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Stay or return? The role of city environment and digital economy in migrants in China

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With the rapid development of digital economy, green environment and digital economy are constantly and deeply integrated. This paper examines the effect of city environment and digital economy on return intentions based on the logit model proposed by McFadden (1974). The results of this study show that both urban environment and digital economy have a significant impact on laborers' decisions about return migration. Moreover, the study reveals that the older individuals are more responsive to the environmental quality, while the decision-making process regrading return migration is more evidently influenced by the digital economy for individuals with higher abilities and those within province. Furthermore, the wages of the migrants who intend to return also increase with the growth of the city's digital economy, which may be attributed to the enhanced work efficiency. In addition, the increased impact of the green environment and digital economy on wages for the migrants intending to return is primarily observed in the middle-skilled and middle-income laborers.

KEYWORDS

city environment, digital economy, return migration, return intentions, China

1 Introduction

In recent years, the digital economy has experienced significant growth due to the integration of digital technology and economic activities. It accounted for 41.5% of the GDP in 2022 (CAICT, 2023), making it a crucial driver of economic development. However, the rapid economic development and urbanization have led to an increasingly serious issue of environmental pollution (Du et al., 2023). As a result, environmental health has become a focal point of public attention. Labor flow is the prerequisite for realizing the reasonable and effective allocation of labor resources and the efficient operation of the labor market. Previous studies have established a connection between labor mobility and China's economic development (Liu, 2018; Gao et al., 2021; Zhang et al., 2021). Additionally, labor flow has significantly contributed to the transformation and upgrading of industrial structure (Cao et al., 2020; Dong and Zhang, 2021; Zhang et al., 2021).

Environmental factors are recognized as an important driver of migration. Cui et al. (2019) based on smartphone location data and confirmed that air pollution leads to population outflow. Especially, skilled workers have a stronger demand for high-quality environment compared to their unskilled counterparts (Cheng et al., 2014; Liu and Shen, 2014). Chen et al. (2022) estimated the impact of air pollution on population distribution at the county level in China and found that air pollution leads to a 5% increase in net migration of population in counties from 1996 to 2010, highlighting the increased sensitivity of labor to air pollution. Xiao (2016) conducted an empirical study using urban macro samples and revealed that pollution emissions result in a certain extent of population loss. Similarly, Hunter (1998) analyzed data from 3,109 counties in the United States between 1985 and 1990 and discovered that counties with higher environmental risks experience lower population migration rates. Environmental issues may shape migration through various mechanisms, such as worsening health conditions, reducing resident safety, and causing land degradation that affects household assets (Lybbert and Sumner, 2012; Porter et al., 2014; Mastrorillo et al., 2016; Liao et al., 2023).

In the study on digital economy's impact on labor flow, Ma and Hu (2022) combined the Digital Financial Inclusion Index of Peking University with the dynamic monitoring survey of the national floating population from 2012 to 2017. They used the conditional logit model to examine the influence of digital finance on labor flow. The study revealed that the development level of digital finance in a city positively influences labor inflow. Li and Zhou (2022) found that driven by digital technology, the nature of many jobs has changed, a large number of jobs have changed from offline to online, and employment has become more flexible and casual. Recent literature has primarily examined the effect of the digital economy on economic growth, focusing on productivity growth, traditional industrial structure adjustment, and resource allocation efficiency as the main paths for promoting economic growth (Liu, 2019; Ning, 2020; Yang, 2020; Liu et al., 2022). The digital economy has a significant influence on the labor market, with the technological revolution driven by digital advancements optimizing capital accumulation efficiency and increasing the demand for comparatively high-skilled laborers (Zhao and Guo, 2018; Acemoglu and Restrepo, 2019; Agrawal et al., 2019). Kennan and Walker (2011) found that expected income is a primary economic factor influencing migration. Moreover, the development of the digital economy accelerates economic integration. Since it narrows down the income gap between home and host cities, it promotes the return migration of migrants (Tezcan, 2019; Zou and Deng, 2022).

Our study focuses on investigating the effect of the city-level environment and the digital economy on migrants' intentions to return, rather than their actual return behaviors. It is possible that the intention to return may remain at the level of intention or changes over time due to changing circumstances. Still, it measures a migrant's decision-making process and reveals a comprehensive consideration of the factors both in the host and home cities (Carling and Erdal, 2014; Tezcan, 2019). Given that our data restrict individuals to select only one preferable expected location, our study precisely reflects their intentions. By analyzing over 50,000 online resumes combined with city-level characteristics, our findings reveal that both the quality of the city's green environment and the development of the digital economy have positive effects on return intentions. Further heterogeneity analyses demonstrate that the elderly are particularly responsive to environmental quality, while high-skilled laborers consider both the environment and the digital economy. In addition, individuals within the same province show a greater likelihood of returning as the digital economy expands. Subsequently, we analyze the consequences of the return. The results suggest that both the green environment and digital economy increase the expected wage of migrants planning to return, with digital economy playing a particularly important role. The results are especially significant for the laborers with middle-level skills.

The study aims to contribute to the existing literature on migration patterns by examining the decision-making process of return migration. Specifically, we make contribution to the existing literature by two ways. First, we complement the determinants of return migration. Existing literature study the factors considering the economic, psychological and emotional factors that could influence the return decisions (Christou, 2006; Baykara-Krumme, 2013; Jain, 2013; Ojo et al., 2013; Giannetti et al., 2015; Kunuroglu et al., 2015). Although some scholars study the migration from environment quality and digital economy separately. We are the first to extend this analysis to combine the green environment and digital economy to examine the effects on return migration intention, given the increasing environment concerns and rapid growth of digital economy. Second, we utilize unique online resumes data combined with city characteristics to provide evidence on the return migration intention, specifically considering the development of the city's green environment and digital economy. This approach enables a comprehensive understanding of the relationship between these variables.

The rest of the study is organized as follows. We first introduce the empirical strategies in Section 2. Then we introduce the data and variables in Section 3. Section 4 presents the empirical results of causes of return intentions. Section 5 displays the consequences of the return migration. In last section, we draw conclusions and remarks.

2 Empirical strategies

2.1 Determinants of return migration intentions

We exploit the logit model provided by McFadden (1974) to examine the characteristics of the destination city c and the personal attributes in determining laborers' return migration intention in another job. Regarding the places to choose, the floating populations have two exclusive options: staying at the present city of the last job ("migrant stayer") or returning to the household registration (*Hukou*) city ("return migrants"). Specifically, let U_{icj} denotes individual i correlated with the j-th treatment, j=0 or 1. i is for individuals.

$$U_{icj} = V_{icj} + \varepsilon_{icj} \tag{1}$$

V_{icj} is the indirect utility function including several deterministic components, and ε_{icj} is the disturbance. The V_{icj} can be further defined as:

$$V_{icj} = f(X_c, Z_{ic}) \tag{2}$$

Where X_c denotes a vector of the city-level characteristics of city c (city of the last job) that might affect worker's migration choice. Z_{ic} is a vector denoting the migrants' characteristics and human capital (e.g., age, gender, education, work experience, management position in the last job, etc.).

Let j= 0 denotes the control group, then V_{ic0}= 0. Since V_{icj} is not observed, we just capture return migration intentions that

TABLE 1 Descriptive statistics of city attributes of the expected city.

Variable	Label	Obs	Mean	Sd	Min	Max
City environment	Comprehensive environmental index in 2015	279	6.28	5.52	0.43	8.22
City digital economy	Digital economy in 2015	279	5.44	9.47	0.34	8.9
GDP *per capita*	Per capital GDP in 2015	279	4.93	0.29	0.1	20.02
Population	Total population in 2015 (1million)	279	4.45	3.18	0.2	33.74
Unemployment rate	Share of the unemployed persons registered in 2015	279	0.06	0.07	0	0.31
Human capital	Average schooling years in 2015	279	9.36	0.9	6.87	12.52
Public services	Hospital-bed number-per capital	279	0.52	0.41	0.1	3.44
Average wage	Average annual wage in 2015(10000Yuan)	279	7.34	1.94	3.52	11.46
Industry structure	The employees in tertiary industries/The total employees (%)	279	0.52	0.13	0.17	0.86
FDI-GDP ratio	Foreign direct investment as a share of city GDP	279	0.02	0.02	0	0.13
Migration distance	City of the expected job and the *Hukou* city (1000 km)	279	0.27	0.43	0	3.68

Note: The data sources include City statistical Yearbook in 2016 of China, etc. The environment index is a composite index constructed with a city's urban ecological environment carrying capacity, industrial wastewater discharge, industrial dust emissions, *per capita* green area, green coverage of built-up area, and harmless treatment rate of domestic garbage.

maximizes individual utility and we denote the options as a binary variable d_j. They are defined as a vector of two choices, that is $d_{ic} = [d_{ic1}, d_{ic2}]$. Therefore, we show that an individual i in city c chooses an alternative city j has the probability of P:

$$P(d_i = 1 \mid X_c, Z_{ic}) = \frac{\exp\left(V_{icj}\right)}{\sum_{k=1}^{J} \exp\ (V_{ick})}$$

Where

$$d_{icj} = \begin{cases} 1\,if\,a\,migrant\,intends\,to\,move\,back\,to\,the\,Hukou\,registration\,city \\ 0\,if\,\,a\,migrant\,remains\,stay \end{cases} \tag{3}$$

2.2 The effects of return migration intentions on wage expectations

We then estimate the following Mincer equation to compare the expected wage among these migrants who intend to return and the non-migrants as follows:

$$ln(wage)_{ijk} = \alpha + \beta_1 return_{ijk} + \gamma X_{ij} + \delta Z_j + ln(wage)_{ij} + \varphi_k + \mu_s + \pi_0 + \varepsilon_{ijk} \tag{4}$$

Where $ln(wage)_{ijk}$ is an interval variable and indicates the logarithm of expected wage of a worker i in city j and intends to work in city k. $return_{ijk}$ represents worker i with the last job in city j intending to re-migrate to the city k, respectively. Our main interested variable is the dummy term as $return_{ijk}$, which captures the different wage expectations compared with the non-migrants.

X_{ij} is a vector denoting the workers' characteristics and human capital (e.g., age, gender, education, work experience and if possessing a managerial position in the previous job, etc.). Z_j is the city-level characteristics of the previous job, including urban population size, unemployment rate, public services (proxied by the numbers of hospitals), GDP *per capita*, human capital (measured by the schooling years of the urban resident population) and average wage (Yankow, 2003; Huttunen et al., 2018).

In addition, we also consider other omitted variables varying from destination cities, industrial sectors and occupations. Thus, we include the city φ_k, industrial sector μ_s , and occupation π_0 fixed effects coming from the next job. Finally, since individual ability of job seekers may be correlated with both return migration intention and expected wage, we make use of the wage ranks in the last job to proxy the ability. ε_{ijk} denotes random error term.

3 Data and choice of variables

3.1 Data sources

We obtain the unique individual data from an online recruitment websites, *Zhaopin.com*[1]. On this website, all job seekers need to register and create personal accounts. They are required to fill in some personal information, such as educational background, career experiences (detail job information ever employed, including number of jobs worked, firm size, wage of jobs, etc.) and preferences of job seekers (expected wage, city and industry, etc.). More importantly, as job seekers are limited to fill in one preferable expected location choice, we can exactly point out if the individual intends to return or not.

In June 2016, we totally got the newest 78,000 resumes across 52 industries from 30 web pages in each industry, with each web page including 30 resumes. Since we mainly pay attention to the return migration intention, we select our sample with laborers (ages between 18 and 65) and has complete information, containing *Hukou* registration cities and expected cities. We drop those

1 The data is available for whom asks for.

sample with part-time job or internships and we also exclude those education background is "Other".

To explore the determinants of work location choice, we combine the individual data with the city-level dataset. Considering that the job change intention is based on knowable city attributes, we utilize previous-year city level characteristics by the 2016 City Statistical Yearbook of China, etc. We obtain 279 cities by matching the two datasets, almost covering 92% Chinese municipal cities.

3.2 Variables of city characteristics

Regarding the variables related to city attributes, one of the main explanatory variables is the degree of environmental-friendliness. Graymore et al. (2010) found that the environmental quality of the anticipated city plays a significant role in labor mobility decisions. We construct a comprehensive green environmental index, by taking average values of several indicators, including industrial dust emissions, waste-water discharge, green coverage of urban built-up areas and harmless treatment rate of domestic garbage. The city-level data for the key variables are from the 2016 City Statistical Yearbook of China and the 2016 China Urban-Rural Construction Statistical Yearbook. According to the calculation, the average index of city environment is 6.28.

Moreover, the second main independent variable measures the digital economy, which is based on digital ICT and digitized knowledge (Zhen et al., 2021). The development of the internet serves as the core of the digital economy (Sturgeon, 2021). To measure the digital economy, we combine the indices representing internet penetration rate and telecommunications services *per capita*. Table 1 shows that the mean value of the digital economy development is 5.44 and the standard deviation is 9.47. To ensure comparability, these indices are aggregated and standardized with a mean of zero and unit standard deviation.

Additionally, the average years of education of the city's population is employed as a measure of human capital (Su et al., 2021). We exploit the number of hospital beds *per capita* to proxy for the public services. Moreover, we use the ratio of the employment rate of secondary and tertiary industries to measure industrial structures, since it reflects the job opportunities. Furthermore, Su et al. (2021) and Florida et al. (2012) highlight the significant role of openness in shaping regional talent distribution. Thus, we include the ratio of FDI-to-GDP to determine the level of openness in cities.

Apart from these city attributes, we also consider the city development on household registration barriers by classifying the cities based on the economic hierarchy. The household registration is vital for urban residents in cities, since it restricts individuals access to public amenities and even affect children's school attendance. We categorize cities into three hierarchies[2]. The *Hukou* constrains are largest for the cities in the first tiers and the third tier or below has the least *Hukou* constrains.

2 Zhang et al. (2019) clarified that this category is not official, but it is widely used by the public. The first tier contains Beijing, Shanghai, Guangzhou, and Shenzhen. The second tier contains relatively developed cities, such as provincial capital cities and regional economic centers. The last category contains the remaining less developed cities.

3.3 Variables of individual characteristics

Table 2 displays the summary statistics for individual information. The individual characteristics of job seekers encompass age, gender, marital status, education and employment status, etc. We also have detailed *Hukou* location, cities of previous jobs, and the expected cities of the next job. Consequently, we can identify two migration types from the pool of migrants. The first type, known as "migrant-stayers," refers to job seekers who have migrated in their last job and choose to remain in the same city for their next position. The second type, known as "return migrants," represents job seekers who had previously worked as migrants but plan to return to the *Hukou* place for their next job. However, due to data limitations, we do not consider the cohort of migrants with *Hukou* transfers.

4 Causes of remigration and return migration incentives

Table 3 shows the estimated results regressed by the logit model. We standardize all regressors to facilitate interpretation. Specifically, how a standard deviation increases in the variables impact the likelihood of job seekers choosing a destination city. In Column (1) of Table 3, our findings indicate that the quality of environment significantly influences the intention to return. In Column (2), we incorporate the digital economy. The estimates also suggest a positive correlation between digital economy and return migration, which is also statistically significant at the 1% level. Then we combine both indices and display the results in Column (3). Our results demonstrate that both factors positively contribute to the attractiveness of cities for job seekers during the job transition process. However, the impact of environment quality is relatively stronger than that of the digital economy. This implies that migrants who intend to return place greater emphasis on urban environment quality. Overall, our results indicate that both the presence of green environment and the availability of digital services consistently and significantly affect a city's appeal to workers during job changes.

Furthermore, we analyze the influence of individual characteristics on return migration intentions. The analysis reveals that individuals with employment are more likely to return to home cities. Additionally, compared to individuals whose education level are high school or below, those with bachelor' or master' degrees (or above) have a higher likelihood of migrating back to their *Hukou* registration city. Moreover, the choice between staying and returning is also related to gender, with males exhibiting a higher tendency to return.

Additionally, our findings are consistent with the majority of studies in demonstrating that both of the population size and GDP *per capita* have a statistically positive effects on city attractiveness. Conversely, higher unemployment rate decreases the appeal of cities. Furthermore, the estimated results indicate that public services and

TABLE 2 The statistical descriptions of individual key variables.

	Non-migrants	Migrant-stayers	Returnees
No. of job seekers	17, 914	21186	1479
%	0.441	0.522	0.036
Expected wage ranks			
<=4000	0.324	0.249	0.189
4001–6000	0.299	0.356	0.322
6001–8000	0.149	0.192	0.198
8001–10000	0.086	0.091	0.123
10000–15000	0.078	0.075	0.096
≥15000	0.065	0.036	0.072
Employment status			
On-the-job seekers	0.391	0.284	0.49
Unemployed	0.609	0.716	0.51
Education level			
High school or below	0.135	0.142	0.094
Junior college	0.369	0.41	0.341
Bachelor	0.46	0.411	0.487
Master's degree or above	0.072	0.038	0.079
Tenure of the last job	2.71	1.753	2.731
Demographics			
Age	30.029	27.333	29.505
Gender(male = 1)	0.579	0.561	0.632
Marital status			
Married	0.281	0.159	0.254
Unmarried	0.281	0.384	0.363
Not displaced	0.438	0.457	0.384
Management position in the last job			
Manager = 1	0.331	0.256	0.242
Wage ranks in the last job (RMB)			
<=4000	0.361	0.323	0.234
4001–6000	0.283	0.337	0.329
6001–8000	0.143	0.168	0.19
8001–10000	0.081	0.084	0.108
10000–15000	0.079	0.064	0.093
≥15000	0.054	0.024	0.046
No. of Project training	2.41	2.45	2.71

Note: The data source is from Zhaopin.com.

TABLE 3 The effect of city environment and digital economy on return migration intention.

	Returnees = 1		
	(1)	(2)	(3)
City environment	1.271***		1.316***
	(0.182)		(0.351)
Digital economy		0.686***	0.564**
		(0.183)	(0.183)
Individual characteristics			
On the job seekers = 1	0.706***	0.648***	0.670***
	(0.067)	(0.068)	(0.141)
Junior college	0.078	0.023	0.257
	(0.116)	(0.117)	(0.284)
Bachelor	0.360***	0.253**	0.716***
	(0.114)	(0.117)	(0.278)
Master's degree or above	0.857***	0.663***	1.601***
	(0.16)	(0.165)	(0.339)
Tenure of the last job	−0.018*	−0.027**	0.122***
	(0.01)	(0.01)	(0.046)
Tenure of the last job^2	0.000	−0.002**	−0.004
	(0.00)	(0.00)	(0.003)
Age	0.003	−0.011	0.032*
	(0.008)	(0.009)	(0.016)
Gender (Male = 1)	0.537***	0.451***	0.476***
	(0.072)	(0.075)	(0.156)
Marital status			
Not displayed	−0.319***	−0.313***	−0.357**
	(0.074)	(0.074)	(0.161)
Married	−0.408***	−0.479***	−0.193
	(0.105)	(0.106)	(0.199)
Management position = 1	0.248***	0.287***	0.056
	(0.08)	(0.086)	(0.158)
City characteristics of the last job			
Population size	0.052***	0.052	0.173***
	(0.02)	(0.032)	(0.064)
Unemployment rate	4.190*	4.073*	−12.616***
	(2.305)	(2.324)	(4.723)
Public services	−0.615**	−0.625**	−1.581**
	(0.312)	(0.315)	(0.64)

(Continued on following page)

TABLE 3 (*Continued*) The effect of city environment and digital economy on return migration intention.

	Returnees = 1		
	(1)	(2)	(3)
GDP *per capita*	−0.175***	−0.277***	−0.175***
	(0.011)	(0.0211)	(0.011)
Human capital	−0.171***	−0.179***	−0.237*
	(0.063)	(0.063)	(0.125)
Average wage(log)	−0.433***	−0.378***	−0.459***
	(0.241)	(0.044)	(0.262)
Industry structure	−0.038***	−0.037***	0.151*
	(0.005)	(0.005)	(0.077)
First-tier cities	−0.027	0.017	0.186*
	(0.256)	(0.257)	(0.10)
Second tier cities	−0.452***	−0.420***	−0.408***
	(0.114)	(0.115)	(0.06)
Distance	Y	Y	Y
Squared distance	Y	Y	Y
Wage of the last job	N	Y	N
Occupational-fixed effects	N	Y	N
Industrial-fixed effects	N	Y	N
Constant	−0.202	0.245	−1.916
	(0.685)	(0.705)	(1.490)
Pseudo R2	0.198	0.212	0.198
N	18,859	18,859	18,859

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are in parentheses.

TABLE 4 Heterogeneous effects: by age, ability, and intra-provincial migration.

	Returnees = 1		
	(1)	(2)	(3)
City environment	1.530***	1.480***	1.563***
	(0.184)	(0.199)	(0.361)
Digital economy	0.580***	0.97***	0.697**
	(0.199)	(0.068)	(0.359)
City environment # age group (>30)	0.225***		
	(0.085)		
Digital economy # age group (>30)	0.097		
	(0.168)		
City environment # High ability		0.109**	
		(0.053)	
Digital economy # High ability		0.229**	
		(0.103)	
City environment # Same province			−0.211
			(0.22)
Digital economy # Same province			0.891***
			(0.498)
Other controls	Yes	Yes	Yes
Pseudo R2	0.227	0.261	0.226
No	18,859	18,859	18,859

Note: 1. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, and the robust standard errors are in parentheses. 2. The other controls are same as those in Table 3. 3. If the wage rank of the last job is higher than the median rank (6000–8000 RMB), we would define them as the cohort of high ability, otherwise the lower ability cohort. 4. Same province represents the city of the last job is of the same province with the *Hukou* city.

the openness of cities also contribute positively. However, the industry structure appears to have no significant influence on the destination decisions of relatively high skilled job seekers. These findings echo the research conducted by Fu and Gabriel (2012), Huttunen et al. (2018), and Su et al. (2021), providing substantial evidence that migration decisions and city choices heavily depend on various city-level attributes such as unemployment status, agglomeration of human capital, and average wage.

Next, in order to implement the logit model, we allow the city environment to vary based on individual characteristics. It should be noted that certain personal characteristics, like age, gender, and education, remain constant with individuals, thus we cannot estimate through a logit model. To conduct the heterogenous analyses induced by the city environment and digital economy on the likelihood of return migration intentions, we interact the city-level key variables with individual characteristics.

Moreover, the influence of city environment on return migration decisions may differ among different groups of individuals. Hence, we investigate heterogeneity across workers in terms of age, abilities, and whether they are migrating within the same province or across provinces. The estimation results are presented in Table 4. Notably, city environment increases the willingness of older individuals and those with higher job abilities to remigrate. Moreover, city digital economy substantially enhances the likelihood of intra-provincial return migrants compared to trans-provincial migrants. This is expected since the cost of remigration within a province is significantly lower than migration across provinces.

5 Consequence of intentions of remigration

Having studied the environment of city that influences return migration, we now investigate whether and how the association between return migration and expected wage varies with the inflow city's environment quality. Using Mincer regressions, we directly compare expected wage differentials between non-migrants and return migrants in the same desired work city, controlling for

TABLE 5 Interval regression estimates for return migration and expected wage.

	Logarithm of expected wage	
	(1)	(2)
Returnees	0.025**	−0.055
	(0.012)	(0.035)
Returnees # City environment		0.038**
		(0.018)
Returnees # Digital economy		0.085 ***
		(0.027)
Other controls	Yes	Yes
Log likelihood	−15032.21	−12345.73
N	18859	18859

Notes: 1. Robust standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. 2. Control variables are the same as in Eq. 4.

unobserved city-level characteristics that may simultaneously affect income and migration decisions. The interval estimation method proposed by Amemiya (1973) and Wooldridge (2002) is employed to assess the function of expected wages. This method takes into account how to use the interval data to estimate. In addition, compared with ordered logit model, these estimated results are the marginal effects corresponding to the control variables and they are easily to explain.

In Column (1) of Table 5, the baseline results indicate that after accounting for other observable characteristics, migrants intending to return have an expected wage that is 2.5% higher than stayers. This substantial difference could be attributed to two potential reasons. Firstly, return migration can be seen as a positive self-selection process based on personal unobservable skills, as suggested by Constant and Massey (2003) and Tuccio and Wahba (2018). Second, temporary migrants who intend to return acquire human capital through learning by doing in the host cities during their migration (Co et al., 2000; Santos and Postel-Vinay, 2003). By taking advantage of the knowledge they learn, they may be more responsive to the city-level factors in the home cities, such as digital economy and gain wage premium compared with stayers.

To further investigate the second potential explanation, we introduce cross-products between return migration and city-level characteristics in our estimation model. The estimated results in Column (2) of Table 5 indicate that the association between return migration and expected wages varies significantly depending on the development of digital economy in the destination city. Specifically, for migrants originating from the same city, an increase of one unit in the level of city environment and digital economy in the destination city leads to a 3.8% and 8.5% increase in expected wages, respectively. Interestingly, we find that the effect of city digital economy on expected wages of migrants is greater compared to environmental quality. In conclusion, these findings demonstrate that migrants are more productive when the environment and digital economy of the destination city are higher. Furthermore, the allocation of labor force resulting from migration varies based on the level of green environment and digital economy in different cities.

(a) Different education levels. To further examine the different effects of city environment and digital economy on labor force return intentions with respect to the different skilled levels of migrants who intend to return, we firstly reproduce the estimation results based on Eq. 4 with four subsamples: high school or below, junior college, bachelor and master or above. Table 6 shows that, only for the migrants with a junior college degree and bachelor's degree, the interaction term between digital economy and return migration is positive and statistically significant. Specifically, for migrants with a bachelor's degree (junior college degree), a one unit increase in city digital economy is associated with a 10%

TABLE 6 Heterogeneous effects: education levels referring to the non-migrants.

	Logarithm of expected wage			
	H.S. or below	Junior college	B.A.	M.A. or above
	(1)	(2)	(3)	(4)
Returnees	0.19	−0.068	−0.065	0.085
	(0.176)	(0.067)	(0.048)	(0.172)
Returnees # City environment	−0.036	0.033	0.054**	−0.029
	(0.065)	(0.033)	(0.025)	(0.062)
Returnees # Digital economy	−0.061	0.095*	0.104***	−0.056
	(0.122)	(0.052)	(0.038)	(0.100)
Other controls	Yes	Yes	Yes	Yes
Log likelihood	−1023.92	−4449.08	−5777.49	−1203.77
N	1842	6770	8017	1792

Note: 1. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, and the robust standard errors are in parentheses. 2. H.S., represents the high school or below; The B.A., represents the bachelor's degree; The M.A., represents the master's degree. 3. Control variables are the same as in Eq. 4.

TABLE 7 Heterogeneous effects: different abilities referring to the non-migrants.

	Logarithm of expected wage		
	≤6000RMB	6001-10000RMB	>10000RMB
	(1)	(2)	(3)
Returnees	0.002	−0.211***	0.059
	−0.048	−0.067	−0.113
Returnees # City environment	0.043*	0.065**	0.034
	−0.025	−0.031	−0.056
Returnees # Digital economy	0.057	0.179***	0.06
	−0.04	−0.046	−0.079
Other controls	Yes	Yes	Yes
Log likelihood	−6538.08	−3955.4	−1594.5
N	10628	4458	2098

Note: 1. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, and the robust standard errors are in parentheses. 2. We used different wage ranks of the last job to proxy the ability levels. And there are totally 6 ranks (i.e., ≤4000, 4000–6000, 6001–8000, 8001–10000, 10000–15000, ≥15000), we equally classified them into three groups as above. 3. Control variables are the same as in Eq. 4.

(9.5%) higher expected wage. This suggests that the impact of the city's digital economy on wage expectations primarily affects individuals in the middle-skilled range, rather than low-skilled or high-skilled return migrants. Consistent with the report published by the CAICT (2021), the development of digital economy significantly replaced many jobs in labor-intensive firms and reduced the demand for low-skilled laborers. Meanwhile, it accelerated the demand for middle-skilled workers in service industries. Conversely, high-skilled migrants are likely to have more flexibility in their choice of cities and may not be as constrained by the digital economy.

(b) Different abilities. Additionally, we explored whether our findings were driven primarily by migrants with different levels of ability. We also divided the full sample into three sub-samples based on the wage ranges of their previous jobs (i.e., less than 6000 RMB, 6001–10000 RMB, and more than 10000 RMB). The results, presented in Table 7, indicate that only for return migrants in the middle wage range, the expected wage differentials vary according to the level of the city's digital economy (green environment), resulting in a 17.9% (6.5%) higher expected wage. Once again, these findings provide clear evidence that the distribution of labor force return migration, influenced by the degree of environment quality in the host city, is primarily concentrated among individuals with middle-level skills.

6 Conclusion and remarks

This paper examines how the green environment and digital economy in China influence migrants' intentions to return and subsequently impact the allocation of labor force across different cities. By utilizing a unique dataset of resumes from a prominent online recruitment platform in China, we initially analyzed the relationship between return migration intentions and the quality of the environment and digital economy in the desired work city. The findings demonstrate that both the green environment and digital economy significantly enhance the willingness to engage in return migration. However, it is noteworthy that better city environment and a stronger digital economy primarily attract comparatively high-skilled migrant workers. Our heterogeneity analyses confirm that labor force distribution resulting from return migration is primarily driven by individuals with middle-level skills.

Additionally, we conduct a thorough investigation into the potential variations in the productivity gap of migrants based on different environment quality and digital economy development in their expected work cities. Our findings provide direct evidence that the increased development of digital economy in inflow cities leads to significantly higher wage expectations among migrants. In other words, the presence of enhanced digital convenience and superior environmental quality in the destination city result in increased productivity for migrants who intend to remigrate to the *Hukou* registration cities. This wage disparity is even more pronounced when considering the level of digital economy in the destination city, as it is approximately twice as large compared to the impact of the city's green environment. Furthermore, our research demonstrates that both the city's green environment and digital economy have a considerable positive effect on the wage expectations of middle-skilled migrant job seekers.

Overall, our analyses suggest that the green environment and urban digital economy of the in-flow city significantly influence migrants' decision. Moreover, both factors contribute to a higher probability of return migration during the job-changing process. The impact of the green environment is particularly pronounced. Additionally, the expected wage of migrants exhibits significant variations based on the degree of green environment in the city, with digital economy playing a particularly important role. The higher the degree of digital economy development in the destination city, the higher the expected wage for migrants. Consequently, our research indicates that updating the public service offerings in destination cities to facilitate the expansion of migrant employment opportunities can further enhance the welfare of return migrant workers and overall productivity across different cities.

Data availability statement

This unique individual-level dataset is available for whom asks for. Requests to access the datasets should be directed to Lanfang Deng, 201910298@m.scnu.edu.cn.

Author contributions

QC: Data curation, Investigation, Supervision, Writing–original draft. PQ: Project administration, Writing–original draft, Writing–review and editing. LD: Conceptualization, Data curation, Methodology, Resources, Supervision, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Acemoglu, D., and Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *J. Econ. Perspect.* 33 (2), 3–30. doi:10.1257/jep.33.2.3

Agrawal, A., Gans, J. S., and Goldfarb, A. (2019). Exploring the impact of artificial intelligence: prediction versus judgment. *Inf. Econ. Policy* 47, 1–6. doi:10.1016/j.infoecopol.2019.05.001

Amemiya, T. (1973). Regression analysis when the dependent variable is truncated normal. *Econ. J. Econ. Soc.* 41, 997–1016. doi:10.2307/1914031

Baykara-Krumme, H. (2013). Returning, staying, or both? Mobility patterns among elderly Turkish migrants after retirement. *Transnatl. Soc. Rev.* 3 (1), 11–29. doi:10.1080/21931674.2013.10820745

CAICT (China Academy of Information and Communications Technology) (2021). *Report on employment effect of digital economy*, 2021.

CAICT (China Academy of Information and Communications Technology) (2023). *Whitepaper on China's digital economy development*, 2023.

Cao, F. F., Cheng, J., Wu, L. P., and Li, X. D. (2020). Does labor mobility promote China's industrial upgrading? Empirical evidence from prefecture-level cities in China. *Industrial Econ. Res.* 1, 57–70. doi:10.13269/j.cnki.ier.2020.01.005

Carling, J., and Erdal, M. B. (2014). Return migration and transnationalism: how are the two connected? *Int. Migr.* 52 (6), 2–12. doi:10.1111/imig.12180

Chen, S., Oliva, P., and Zhang, P. (2022). The effect of air pollution on migration: evidence from China. *J. Dev. Econ.* 156, 102833. doi:10.1016/j.jdeveco.2022.102833

Cheng, Z., Wang, H., and Smyth, R. (2014). Happiness and job satisfaction in urban China: a comparative study of two generations of migrants and urban locals. *Urban Stud.* 51 (10), 2160–2184. doi:10.1177/0042098013506042

Christou, A. (2006). American dreams and European nightmares: experiences and polemics of second-generation Greek-American returning migrants. *J. Ethn. Migr. Stud.* 32 (5), 831–845. doi:10.1080/13691830600704263

Co, C., Gang, I., and Yun, M. (2000). Returns to returning: who went abroad and what does it matter? *J. Popul. Econ.* 13 (1), 57–79. doi:10.2139/ssrn.166551

Constant, A., and Massey, D. S. (2003). Self-selection, earnings, and out-migration: a longitudinal study of immigrants to Germany. *J. Popul. Econ.* 16, 631–653. doi:10.1007/s00148-003-0168-8

Cui, C., Wang, Z., He, P., Yuan, S., Niu, B., Kang, P., et al. (2019). Escaping from pollution: the effect of air quality on inter-city population mobility in China. *Environ. Res. Lett.* 14 (12), 124025. doi:10.1088/1748-9326/ab5039

Dong, L. X., and Zhang, Z. J. (2021). Labor migration and manufacturing structuralchange in China. *J. Technol. Econ.* 40 (11), 84–93. doi:10.3969/j.issn.1002-980X.2021.11.008

Du, M., Wu, F., Ye, D., Zhao, Y., and Liao, L. (2023). Exploring the effects of energy quota trading policy on carbon emission efficiency: quasi-experimental evidence from China. *Energy Econ.* 124, 106791.doi:10.1016/j.eneco.2023.106791

Florida, R., Mellander, C., Stolarick, K., and Ross, A. (2012). Cities, skills and wages. *J. Econ. Geogr.* 12 (2), 355–377. doi:10.1093/jeg/lbr017

Fu, Y., and Gabriel, S. A. (2012). Labor migration, human capital agglomeration and regional development in China. *Regional Sci. Urban Econ.* 42 (3), 473–484. doi:10.1016/j.regsciurbeco.2011.08.006

Gao, C., Tao, S., He, Y., Su, B., Sun, M., Mensah, I. A., et al. (2021). Effect of population migration on spatial carbon emission transfers in China. *Energy Policy* 156, 112450. doi:10.1016/j.enpol.2021.112450

Giannetti, M., Liao, G., and Yu, X. (2015). The brain gain of corporate boards: evidence from China. *J. Finance* 70 (4), 1629–1682. doi:10.1111/jofi.12198

Graymore, M. L., Sipe, N. G., and Rickson, R. E. (2010). Sustaining human carrying capacity: a tool for regional sustainability assessment. *Ecol. Econ.* 69 (3), 459–468. doi:10.1016/j.ecolecon.2009.08.016

Hunter, L. M. (1998). The association between environmental risk and internal migration flows. *Popul. Environ.* 19 (3), 247–277. doi:10.1023/a:1024644003699

Huttunen, K., Møen, J., and Salvanes, K. G. (2018). Job loss and regional mobility. *J. Labor Econ.* 36 (2), 479–509. doi:10.1086/694587

Jain, S. (2013). For love and money: second-generation Indian-Americans 'return'to India. *Ethn. Racial Stud.* 36 (5), 896–914. doi:10.1080/01419870.2011.641576

Kennan, J., and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica* 79 (1), 211–251. doi:10.3982/ECTA4657

Kunuroglu, F., Yagmur, K., Van de Vijver, F. J., and Kroon, S. (2015). Consequences of Turkish return migration from western europe. *Int. J. Intercult. Relat.* 49, 198–211. doi:10.1016/j.ijintrel.2015.10.004

Li, L. X., and Zhou, G. S. (2022). Platform economy, labor market, and income distribution: recent trend and policy options. *Int. Econ. Rev.* 2, 46–59.

Liao, L., Du, M., and Chen, Z. (2023). Environmental pollution and socioeconomic health inequality: evidence from China. *Sustain. Cities Soc.* 95, 104579. doi:10.1016/j.scs.2023.104579

Liu, S. C. (2019). Targeting path and policy supply for the high-quality development of China's digital economy. *Economist* 6, 52–61. doi:10.16158/j.cnki.51-1312/f.2019.06.006

Liu, Y., and Shen, J. (2014). Spatial patterns and determinants of skilled internal migration in China, 2000-2005. *Pap. Regional Sci.* 93 (4), 749–771. doi:10.1111/pirs.12014

Liu, Y., Yang, Y., Li, H., and Zhong, K. (2022). Digital economy development, industrial structure upgrading and green total factor productivity: empirical evidence from China's cities. *Int. J. Environ. Res. Public Health* 19 (4), 2414. doi:10.3390/ijerph19042414

Liu, Y. W. (2018). Labor mobility, income inequality and rural poverty. *Finance Trade Res.* 29 (5), 10. doi:10.19337/j.cnki.34-1093/f.2018.05.006

Lybbert, T. J., and Sumner, D. A. (2012). Agricultural technologies for climate change in developing countries: policy options for innovation and technology diffusion. *Food policy* 37 (1), 114–123. doi:10.1016/j.foodpol.2011.11.001

Ma, S. Z., and Hu, Z. X. (2022). Does digital finance affects labor mobility? --Based on the micro perspective of China's floating population. *China Econ. Q.* 22 (01), 303–322. doi:10.13821/j.cnki.ceq.2022.01.15

Mastrorillo, M., Licker, R., Bohra-Mishra, P., Fagiolo, G., Estes, L. D., and Oppenheimer, M. (2016). The influence of climate variability on internal migration flows in South Africa. *Glob. Environ. Change* 39, 155–169. doi:10.1016/j.gloenvcha.2016.04.014

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Front. Econ.*, 105–142.

Ning, C. S. (2020). Research on the multi-dimensional impact of digital economy on high quality economic development based on the three-dimensional perspective of quality, efficiency, and power. *Guizhou Soc. Sci.* 4, 129–135.

Ojo, S., Nwankwo, S., and Gbadamosi, A. (2013). Ethnic entrepreneurship: the myths of informal and illegal enterprises in the UK. *Entrepreneursh. Regional Dev.* 25 (7-8), 587–611. doi:10.1080/08985626.2013.814717

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., et al. (2014). "Food security and food production systems," in *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change* (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 485–533.

Santos, M. D. D., and Postel-Vinay, F. (2003). Migration as a source of growth: the perspective of a developing country. *J. Popul. Econ.* 16 (1), 161–175. doi:10.1007/s001480100117

Sturgeon, T. J. (2021). Upgrading strategies for the digital economy. *Glob. strategy J.* 11 (1), 34–57. doi:10.1002/gsj.1364

Su, Y., Hua, Y., and Deng, L. (2021). Agglomeration of human capital: evidence from city choice of online job seekers in China. *Regional Sci. urban Econ.* 91, 103621. doi:10.1016/j.regsciurbeco.2020.103621

Tezcan, T. (2019). Return home? Determinants of return migration intention amongst Turkish immigrants in Germany. *Geoforum* 98, 189–201. doi:10.1016/j.geoforum.2018.11.013

Tuccio, M., and Wahba, J. (2018). Return migration and the transfer of gender norms: evidence from the Middle East. *J. Comp. Econ.* 46 (4), 1006–1029. doi:10.1016/j.jce.2018.07.015

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Xiao, T. (2016). Whether the environmental quality is the leading factor of labor mobility? *Econ. Rev.* 2, 3–17. doi:10.19361/j.er.2016.02.001

Yang, P. Q. (2020). The value, development emphasis and policy supply of digital economy. *J. Xi'an Jiaot. Univ. Soc. Sci.* 40, 57–65. doi:10.15896/j.xjtuskxb.202002007

Yankow, J. J. (2003). Migration, job change, and wage growth: a new perspective on the pecuniary return to geographic mobility. *J. Regional Sci.* 43 (3), 483–516. doi:10.1111/1467-9787.00308

Zhang, J., Wang, R., and Lu, C. (2019). A quantitative analysis of Hukou reform in Chinese cities: 2000–2016. *Growth Change* 50 (1), 201–221. doi:10.1111/grow.12284

Zhang, J. T., You, B., and Zhu, Y. (2021). The influence of mobility of rural labor on the transformation of urban -rural dual economic structure: based on the intermediary effect of economic growth. *Inq. Into Econ. Issues* 6, 125–137.

Zhao, X. J., and Guo, Q. W. (2018). Industrial structure change and business cycle fluctuation-analysis and test based on labor market perspective. *Manag. World* 34 (3), 51–67. doi:10.19744/j.cnki.11-1235/f.2018.03.005

Zhen, Z., Yousaf, Z., Radulescu, M., and Yasir, M. (2021). Nexus of digital organizational culture, capabilities, organizational readiness, and innovation: investigation of SMEs operating in the digital economy. *Sustainability* 13 (2), 720. doi:10.3390/su13020720

Zou, J., and Deng, X. (2022). To inhibit or to promote: how does the digital economy affect urban migrant integration in China? *Technol. Forecast. Soc. Change* 179, 121647. doi:10.1016/j.techfore.2022.121647