched to nonagricultural activity. This pattern is consistent with the fact that these two occupational groups primarily perform agricultural and industrial production tasks, respectively. Clerical workers, professional technicians, and commercial and service workers mainly perform production-support services. Among these groups, clerical workers respond more strongly to prefecture-level industrial structure, while professional technicians exhibit a stronger response to some extent. Commercial and service workers display no heterogeneous effect, probably because sales and household services are demanded in both sectors. By comparison, the agricultural sector has substantially less demand for clerical workers and engineering technicians than the nonagricultural sector.

Table 10
Heterogeneity Analysis: Occupation

	(1)	(2)	(3)	(4)
	Choice	***Choice***	***Choice***	***Choice***
A/N-A	-1.480***	-3.339***	-4.014***	-2.956***
	(0.427)	(0.170)	(0.240)	(0.676)
A/N-A×*APP*	2.589***	4.603***	4.753***	5.089***
	(0.454)	(0.204)	(0.283)	(0.778)
A/N-A×*PTEO*	-2.367***	-0.441***	-3.373***	-0.709
	(0.429)	(0.162)	(0.241)	(0.669)
A/N-A×*CP*	-4.733***	-2.910***	-6.303***	-1.126
	(0.656)	(0.388)	(0.398)	(0.863)
A/N-A×*PT*	-2.593***	0.054	-0.932***	0.367
	(0.693)	(0.302)	(0.289)	(0.718)
A/N-A×*CSP*	-0.693	0.640***	-0.193	1.039
	(0.437)	(0.170)	(0.241)	(0.669)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.282	0.310	0.253	0.178

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

The occupational heterogeneity results are closely aligned with the baseline results based on industrial classifications, indicating that each industry attracts migrants working in the relevant occupations. An individual's industry classification is determined by the economic activity of the employing entity rather than by the tasks performed. Occupational classifications therefore provide a better measure of migrants' actual work after relocation. Table 10 offers suggestive evidence that the migration effect of industrial structure is driven by the occupational task structure. Migrants choose destinations in response to differences in the occupational tasks demanded across prefectures, rather than solely to differences in sectoral composition.

Table 11
Heterogeneity Analysis: Gender, Age, and Education

	Panel A. Gender			
	(1)	**(2)**	**(3)**	**(4)**
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-3.652***	-4.050***	-6.870***	-3.338***
	(0.134)	(0.112)	(0.101)	(0.253)
A/N-A×*Gender*	1.155***	1.392***	1.646***	1.061***
	(0.126)	(0.089)	(0.088)	(0.204)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.280	0.309	0.251	0.177
	Panel B. Age			
	(1)	(2)	(3)	(4)
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	-7.250***	-7.928***	-12.545***	-8.852***
	(0.213)	(0.174)	(0.159)	(0.384)
A/N-A×*Age*	0.147***	0.154***	0.203***	0.180***
	(0.006)	(0.004)	(0.004)	(0.009)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.282	0.310	0.253	0.179
	Panel C. Education Level			
	(1)	(2)	(3)	(4)
	Choice	*Choice*	*Choice*	*Choice*
A/N-A	0.789***	0.587***	-4.099***	-1.055***
	(0.246)	(0.173)	(0.176)	(0.392)

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

	Panel A. Gender			
	(1)	(2)	(3)	(4)
A/N-A× *Education level*	-1.317***	-1.275***	-0.529***	-0.460***
	(0.084)	(0.059)	(0.051)	(0.096)
Controls	Yes	Yes	Yes	Yes
N	5,145,182	17,070,615	42,604,520	7,088,235
$PseudoR^2$	0.281	0.309	0.251	0.177

Note: Columns 1–4 use the 2000, 2005, 2010, and 2015 samples, respectively. Controls include the logarithms of candidate prefectures' GDP, population, and fiscal expenditure and measures of fixed-asset investment, medical services, secondary education services, primary education services, and transportation services. *** p < 0.01, ** p < 0.05, * p < 0.10.

Using Eq. (2), the paper also examines heterogeneity associated with other individual characteristics, as reported in Table 11. First, the model includes an interaction between prefecture-level industrial structure and an indicator for gender (Gender; male = 1, female = 0). Second, it includes an interaction with age (Age; 16–64). Third, it examines education level (Education level)[8]. Panel A shows that women are more responsive to prefecture-level industrial structure than men. Panel B shows that younger workers are more responsive in their destination choices. Panel C indicates that the effect of prefecture-level industrial structure is stronger among workers with higher levels of education. These findings can be interpreted as reflecting the stronger pull effect of the nonagricultural sector on these groups. Compared with the traditional agricultural sector, the rapidly developing nonagricultural sector demands younger and more highly educated workers and absorbs more women. These findings are consistent with the literature reviewed in Section 2. The destination choices of these groups also depend more strongly on the wage income and employment opportunities available in candidate prefectures. In other words, their labor supply is more responsive to the economic returns offered by potential destinations.

6 Conclusion

Industrial structure has a significant effect on cross-regional labor migration. The results show that prefectures with larger nonagricultural sectors exert a significantly stronger pull effect on migrants' destination choices than prefectures with larger agricultural sectors. The magnitude of this effect follows an inverted-U pattern over the two-decade study period, increasing initially and declining after 2010. Within the nonagricultural sector, prefectures with larger tertiary industries exert a stronger pull effect than those with larger secondary industries. The empirical evidence further suggests that industrial structure affects migration through the wage-income and employment-opportunity channels. However, nonagricultural agglomeration may generate diminishing marginal wage gains and rising living costs, weakening the dynamic effect of prefecture-level industrial structure after 2010. The effect of the nonagricultural sector is also stronger among workers engaged in industrial production and production-support tasks, as well as among women, younger workers, and more highly educated workers.

The Chinese experience with labor migration has implications for other countries in the Global South undergoing structural transformation. As the nonagricultural sector continues to expand, the results indicate that its pull effect has begun to weaken. Stabilizing income growth and alleviating living costs could help preserve the sector's relative attractiveness. Within the nonagricultural sector, the pull effect of the secondary industry has declined continuously relative to that of the tertiary industry. Restoring the secondary industry's capacity to attract migrant workers may therefore offer another means of sustaining the overall pull effect of the nonagricultural sector. The paper does not, however, identify the causal mechanisms underlying the changing effect of industrial structure; further analysis is required to develop more precise policy implications. The paper also documents heterogeneous effects across migrant groups, identifying those whose migration choices are more responsive to industrial structure and who may therefore warrant particular policy attention.

Declarations

A Effects of the Agricultural and Nonagricultural Sectors

Section 4.1 uses the ratio of the agricultural sector to the nonagricultural sector as the key independent variable when estimating the effect of prefecture-level industrial structure on labor migration. The estimates in Table 1 therefore capture the relative effects of the two sectors. To estimate their separate effects, Appendix A replaces the key independent variable. Table A1 uses the agricultural share (A), measured as primary-industry value added relative to GDP, and the nonagricultural share (N-A), measured as the combined value added of the secondary and tertiary industries relative to GDP.

C Trends in Housing Prices

Housing prices are commonly used as a proxy for regional living costs and to assess whether living costs affect labor migration. The paper classifies prefectures into groups with large and small nonagricultural sectors using either the mean or the median agricultural-to-nonagricultural ratio calculated from the 2005, 2010, and 2015 census samples. For example, during 2000–2004, a prefecture is assigned to the large-nonagricultural-sector group if its agricultural-to-nonagricultural ratio is below the mean or median calculated from the 2005 sample; otherwise, it is assigned to the small-nonagricultural-sector group. The paper then collects annual prefecture-level housing prices for 2000–2014 and plots the trends over time.

D Summary Statistics

Table D1 reports summary statistics for the four migration samples. Panel A covers 1996–2000 and includes 227 candidate prefectures and 22,666 individuals. Panel B covers 2001–2005 and includes 279 candidate prefectures and 61,185 individuals. Panel C covers 2006–2010 and includes 280 candidate prefectures and 152,159 individuals. Panel D covers 2011–2015 and includes 285 candidate prefectures and 24,871 individuals.

Author Contribution

Xiaolan Yang: Designed the paper framework and finalized the manuscript.Xingzhi Yao: Performed empirical implementation and data analysis (programming, model estimation, robustness checks).Xuankai Zhao: Collected data and conducted the literature review.Xinyue Zhu: Wrote the manuscript and performed empirical analysis.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Footnotes

1. National Bureau of Statistics of China. 2019. 'Steady Growth in Total Population, Remarkable Improvement in Population Quality.' Available at https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900430.html.
2. GDP is measured at constant 2015 prices.
3. Occupation is classified according to the tasks performed by an individual, whereas industry is classified according to the output of the individual's employing entity.
4. The prefecture-level summary statistics in Appendix D show substantial cross-prefectural variation in the agricultural-to-nonagricultural ratio.
5. During the Cultural Revolution, from 1968 to 1978, China's central government launched the Send-Down Movement, which required urban youths to resettle temporarily in rural areas. Sent-down youths were primarily assigned to agricultural production and were expected to be 're-educated' by poor farmers.
6. The paper also re-estimates the models while sequentially excluding each candidate prefecture. The results remain robust and continue to support the IIA assumption. Detailed estimates are omitted for reasons of space.
7. The 2000 census and 2005 mini-census use the 1999 Classification and Codes of Occupations, the 2010 census uses the 2009 classification, and the 2015 mini-census uses the 2015 classification. Although the

detailed occupations in CCO2015 differ from those in CCO1999 and CCO2009, the eight broad categories remain unchanged. The analysis therefore uses the broad categories reported in the main text.

8. Education is coded as follows: illiterate or literacy class = 1; primary school = 2; junior high school = 3; senior high school or technical secondary school = 4; junior college = 5; bachelor's degree = 6; postgraduate degree = 7.

Supplementary Files

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