







# Influential Factors in Employment Location Selection Based on “Push-Pull” Migration Theory—A Case Study in Three Gorges Reservoir Area in China


**XU Ding-de**<sup>1,2</sup>  <http://orcid.org/0000-00001-6359-6540>, e-mail: Xudingde@imde.ac.cn

**ZHANG Ji-fei**<sup>1</sup>  <http://orcid.org/0000-0002-3102-0018>, e-mail: jfzhang@imde.ac.cn

**XIE Fang-ting**<sup>3</sup>  <http://orcid.org/0000-0001-8570-5402>, e-mail: xiefangting@imde.ac.cn

**LIU Shao-quan**<sup>1</sup>  <http://orcid.org/0000-0002-6853-0783>,  e-mail: liushq@imde.ac.cn

**CAO Meng-tian**<sup>1,2</sup>  <http://orcid.org/0000-0002-7229-6619>, e-mail: CaoMengtian@imde.ac.cn

**LIU En-lai**<sup>1,2</sup>  <http://orcid.org/0000-0001-7820-5274>, e-mail: enlailiu@imde.ac.cn

*1 Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu 610041, China*

*2 University of Chinese Academy of Sciences, Beijing 100049, China*

*3 The new rural development research institute, Jiangxi agricultural university, Nanchang 330000, China*

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**Abstract:** In China, farmers employed in non-farm work have become important socio-economic actors, but few studies have examined the farmers’ perspective in making their work location choices. Based on “push-pull” migration theory, this paper utilizes sectional data from a 2013 survey of farmers in China’s Three Gorges Reservoir area to empirically analyze the factors influencing migrant workers’ choice of employment location. The results indicate that 60.46% of laborers have migrated from their home province, whereas 39.54% have remained in their home province. Focusing on personal, household, and community characteristics—in addition to the economic characteristics of the sample counties—multinomial logistic regression models reveal that farmer-laborers’ employment location decisions are influenced by their personal capital endowment (age, years of education and social networks), family structure (the number of laborers, elders, children and students), home village characteristics (location, economic development level

and the degree of relief of the land) and home county economic development level. Notably, male and female laborers’ location decisions reveal a converging trend, and their differences are not pronounced. Per capita arable land area has little influence on location decisions, whereas the educational level of laborers has a significant impact. The results differ significantly from those found in previous studies.

**Keywords:** Off-farm employment; Location selection; Migrants; Push-Pull migration theory; Three Gorges Reservoir region; China

## Introduction

Since the economic reforms that began in the 1980s, China has entered a stage of development characterized by rapid urbanization and industrialization. Rapid industrial development and urban expansion have created strong demand

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for labor, whereas the concentration of more people on less land (China's per capita arable land area is 0.007ha) and agricultural seasonality have caused rural areas to produce a large surplus of laborers. Moreover, the maintenance of family livelihoods and increased living expenses (rising prices) has required the surplus rural labor force to move away from their home provinces. As national restrictions (such as 'hukou' system, which is used in China for the household registration policy and a family can be defined as either an agricultural household or an urban resident household) on population flows have weakened and the "comparative income" of migrant work has become more attractive, a substantial number of rural migrant workers now leave their villages and "flow" to industrial work in myriad cities across China every year. Farmers employed in non-farm work have become an important socio-economic actors (Li and Li 2014; Liang and Li 2014). According to recent statistics, the total number of rural laborers engaged in non-farm work nationwide reached 262.61 million in 2012. Among these workers, 163.36 million (62.21%) are migrant workers (CNSB 2013a). Additionally, wage income earned by farmers in 2012 accounted for 43.17% of the net income of rural households, which represents an increase of 22.94% since 1990 (CNSB 2013b).

China's labor flow has its own characteristics that differ from those of developed countries. Since the beginning of the wave of migrant labor in the 1990s, China has gradually eased policies restricting the flow of labor—now there are few restrictions, and laborers can move freely among various regions (Wang 2010). Thus, for farmers with relatively little human capital, the most practical and effective way to increase their income is to leave their native villages for non-farm work elsewhere (Prayitno et al. 2013; John et al. 2011; Jia et al. 2013). However, migrant laborers' low levels of human capital (such as little education and few skills) and underdeveloped social networks are impediments to the transfer of the labor force from mountainous areas (Li and Li 2014; Li et al. 2009; Xu et al. 2015). Thus, identifying the key factors that promote and hinder the transfer of the labor force from the perspective of laborers' resource endowments has clear policy implications for the rational direction

of the labor flow and represents one of the starting points for this study.

Moreover, China is a large country with vast mountainous areas that account for 70% of the nation's total area, although the population in these areas accounts for only 45% of the total population (Chen et al. 2007). Moreover, there are significant differences in the levels of economic development between the eastern coastal areas and the Midwestern mountainous areas due to differences in resource endowments and national strategic positioning. Thus, China's poor areas and impoverished population are concentrated in the Midwestern mountainous areas, particularly in the mountains of southwest China, where transportation is underdeveloped and the environment is fragile (Chen et al. 2007; Xu et al. 2015). Because of the differences in regional development levels, the lateral transfer of migrant workers has thus far meant laborers moving from China's Midwest and Southwest to the East (Liu et al. 2011). However, with the rapid development of the economy in Midwestern China, surplus labor has flowed back as migrant laborers have chosen to work closer to home. Thus, because the employment location decisions of laborers from the mountains have changed slightly, identifying the characteristics that have come to influence such decisions has clear policy implications for the rational direction of mountain laborers' migration and represents the other starting point for this study.

This study examines laborers in the Three Gorges Reservoir area, which is a typical mountainous area in southwestern China, to investigate the patterns and factors that influence the flow of rural individuals from China's poor mountainous areas to its cities. In this way, this paper can inform the reasonable allocation of labor resources in the mountainous areas and policymaking regarding the direction of the labor flow.

## **1 Literature Review and Theoretical Framework**

### **1.1 Literature review**

It has become common for Chinese farmers to

engage in non-farm work, and this development has greatly impacted on the development of the entire social economy. Where to work is an important decision faced by all migrant workers. From a spatial perspective, the migration process refers to workers leaving their hometowns for other places. The decision regarding whether and where to migrate is determined by residential factors, such as personal and household characteristics that are influenced by the possibility of long-term habitation in the home and the native town's characteristics. Deciding where to migrate is a choice based on the residential location's characteristics (Li et al. 2009). However, there are relatively few micro-empirical studies on the factors that affect migrant workers' employment location choices (Liu et al. 2014; Li et al. 2009). In the few extant studies focusing on this subject, the factors that affect migrant workers' employment location choice are often analyzed using the migrant workers' personal characteristics, household characteristics and community characteristics.

The personal characteristics of migrant workers—such as gender, age, educational level and skills—are important factors that influence employment location choices. In fact, social, cultural, economic and other personal characteristics are the most important factors affecting a migrant worker's decision regarding whether and where to migrate (Li et al. 2009; Clark 1996; Lamonica and Zagaglia 2013). Studies show that women are more likely to be pulled out of the rural area while men are more likely to be pushed (Sridhar et al. 2012). Studies also show that the location selection process of migrant workers is strongly influenced by age and skill (Coffey et al. 2015; Liu et al. 2011). Each additional 10 years of age reduces a migrant worker's probability of choosing employment outside the home province by 3.67%. Compared with local county employment, skill advantages are more salient in choosing cross-regional employment (Liu et al. 2011). Zhou (2001) shows that different age groups have different migration probabilities and that rural migrant workers under the age of 35 are the primary migrant group. In addition, studies also indicate that an individual's gender and age significantly impact relocation distance (Gao et al. 2009; Larry et al. 2012; Coffey et al. 2015). Some

studies show that rural laborers with relatively high educational levels are more likely to be employed outside of their home town (Fu and Gabriel 2012; Thissen et al. 2010; Sridhar et al. 2012). Sridhar et al. (2012) found that the less educated are more likely to be pushed out of rural areas, whereas the better educated are pulled towards opportunities in urban areas. Coffey et al. (2015) found that migration is negatively selective for education and economic status. Moreover, well-educated and wealthier villagers with longstanding political backgrounds are more likely to engage in off-farm employment in or adjacent to their home villages (Lei and Zheng 2005).

Analyses of the choice of employment location should consider not only personal characteristics but also household characteristics. An individual is only one member of a household; thus, the migration decisions of individuals also consider maximizing the interests and minimizing the risk of their households. The importance of household characteristics to farmers' migration has been emphasized in recent years (Lawson 1998; Liu et al. 2014; Gao et al. 2009; Hossain 2001). Household variables also affect the choice of employment location. These variables include the number of laborers, children, the elderly and students in a household; the per capita arable land area farmed by the household; and the social network of the laborer's family. Hossain (2001) found that poverty and family influence are the main push factors for out-migration. Studies show that young children in the household lower the likelihood of a household's members engaging in off-farm employment far from home. However, households with elderly relatives who can care for children promote labor mobility (Liu et al. 2014). Studies also show that school attendance and work are negatively related, i.e., the larger the number of a family's children who are attending school, the higher the likelihood that the parents work locally (Gao et al. 2009). Meanwhile, research also shows that having limited areas of cultivated land encourages rural laborers to migrate to urban areas to seek off-farm employment (Mullan et al. 2011; Alasia et al. 2009; Liu et al. 2014; Li et al. 2009). Additionally, the social networks of laborers' families have a significant impact on workers' selection of employment locations. Studies show that families with more extensive

social networks are more likely to have members working far away from the home village (Gao et al. 2009). Work groups (wage clusters) that are formed on the basis of kinship and geopolitical relationships can enhance rural laborer mobility and enable them to migrate long distances for employment (Zhang et al. 2008).

Community characteristics are also important factors that affect the employment location choices of migrant workers. Traffic conditions, per capita net income and the community's terrain have a significant effect on workers' employment location choices. Studies show that the more developed that public transportation is in a particular location, the higher the likelihood is that laborers are migrating there (Li et al. 2009). Moreover, the more developed a local economy is, the higher the likelihood is that laborers from nearby areas are working there (Liu et al. 2011). Additionally, one study shows that migrant workers from mountainous villages are 7.57% less likely to be employed outside their home province than workers from non-mountainous villages (Liu et al. 2011).

In addition to these factors that might influence migrant workers' employment location selection, the development level of the manufacturing industry, the level of economic development, the salary level and the working environment also directly affect the choice of employment location. For potential migrant workers, job availability, wages, work intensity and environmental conditions in the employment location directly influence the decision regarding whether and where to migrate. Because migrant workers have multiple employment location choices, and reliable data regarding these locations are difficult to obtain, there are relatively few empirical studies on this subject, although some research has been conducted recently. For example, Liu et al. (2014) found that provision of housing and meals which reflects the environmental conditions of the employment location, can increase the likelihood of long distance off-farm employment. Moreover, laborers may be pushed to migrate by poor access to credit, by debt or by commodity price crashes (Deshingkar 2003).

In conclusion, although a plethora of studies have examined the employment location choices of migrant workers, two aspects remain insufficiently

explored. First, most studies have focused only on the migration decision (to move or not to move) or the decision-making formation mechanism and the factors that influence migration choices (intra-provincial vs. inter-provincial migration). However, studies on a wide selection of decision-making issues are relatively scarce. Second, there are relatively few studies of the farmer-laborers' perspective on work location choices, particularly in the employment location choices of poor rural workers from the mountain settlement villages of southwest China.

## 1.2 Theoretical framework

### 1.2.1 Push-pull migration theory for understanding labor migration

The process of migration is not only the process of selection but also the process of weighing costs and benefits (Liu et al. 2011; Schultz 1961; Sridhar et al. 2012). By analyzing workers' employment location choices from the perspective of migration costs and income, human capital theory shows that the choice of employment location is based on a migrant worker's human capital reward probability distribution and migration costs. Alternatively, differences in income are likely the most commonly used and most important variable for explaining differences in utility (Schultz 1961). From the perspective of migration employment wage income, Todaro (1969) posits that the urban-rural income gap is the main motivation for migration among laborers and those potential migrants choose a place to work with relatively high wages. However, in some empirical studies, scholars have found that individual decisions are influenced not only by personal income expectations but also by strong family relationships, and these scholars have begun to analyze migration decision behaviors under the lens of family welfare maximization (Oded and Edward 1991; Liu et al. 2011; Siriwardhana et al. 2015).

In a theoretical discussion, Bai (2009) examines the influence of human and social capital on migrant workers' inter-provincial migration decisions. Bai (2009) concludes that the degree of matching between the accumulation of human capital and the available employment

opportunities in the employment location determines employment location selection, whereas social capital determines the degree of agglomeration. Li et al. (2009) also found that the more those villages are remote, the more important the blood relationship of social capital is to individuals. Moreover, several studies have used "push-pull" theory to analyze the factors that influence the selection of migration in large cities or in different countries (Clark 1996; Molho 1984; Czaika 2009; Etzo 2011; Lamonica 2013; Hossain 2001; Sridhar et al. 2013).

Subsequent researchers have developed new theoretical perspectives (such as human capital theory and social network theory) to enrich "push-pull" theory. Certain of these authors have thus proposed the "double pull model" (Qi et al. 2012; Li 2003) and have conducted studies on rural laborers' migration by focusing on different aspects of it. Based on the previously discussed theoretical perspectives and empirical studies, this paper divides the influencing factors in rural laborers' employment location decisions into personal characteristics, household characteristics, community characteristics and county economic conditions. Then, multinomial logistic econometric models are constructed to quantitatively reveal the effect of these factors on laborers' employment location selection decisions. Thus, this research not only enriches the relevant theoretical studies but also can serve as a reference for the development of related policies.

### 1.2.2 Definition of variables and hypotheses

The objective of this paper is to improve our understanding of the patterns and factors that influence the flow of rural migrant workers from China's poor mountainous areas to the nation's cities. Building on the previous literature review and developing related theory, this study divides the employment location choice of migrant farmers into five categories: home village (HV), home town but outside of home village (HT), home county but outside of home town (HC), home province but outside of home county (HP) and outside of home province (OHP). Corresponding to these categories, the dependent variables are coded from one to five for all rural migrant workers. Specifically,  $Y_i=1$  denotes HV,  $Y_i=2$  denotes HT,  $Y_i=3$  denotes HC,  $Y_i=4$  denotes HP,

and  $Y_i=5$  denotes OHP. Meanwhile, we also divide the factors that affect the employment location choice of migrant farmers into individual factors, household factors, community factors and county economic development factors (Table 1). In this study, a laborer is a 16- to 64-year-old healthy individual who can engage in manual labor and who is not a student. If a migrant worker in our sample worked in more than one place during the survey year, we consider the place in which the most income was earned as their work location.

As shown in Table 1, we use those individual factors that are commonly used in the literature as variables, including gender (GEN), age (AGE), years of education (EDU) and whether the worker has master skills (SKI). In addition, the laborer's skills training, employment information acquisition channel and the work groups (wage clusters) formed by a worker's kinship and geopolitical relationships might affect their employment location choice. Thus, we add the following three indicators to our model: laborers' training information (TRA), the acquisition channel of non-agricultural work (CHA) and the number of friends and family members working together (WOM).

In general and in contrast to females' employment choices in some developed countries, Chinese culture has always emphasized the paradigm of "men work outside of the home, while women take care of the family". In the rural labor force in mountainous areas, men are more adventurous than women (Li et al. 2009; Gao et al. 2009; Coffey et al. 2015). Thus, we assume that male workers' distance traveled for employment will be greater than that for women. In addition, younger migrant workers may tend to work far away from home because they have stronger bodies and fewer reasons not to leave home, are more adventurous and expect higher wages (Liu and Xie 2014; Liu and Wang 2011; Sridhar et al. 2012). In addition, those with higher education levels can find jobs more easily in those employment locations that offer higher incomes; thus, when such workers are confident in themselves, they tend to work further from home (Liu and Xie 2014; Liu and Wang 2011; Li et al. 2009).

Laborers who have acquired non-agricultural skills and have participated in non-agricultural

**Table 1** Definitions and values for the variables

Variable	Unit	Level	Definition and assignment	Min	Max	Mean	SD
<b>Explanatory variables</b>							
<i>Individual characteristics</i>							
GEN	1/0	Indiv.	GEN = 1 for male, GEN = 0 for female	0	1	0.63	0.48
AGE	years	Indiv.	Ages of rural migrant laborers	16	64	35.61	10.58
EDU	years	Indiv.	Years of education of rural migrant laborers	0	16	8.65	3.18
SKI	1/0	Indiv.	SKI = 1 for yes, SKI = 0 for no	0	1	0.33	0.47
TRA	—	Indiv.	TRA = 1 for agricultural training, TRA = 2 for non-farm training, TRA = 3 for none	1	3	2.66	0.53
CHA	1/0	Indiv.	CHA = 1 for found by laborers themselves, CHA = 0 for others	0	1	0.49	0.50
WOM	persons	Indiv.	Number of relatives and friends working together	0	40	3.53	4.79
<i>Household characteristics</i>							
LAB	persons	HH	Number of laborers in a household	1	7	3.44	1.23
OLD	persons	HH	Number of senior citizens over 75 years old in a household	0	2	0.15	0.44
CHI	persons	HH	Number of children under the age of 6 in a household	0	3	0.33	0.57
STUS	persons	HH	Number of students in a household	0	3	0.82	0.81
AREA	mu <sup>a</sup>	HH	Per capita cultivated land area in a household	0	4.17	0.75	0.68
CASH	Yuan <sup>b</sup>	HH	Total income of migrant workers	5000	226,000	59,248	32,241
<i>Community characteristics</i>							
INC	Yuan <sup>b</sup>	Com.	Per capita income in the village	1894	7641	5194	1883
DISC	kilometers	Com.	Distance to the nearest county	19	75	43.85	18.69
RDLS	m	Com.	The degree of relief of the land surface in the village	168	1512	505.4	412.65
<i>County economic development level</i>							
GVIO	Yuan <sup>b</sup>	Coun.	Per capita gross value of the industrial output of the laborers' home county	3305	128,340	38,843	49,250
<b>Dependent variable</b>							
Y	—	Indiv.	Y = 1 for HV, Y = 2 for HT, Y = 3 for HC, Y = 4 for HP, Y = 5 for OHP	1	5	4.08	1.37

**Notes:** GEN = Gender; EDU = Years of education; SKI = Whether the worker has master skills; TRA = Laborers' training information; CHA = The acquisition channel of non-agricultural work; WOM = The number of friends and family members working together; LAB = The number of family laborers; OLD = The number of elderly individuals aged 75+ in the household; CHI = The number of children aged 6 and under in the household ; STUS = The number of children attending school ; AREA = Per capita cultivated arable land area; CASH = The total income of the migrant workers; INC = Per capita income in the village; DISC = Distance to the nearest county ; RDLS = The degree of relief of the land surface in the village; GVIO = Per capita gross value of industrial output; Indiv. = Individual; HH = Household; Com. = Community; Coun. = County; and SD = standard deviation; HV = Home village; HT = Home town but outside of home village; HC = Home county but outside of home town; HP=Home province but outside of home county; OHP = Outside of home province. <sup>a</sup> 1 mu  $\approx$  667 m<sup>2</sup> or 0.067 ha. <sup>b</sup> During the study period, 1 US dollar was equal to 6.19 Chinese Yuan.

skills training find it easier to obtain high-income jobs in distant places and may thus be more likely to work far from their home villages.

Conversely, laborers who have acquired agricultural skills and who have participated in agricultural skills training may be more likely to work closer to their homes. Laborers with broad access to employment information may find useful employment information more easily and might therefore be more likely to obtain a high-income job in a distant location, which makes them more likely to work far from their home villages.

Laborers with more WOM may be more likely to work far from their home villages because they are more likely to receive aid in work and life, which makes it easier to find useful employment information. Based on these assumptions, we propose the following hypotheses:

H1: Male laborers prefer working far from their home villages, whereas female laborers prefer working near their home villages.

H2: Younger laborers prefer working far from their home villages, whereas older laborers prefer working near their home villages.



H3: Laborers with higher EDU have a higher likelihood of working far from their home villages.

H4: Laborers who have acquired non-agricultural skills prefer working far from their home villages, whereas laborers who have acquired agricultural skills prefer working near their home villages.

H5: Laborers who have received non-agricultural training tend to work far from their home villages, whereas laborers who have received agricultural training tend to work in nearby areas.

H6: The wider the CHA is, the higher the likelihood is that laborers are working far from their home villages.

H7: The higher WOM is, the higher the likelihood is that laborers are working far from their home villages.

As shown in Table 1, household characteristics are measured using the following six indicators: the number of family laborers (LAB), per capita cultivated arable land area (AREA), the total income of the migrant workers (CASH), the number of elderly individuals aged 75+ in the household (OLD), the number of children aged 6 and under in the household (CHI) and the number of children attending school (STUS).

In general, the higher the LAB, the higher the likelihood is that the household has surplus labor under the realistic conditions of "more people and less land" and other standard economic characteristics. This surplus labor may be more likely to work far from the home village (Liu and Wang 2011; Liu and Xie 2014). The larger that AREA is, the higher the consumption of laborers; concurrently, farming at home may result in higher agricultural income, and laborers will be more likely to work near their home villages during the slack season and not to migrate for work (Li et al. 2009; Gao et al. 2009). Outside work, particularly work in the economically developed coastal provinces, can provide higher wages; therefore, the higher that CASH is, the higher the likelihood is that laborers will choose to work far from their home villages. The higher that the values for STUS, OLD and CHI are, the more likely it is that laborers will choose to work in nearby areas such that they can care for their families (Liu et al. 2014; Gao et al. 2009). Based on this reasoning, we propose the following hypotheses:

H8: Higher values for LAB indicate a higher likelihood that laborers are working far from their home villages.

H9: Higher values for AREA indicate a higher likelihood that laborers are working in areas that are near the home village.

H10: Higher values for CASH indicate a greater likelihood that laborers are working far from the home village.

H11: Higher values for OLD indicate a greater likelihood that migrant workers are working in areas that are near the home village.

H12: Higher values for CHI indicate a greater likelihood that laborers are working in areas that are near the home village.

H13: Higher values for STUS indicate a greater likelihood that laborers are working in areas that are near the home village.

Table 1 shows that community characteristics are measured using the following three indicators: per capita income in the village (INC), distance to the nearest county (DISC) and the degree of relief of the land surface in the village (RDLS). INC and DISC are used to reflect the home village's economic development level and its location, whereas RDLS is used to reflect the village's natural environment.

In general, traffic conditions and the level of economic development of the villages with higher DISC and RDLS are relatively poor, and it is difficult for laborers to work in nearby areas. Therefore, laborers from these areas may be more likely to work far from their home villages (Liu et al. 2014; Gao et al. 2009). Laborers living in villages with higher economic development levels are likely to be able to find a local job more easily and will often choose to work near the home village (Liu et al. 2011; Li et al. 2009). Based on this reasoning, we propose the following hypotheses:

H14: The higher that DISC is, the higher the likelihood is that laborers are working far from their home villages.

H15: The higher that INC is, the higher the likelihood is that laborers are working near the home village.

H16: The higher that RDLS is, the higher the likelihood is that laborers are working far from the home village.

In addition, the sample counties are classified

by per capita gross industrial output value, so we added an indicator that reflects the status of the sample counties' economic development, i.e., the per capita gross industrial output (GVIO) of the sample counties.

In general, the higher that GVIO is—which indicates a more advanced industrial county—the higher the likelihood is that workers can find work in the county. Based on this reasoning, we assume the following:

H17: The higher that GVIO is, the higher the likelihood is that laborers work in areas that are near the home village.

## 2 Survey Design and Data

### 2.1 Study area

The Three Gorges Reservoir area consists of 19 county-level administrative areas over an area of 54,200 km<sup>2</sup> that was affected by inundation as a result of the Three Gorges Project (TGP). In this area, the agriculture sector mainly consists of crop cultivation and livestock management and rarely of large-scale forestry. The area is an important part of the upper reaches of the Yangtze River economic zone. By the end of 2012, the area had a population of 14.5 million and a population density of 374 people/km<sup>2</sup>, which is nearly 2.7 times the national average. Arable land accounts for 40% of the land area, and the arable land per capita is 0.005 hm<sup>2</sup>, which is less than the national average (0.007 hm<sup>2</sup>). The land area that is characterized by a falling gradient of over 25 is 1989.67 km<sup>2</sup>, which accounts for 21.95% of the total area of dry land. Of the total population, 60% work in agriculture, although agricultural income accounts for only 19.8% of total revenue. The narrow strip of land is extremely densely populated, which leads to tension among the people and an overexploited and degraded environment. Per capita GDP is 27,500 Yuan (\$4443), which is 28.4% lower than the national average of 38,400 Yuan (\$6204). There are significant differences in economic development between the county-level administrative areas, and 8 counties are listed as key national poverty-alleviation counties.

### 2.2 Data source

This study mainly used data from a survey that was conducted in August 2013 in the Three Gorges Reservoir area. The sample was determined using a combination of stratified sampling and equal probability random sampling. Sample counties were first selected by building a target system that considered economic development, industrial structure, social development, resources, environmental conditions, and traffic accessibility, with a total of 19 indicators. To complete the field research, principal component analysis and system clustering were used to divide the 19 counties (districts) in the Three Gorges Reservoir area into four categories, and one county was selected at random from each category to provide four sample counties: Yubei, Zhongxian, Wanzhou, and Wuxi.

Following the selection of the sample counties, which made the 109 townships in the four counties the study unit, we considered the undulating terrain features of the mountainous areas and the workload to complete the field survey, and we divided the 109 townships into two categories based on the altitude of the townships and randomly selected one sample township from each category. Each sample county (district) therefore has two sample townships, yielding a total of 8 townships. Then, in consideration of project funding and the field investigation workload, we used hierarchical clustering to divide the 107 villages into two categories based on the villages' economic development level and the distance from the township. Considering the remote and closed nature of the study area, sporadically scattered farmers live in the mountains, and the homogeneity of the farmers living in the same village is relatively strong. Thus, from 5,345 total sample households, we randomly selected 22 sample households from the roster of each sample village, and 11 researchers were selected to receive rigorous training at conducting household questionnaire surveys (Figure 1). Each researcher investigated two sample households in every sample village. The survey primarily concerned the characteristics of the farmers' households (such as the number of laborers, elders and children and the size of the cultivated land area), the laborers' personal characteristics (such as years of education, skill mastery and social networks), and community characteristics (such as the economic



development level of the village and the village's location). An average of 30 minutes was required to complete the questionnaire.

Additionally, the statistical data on the sample counties and communities were mainly derived from the relevant statistical data sources, such as the 2013 Chongqing Statistical Yearbook and rural township agricultural production management statistics. Meanwhile, RDLS of the 16 sample villages was extracted from a 30 m Digital Elevation Model (DEM) of the Three Gorges Reservoir Area using Geographic Information System (GIS) analytical tools.

### 2.3 Empirical specifications

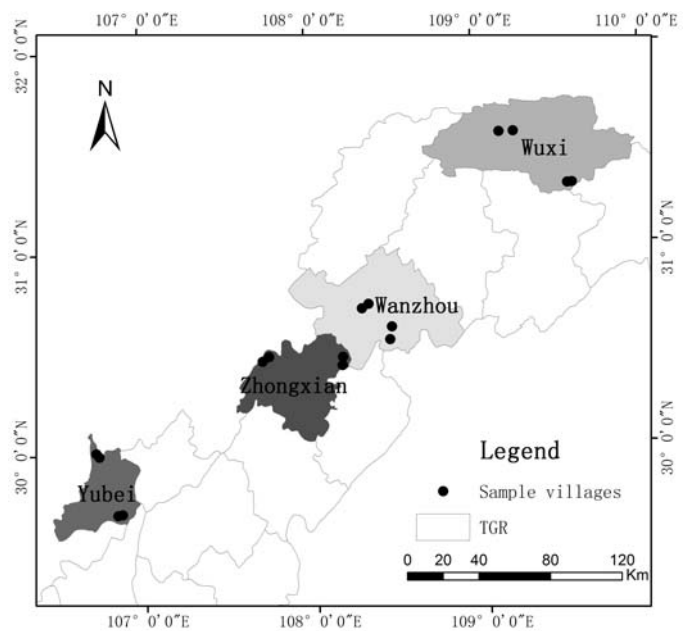
The dependent variable of the migrant farmers' work location is an unordered categorical variable, and the independent variable contains not only continuous variables (such as the number of laborers in a family) but also categorical variables (such as gender). For these reasons, we built multinomial logistic regression models to model the decisions of rural laborers to migrate to each location.

For the dependent variable,  $Y_i=1$  denotes HV,  $Y_i=2$  denotes HT,  $Y_i=3$  denotes HC,  $Y_i=4$  denotes HP, and  $Y_i=5$  denotes OHP. We designate the probability of each of these five events as  $P_1, P_2, P_3, P_4$  and  $P_5$ , respectively. Using a logit model ensured that each estimated  $P$  lies within the bounds of zero and unity. Negative probabilities and probabilities greater than one are impossible by design. The multinomial logit (MNL) model also ensures that the relevant probabilities (in our case,  $P_1, P_2, P_3, P_4$  and  $P_5$ ) sum to unity.

In the MNL model, one possibility—Home Village (HV)—is denoted as the base or reference position. The logarithm of the odds (relative to the base) of each remaining response is assumed to follow a linear model:

$$\begin{aligned} \ln(P_1 / P_0) &= z_1 = \sum \beta_{1i} x_i \\ \ln(P_2 / P_0) &= z_2 = \sum \beta_{2i} x_i \\ &\dots \\ \ln(P_5 / P_0) &= z_5 = \sum \beta_{5i} x_i \end{aligned} \tag{1}$$

where  $\beta_{1i}, \beta_{2i}, \beta_{3i}, \beta_{4i}$  and  $\beta_{5i}$  are coefficients of the  $i$ th explanatory variable  $x_i$ , these five equations are estimated simultaneously.



**Figure 1** Distribution of the sample counties and villages in the Three Gorges Reservoir Area.

Additional equations can be added to accommodate six, seven, and even more responses. When there are two responses, the model reduces to a binary logit model, leaving only one equation. In our notation, the equation for choosing OHP would be  $\ln \{ (P_5 / (P_1 + P_2 + P_3 + P_4 + P_5)) \}$ , which is equivalent to  $\ln (P_5 / (1 - P_5))$ . Logarithms of odds are known as “logits”, which leads to the term “logit regression”. Odds ratios have no upper limit, but they do have a lower bound of zero. Logits can have any value, positive or negative. A curve that is linear for the logit of  $P$ , which is easily estimated using linear regression techniques, is non-linear in  $P$ , taking a familiar S-shaped logistic curve that approaches—but never reaches—values of zero and unity. The slope of the logistic curve is steepest (marginal effects are greatest) at the point of inflection, at which point the odds are equal and  $P = 1/2$ . Non-linearity can be accommodated by adding squared terms to the list of explanatory variables; in this case, the curve for  $P$  is U-shaped or inverse U-shaped with the tails of the U (inverted U) approaching—but never reaching—the upper (lower) bound of unity (zero).

Maximum likelihood estimation (MLE) is used in lieu of ordinary least squares (OLS) for both binary and multinomial logit regression. MLE is an iterative procedure that yields results with excellent large sample properties. The technique is

straightforward and intuitive but also unusual in that none of the observed values of  $P$  lie on the logistic curve. Moreover, the logit of any observed  $P$  is either negative infinity or positive infinity; neither is an actual number and therefore does not lie on the logit curve.

The MNL model may also be written in terms of probabilities ( $P_s$ ) rather than odds ratios. Exponentiating Equation 1 above yields  $P_2=P_1 \times \exp(z_2)$ ,  $P_3=P_1 \times \exp(z_3)$ ,  $P_4=P_1 \times \exp(z_4)$  and  $P_5= P_1 \times \exp(z_5)$ . Considering that  $P_1+P_2+P_3+P_4+P_5=1$ , we know that the base probability is  $(P_1) =1/\{1+\exp(z_1) +\exp(z_2) +\dots+\exp(z_5)\}$ . The other four probabilities are as follows:

$$\begin{aligned}
 P_2 &= \exp(z_2) / \{1 + \exp(z_1) + \exp(z_2) + \exp(z_3) + \exp(z_4) + \exp(z_5)\} \\
 P_3 &= \exp(z_3) / \{1 + \exp(z_1) + \exp(z_2) + \exp(z_3) + \exp(z_4) + \exp(z_5)\} \\
 &\dots \\
 P_5 &= \exp(z_5) / \{1 + \exp(z_1) + \exp(z_2) + \exp(z_3) + \exp(z_4) + \exp(z_5)\}
 \end{aligned}
 \tag{2}$$

This way of writing the MNL model demonstrates that choices are determined simultaneously, with the determinants of one choice affecting the determinants of the others. Moreover, it is helpful to note that the regression coefficients ( $\beta_{1i}$ ,  $\beta_{2i}$ ,  $\beta_{3i}$ ,  $\beta_{4i}$  and  $\beta_{5i}$ ) measure effects relative to the base (choosing HV) because all coefficients of the base equation (the  $\beta_{1i}$ ) equal zero by definition.

### 3 Empirical Results

#### 3.1 Descriptive statistical analysis

##### 3.1.1 Variables

Regarding laborers' personal characteristics, the number of men is much larger than the number of women (334>192), the number of individuals without professional skills is much larger than those who had acquired professional skills (351>175), and the number of individuals without technical training is much larger than those who have had technical training (365>161). Regarding non-farm work, there is little difference between the numbers of laborers who found works themselves and those who found work through family members, close friends and other methods. The laborers are mainly middle-aged to young, and the average age is 35.61

years. The level of education is generally not high, i.e., the average number of years of education is 8.65. The number of relatives and friends working together in the same location is as high as 40, whereas the lowest values involve only the laborer (0); the mean is 3.53.

Regarding laborers' household characteristics, the mean number of laborers is 3.44. The number of children and elderly in the family and the number of students in school are relatively small, with average values of less than one. Specifically, the number of people who are older than 75, the number of children who are under 6 and the number of children who attend school are 0.15, 0.33 and 0.82 on average, respectively. Per capita arable land area is 0.05 ha, which is only one-half of the national per capita arable land area (0.10 ha). Additionally, the mean value of CASH is 59,248 Yuan (\$9572).

Regarding the characteristics of the laborers' communities, the farthest distance from the community to the nearest county is 56 km, and the mean is 43.85 km. The high end of the range of the communities' RDLS is 1344 meters, and the mean RDLS of the communities is 505.40 meters. Additionally, the mean per capita net income of farmers in the community is 5194 Yuan (\$839), which is far less than the national average (\$1279) at the end of 2012 (Bureau 2013a). Although there are 16 sampled communities, the maximum value of the per capita net income of farmers in a community is 7641 Yuan (\$1234), which is 276 Yuan (\$45) less than the national average.

With respect to the economic characteristics of the sample counties, the per capita industrial output difference is significant. The highest per capita industrial output value is 128,340 Yuan (\$20,733) in Yubei, which is 38.83 times higher than the lowest per capita industrial output value of 3305 Yuan (\$534) in Wuxi. The four counties' average per capita total industrial output is 38,843 Yuan (\$6275). The minimum, maximum, mean and standard deviation values of each index are shown in Table 1.

##### 3.1.2 Laborers' work location choices under various economic conditions

In the survey of 329 farmers in the four sample counties, there is a total workforce of 1,026 people. Among these, the number of workers who

perform off-farm work for more than six months is 523, accounting for 28.93% of the total sample. With respect to each county, the number of laborers in the Wuxi, Zhongxian, Wanzhou and Yubei survey samples is 533, 448, 443 and 384, respectively. Among these, the number of laborers who are employed in off-farm work for more than six months is 150, 129, 128 and 116, respectively, which accounts for 28.14%, 28.79%, 28.89%, and 30.21% of the survey sample in each county, respectively.

As for GVIO, the differences between the four counties are significant. The GVIO of the highest county (Yubei) is 38.83 times that of the lowest county (Wuxi). With respect to the five categories of the working location choice for the four counties, OHP is the first choice for migrant workers, and there is no difference between the other four location categories. In particular, in addition to the low proportion in Yubei (21.55%), the proportion of migrant workers in the other three counties who chose OHP are all over 60%. The proportion for Wuxi is the highest (76.67%), whereas the proportion for Zhonxian is the lowest (63.57%). The county economic development and labor transfer location frequency distribution of the four survey samples are shown in Table 2.

### 3.1.3 Comparisons of migrant types

As shown in Table 3, in the surveyed samples, the majority of the migrant laborers have chosen off-farm employment far from their home villages (HP and OHP), and most have selected OHP employment (318). The proportions of migrant laborers who have selected employment in HV, HT, HC, HP, and OHP are 9.89%, 8.37%, 5.89%, 15.40%, and 60.46%, respectively.

With respect to individual characteristics, for GEN, the lowest proportion of male migrants is

found in the HP migration stream (0.54), and the highest proportion is found in the HT migration stream (0.70). Regarding AGE, the mean ages of the laborers who took off-farm jobs in HV, HT, HC, HP, and OHP are 42.06, 42.34, 32.97, 30.78, and 35.11, respectively. As for EDU, rural laborers who work in HT have the fewest number of years of education (7.64), and those who work in HP have the highest number (9.88). As for SKI, the proportion of laborers with master skills who work in HP is 42%, but the proportion of such workers in HV is only 29%. For TAR, the proportion of laborers who work in HV is far greater than the proportion of laborers who work in OHP (8% > 2%). The proportion of laborers who have received non-agricultural training is highest among those who work in HP (44%); for those who work in HT and HV, the proportions are 23% and 27%, respectively. As for CHA, the proportions of migrant laborers who work in HV and HT are 75% and 64%, respectively, which is higher than for laborers who work in HP and OHP (51% and 43%, respectively). As for WOM, the number of relatives and friends with whom the laborers work is far higher in HP and OHP (3.22 and 3.93, respectively) than in HV and HT (1.67 and 2.68, respectively).

With respect to household characteristics, as for LAB, the number of laborers who work in HP and OHP (3.80 and 3.50, respectively) is higher than the number of laborers who work in HV and HT (2.83 and 3.16, respectively). As for OLD > 75 years of age, laborers who work in HV have the highest number of senior citizens in their household, with a mean value of 0.21. Meanwhile, as for CHI < 6 years of age, laborers who work in HT have the highest number of children, with a mean value of 0.39. With respect to STUS, laborers who work in HT have the highest number of students, with a mean value of 0.91. Regarding

**Table 2 Migration patterns in counties with different economic conditions**

Counties	GVIO (Yuan <sup>a</sup> )	RL	RML	HV	HT	HC	HP	OHP
Wuxi	3305	533	150	13	8	6	8	115
Zhonxian	5890	448	129	12	16	5	14	82
Wanzhou	32,201	443	128	5	11	8	11	93
Yubei	128,340	384	116	22	9	12	48	25
Total	169,736	1808	523	52	44	31	81	315

**Notes:** Definitions of the variables are given in the note for Table 1. RL = Rural laborers investigated; RML = Rural migrant laborers investigated. <sup>a</sup> During the study period, 1 US dollar was equal to 6.19 Chinese Yuan.

See Table 1 for the abbreviations.

**Table 3 Comparisons of the mean values for the five migrant types**

Variable	Unit	HV (N=52)	HT (N=44)	HC (N=31)	HP (N=81)	OHP (N=318)
<b>Individual characteristics</b>						
GEN(o) <sup>a</sup>	1/0	0.69	0.70	0.58	0.54	0.64
AGE	years	42.06	42.34	32.97	30.78	35.11
EDU	years	9.54	7.64	8.58	9.88	8.34
SKI(o) <sup>a</sup>	1/0	0.29	0.36	0.39	0.42	0.31
TRA(1) <sup>b</sup>	—	0.08	0.07	0.00	0.05	0.02
TRA(2) <sup>b</sup>	—	0.27	0.23	0.36	0.44	0.23
CHA(1) <sup>c</sup>	1/0	0.75	0.64	0.39	0.51	0.43
WOM	persons	1.67	2.68	4.61	3.22	3.93
<b>Household characteristics</b>						
LAB	persons	2.83	3.16	3.23	3.80	3.50
OLD	persons	0.21	0.11	0.16	0.20	0.13
CHI	persons	0.13	0.39	0.26	0.26	0.37
STUS	persons	0.54	0.91	0.45	0.88	0.85
AREA	mu <sup>d</sup>	0.84	0.79	0.80	0.72	0.69
CASH	Yuan <sup>e</sup>	45734	43874	48729	55352	65603
<b>Community characteristics</b>						
INC	Yuan <sup>e</sup>	5690.23	5509.57	5909.87	6283.54	4722.54
DISC	kilometers	37.04	49.50	42.06	38.17	44.30
RDLS	m	589.98	444.84	478.71	358.27	540.02
<b>County economic development level</b>						
GVIO	Yuan <sup>e</sup>	59579.42	37044.34	59579.61	81770.75	22744.27

**Notes:** Definitions of the variables are given in the notes of Table 1. <sup>a</sup> The reference category is 0. <sup>b</sup> The reference category is 3. <sup>c</sup> The reference category is 1. <sup>d</sup> 1 mu≈667 m<sup>2</sup> or 0.067 ha. <sup>e</sup> During the study period, 1 US dollar was equal to 6.19 Chinese Yuan.

AREA, the mean per capita arable land area is largest among laborers who work in HV (0.84). As for CASH, the mean total income of migrant workers is highest among laborers who work in OHP (\$10,511).

With respect to community characteristics, INC is the highest among laborers who have migrated to HP (\$1015), whereas this value is lowest among OHP migrants (\$763). As for DISC, the mean DISC is highest among those who have migrated to HT (49.50) and lowest for those who have migrated to HV (37.04). As for RDLS, the mean RDLS of the villages is highest among those who work in HV (589.98).

With respect to county economic conditions, those migrant laborers who work in HP have the highest mean value of GVIO (\$13,210), whereas those migrant laborers who work in OHP have the lowest GVIO value (\$3674).

### 3.2 Impact of various factors on location choices

This study used SPSS20.0 software to build multinomial logistic regression models to explore the factors that affect migrant workers'

employment location choice. Because the same household may contain several migrant laborers (and household characteristics with significant effects on migrant workers' employment location choice may mask the different personal characteristics of laborers in the same household), this study used a backward stepwise regression to construct the models and to eliminate possible multicollinearity among the variables. Model 1 explores the influence of the personal characteristics of the migrant laborers on their employment location choice, whereas Model 2 introduces the household characteristics of the migrant laborers into Model 1, and Model 3 introduces community characteristics and the developmental level of the migrant laborers' county into Model 2.

#### 3.2.1 Personal characteristics

As shown in Table 4, model 1 highlights the results of the regression analysis with respect to personal characteristics, i.e., AGE, EDU, TRA and CHA have significant effects on migrant workers' employment location choice. In particular, the results for AGE and TRA are consistent with hypotheses H2 and H5, whereas the results for

**Table 4 Results of the influence of individual characteristics and household characteristics on migrant laborers' working location choice model <sup>a</sup>**

Variable	Coefficients in Model 1				Coefficients in Model 2			
	HT (OR)	HC (OR)	HP (OR)	OHP (OR)	HT (OR)	HC (OR)	HP (OR)	OHP (OR)
<b>Individual characteristics</b>								
GEN(o) <sup>b</sup>	—	—	—	—	—	—	—	—
AGE	-0.145	-1.025*** (0.359)	-1.198*** (0.332)	-0.806*** (0.446)	0.015	-0.957*** (0.384)	-1.167*** (0.311)	-0.751*** (0.472)
EDU	-0.653*** (0.520)	-0.650** (0.522)	-0.340* (0.711)	-0.589*** (0.555)	-0.616** (0.540)	-0.771*** (0.463)	-0.346* (0.708)	-0.705*** (0.494)
SKI(o) <sup>b</sup>	—	—	—	—	—	—	—	—
TRA(1) <sup>c</sup>	-0.114	-18.903	0.307	-1.463** (0.231)	-0.040	-20.277	0.065	-1.742** (0.175)
TRA(2) <sup>c</sup>	0.170	0.557	0.808* (2.244)	-0.008	0.284	0.302	0.678	-0.104
CHA(o) <sup>b</sup>	-0.370	-1.373*** (0.253)	-0.882** (0.414)	-1.205*** (0.300)	—	—	—	—
WOM	—	—	—	—	0.383	0.879*** (2.409)	0.575* (1.777)	0.706*** (2.026)
<b>Household characteristics</b>								
LAB	—	—	—	—	0.333	0.177	0.737*** (2.091)	0.417* (1.517)
OLD	—	—	—	—	-0.205	-0.198	0.009	-0.302** (0.739)
CHI	—	—	—	—	—	—	—	—
STUS	—	—	—	—	0.195	-0.545* (0.580)	0.381* (1.463)	0.090
AREA	—	—	—	—	—	—	—	—
CASH	—	—	—	—	-0.158	0.097	0.191	0.736*** (2.088)
Constant	0.127	0.400	0.866**	2.846***	-0.001	-0.168	0.632**	2.535***
<b>Test statistics</b>								
Likelihood ratio tests	Chi-Square=116.833***(df=20)				Chi-Square=196.525***(df=40)			
Nagelkerke R <sup>2</sup>	0.219				0.343			
Correct predictions	62.9%				63.3%			

**Notes:** OR = Odds ratio. Definitions and values of the variables are given in the notes of Table 1. <sup>a</sup> The reference category is HV. <sup>b</sup> The reference category is o. <sup>c</sup> The reference category is 3. \*Significant at  $\alpha = 0.10$ ; \*\*significant at  $\alpha = 0.05$ ; \*\*\*significant at  $\alpha = 0.01$ .

EDU and CHA are inconsistent with hypotheses H3 and H6.

Consistent with previous research (Liu et al. 2011; Gao et al. 2009), with respect to age, younger laborers, in particular, prefer working far from their home villages, whereas older laborers prefer working nearby. Compared with selecting HV, a one-year increase in age decreases the probabilities of migrating to HC, HP and OHP by 64.1%, 66.8% and 55.4%, respectively. As for TRA, compared with those laborers who have chosen to work in HV and have not received agricultural or non-agricultural technical training, the laborers who have received agricultural training tend to work nearby, whereas laborers who have received non-agricultural technical training tend to work farther from their home villages. In particular, for

those who have chosen to work in OHP, the number of laborers who have received agricultural training is 0.231 times the number of laborers who have not received agricultural or non-agricultural technical training, whereas for those who have chosen to work in HP, the number with non-agricultural training is 2.244 times the number of those who have not received agricultural or non-agricultural technical training.

Notably, EDU and CHA are inconsistent with hypotheses H3 and H6; laborers with a higher educational level and a broader employment information channel are more likely to work in nearby areas. In particular, compared with selecting HV, a one-year increase in educational level decreases the probabilities of migrating to HT, HC, HP and OHP by 48.0%, 44.8%, 28.9% and

44.5%, respectively. Moreover, Liu and Wang (2011), Gao et al. (2009), Liu and Xie (2014) found that laborers' years of education do not remarkably affect their employment location selection decisions, so our result provides a very interesting contrast.

The results are completely different across various study areas in China. In terms of the reasons for the insignificant influence of EDU on laborers' employment location decisions, Liu et al. (2014) indicate that the explanation lies with the generally few years of education for laborers in the study areas, while Gao et al. (2009) do not explain the results. With regard to this study, the differences in laborers' years of education make their employment location selection decisions remarkably different. Consistent with previous research (Liu et al. 2011), those laborers who have found jobs themselves tend to work nearby, compared with laborers who have chosen to work in HV and laborers who have found non-farm work through their relatives and friends. The probability that they have chosen to work in HC, HP and OHP are 0.253, 0.414 and 0.300 times those of laborers who have acquired work through their relatives and friends, respectively. One possible explanation for this finding is that when applying for the same job, laborers with higher education levels and broader employment information channels are more likely to be hired. When working near the home can yield higher income, laborers may be more inclined to work nearby for the convenience of taking care of their families.

Additionally, inconsistent with hypotheses H1 and H7, laborers' gender and level of skill acquisition have no significant effect on their choice of work location. As for GEN, under the realistic conditions of "more people and less land" and the attraction of higher "comparative income", many young couples in mountainous regions leave their home areas for work. Some of these laborer couples work in the same industry (e.g., a leather shoe factory), whereas others work in different industries but live together. Some non-working women even migrate with their husbands and perform housework. This result is inconsistent with previous research (Li et al. 2009; Liu et al. 2014). Li et al. (2009) which emphasizes that it is more likely for males to work far from home than

females, while Liu et al. (2014) indicate that gender differences are only obvious in HV. Importantly, the study area in Liu et al. (2014) and this research are both mountainous areas, while the study area in Li et al. (2009) is a plain.

Comparing the above findings, the convergence effect of the transfer of the labor force in mountainous areas may be stronger than it is in the plains. This result might serve as a good research hypothesis to be validated in future studies. As for SKI, whether laborers had skills does not seem to affect their choice of employment location. Notably, this result is inconsistent with previous research (Liu et al. 2011). Those authors' results show that technical advantages are mainly embodied in cross-provincial employment location selection compared with local county employment. One possible reason for this result is that most of the skills acquired by laborers are related to agriculture (such as aquaculture), whereas non-agricultural skills that are acquired by laborers are not relevant for non-farm work (such as having the skill to drive a car but being employed in the construction industry rather than in the transportation industry).

### 3.2.2 Household characteristics

Because the results from Model 1 only consider the personal characteristics of the laborers, there may be some discrepancy between its conclusions and reality.

As shown in Table 4, model 2 combines personal and household characteristics in the regression analysis. The model's fit is greatly improved, and the Nagelkerke  $R^2$  increases from 0.219 to 0.343. The correct predictions of the model increase from 62.9% to 63.3%. Additionally, the significance level of the model remains high, with a value of 0.000.

Regarding personal characteristics in Model 2, AGE, EDU, TRA and WOM have significant effects on migrant workers' employment location choice. Thus, the effects of AGE, EDU and TRA on migrant workers' location choices are similar to Model 1, and only the values of the partial regression coefficients and the odds ratios change in size. As with Model 1, GEN and SKI have no significant effect on laborers' employment location choice. Notably, CHA is not significant in Model 2 but is significant in Model 1. Conversely, WOM is



not significant in Model 1 but is significant in Model 2. To some extent, these findings indicate that WOM is more important during the process of determining rural migrant workers' employment location choice. Consistent with previous research (Gao et al. 2009), we find that when laborers' social networks are more developed, they are more inclined to work farther from home. A possible reason for this result is that the employment information that such migrant workers receive is provided by relatives and friends who are working with the subject migrant workers. Likewise, when many friends and relatives are working together, it not only provides a convenient situation for life and work but also enhances the group's ability to withstand external risk.

As for household characteristics, LAB, OLD, STUS and CASH have significant effects on migrant workers' employment location choice. Thus, the result for LAB is consistent with hypothesis H8: the higher that LAB is, the greater the likelihood is that laborers are working far from their home villages. In particular, compared with selecting HV, a one-person increase in the family labor force increases the likelihood that a laborer has chosen HP and OHP by 109.1% and 51.7%, respectively. The result for OLD is consistent with hypothesis H11: the higher that OLD is, the greater the likelihood that laborers are working in areas that are near the home village. In particular, compared with selecting HV, a one-person increase in the number of citizens >75 years of age decreases the likelihood that a laborer has chosen OHP by 26.1%. Notably, the higher that STUS is, the greater the likelihood is that laborers are working far from their home villages, which is inconsistent with hypothesis H13. In particular, compared with selecting HV, a one-person increase in the number of children who attend school in a household increases the likelihood that a laborer has chosen HP by 46.3%.

A possible reason for this result is that older family members who are in good health can help take care of children while being engaged in farming, which alleviates some of the young laborers' pressure insofar as taking care of their family is concerned. Meanwhile, because individuals over 75 years old can typically no longer take care of children effectively and simultaneously continue to engage in farming due

to their physical condition (and sometimes for other reasons), younger migrant workers are more likely to work near home for the convenience of taking care of both children and the elderly.

Notably, inconsistent with hypothesis H9 and previous research (Liu et al. 2014), per capita arable land area had no significant effect on laborers' choice of employment location. A reason for this result might be that the mismatch of humans and land in this study area is very pronounced, and the per capita arable land area is less than 0.067 ha (the mean is 0.050 ha). In addition, agricultural income is far less than off-farm income. According to the survey statistics, household off-farm income accounts for 71.9% of total income, which is higher than the proportion of agricultural income (71.9% > 28.1%). This finding may prompt laborers (particularly young laborers) to leave their home villages for work, but it is not the key factor affecting migrant workers' employment location choice.

In previous literature (Liu et al. 2011), this indicator is only faintly significant (at 0.1 level) on HC. This result may be related to the actual situation in the study areas. The study area of Liu et al. (2014) and this research both are mountainous areas, whereas the study area of Li et al. (2009) is a plain. In the plains, per capita arable land area is larger, and mechanization can be more extensively used. Moreover, agricultural income in plains areas is much higher than that in mountainous areas. Thus, the influences of this indicator on laborers' employment location selection decisions may be significantly different in different areas.

Additionally, the results for CASH are consistent with hypothesis H10 and previous research (Zhang and Song 2003): the higher that CASH is, the greater the likelihood is that laborers are working far from their home villages. In particular, compared with selecting HV, each 1 Yuan increase in CASH increases the likelihood that laborers have chosen OHP by 108.0%. Working in the economically developed coastal provinces can yield more money and therefore, the higher that CASH is, the higher the likelihood is for those laborers to choose to work far from their home villages.

### **3.2.3 Community characteristics and county economic conditions**

The results from Model 2 consider only personal and household characteristics and may be somewhat biased. In order to obtain the parameter estimators without bias, the community characteristics and the county economic development level should be considered.

As shown in Table 5, model 3 shows the results of combining the personal, household and community characteristics of the sample in addition to the county economic development level in the regression analyses. After adding community characteristics and county economic conditions, the model's fit is greatly improved, and the Nagelkerke R<sup>2</sup> increased from 0.343 to 0.529. Meanwhile, the correct predictions of the model increase from 63.3% to 69.0%. Additionally, the significance level of the model remains high, with a value of 0.000.

In Model 3, the results of the personal and household characteristics of the migrant workers regarding their employment location choice are similar to those in Model 2; the values of the partial regression coefficients and odds ratios only change in size. Thus, a notable change is that CHI is not significant in Model 2 but is significant in Model 3. Consistent with hypothesis H12, a one-person increase in the number of family members <6 years of age increases the likelihood that a laborer has chosen HT by 74.7% compared with selecting HV.

In terms of community characteristics, DISC, INC and RDLS showed significant effects on migrant workers' choice of employment location, which is consistent with hypotheses H14, H15 and the previous literature (Liu et al. 2011; Gao et al. 2009), i.e., the farther that DISC is, the higher the

**Table 5 Multinomial logistic regression estimates and test statistics for the migrant location selection model <sup>a</sup>**

Variable	Coefficients in Model 3			
	HT, (OR)	HC, (OR)	HP, (OR)	OHP, (OR)
<b>Individual characteristics</b>				
GEN(o) <sup>b</sup>	---	---	---	---
AGE	-0.014	-1.088*** (0.337)	-1.457*** (0.233)	-0.772*** (0.462)
EDU	-0.628** (0.534)	-0.778*** (0.459)	-0.360	-0.670*** (0.512)
SKI(o) <sup>b</sup>	---	---	---	---
TRA(1) <sup>c</sup>	-0.079	-20.739	-0.673	-2.386** (0.092)
TRA(2) <sup>c</sup>	0.223	0.181	0.385	-0.234
CHA(o) <sup>b</sup>	---	---	---	---
WOM	0.343	0.788*** (2.199)	0.712** (2.038)	0.527** (1.694)
<b>Household characteristics</b>				
LAB	0.260	0.180	0.848*** (2.335)	0.377
OLD	-0.279	-0.313	-0.084	-0.476*** (0.621)
CHI	0.558** (1.747)	0.142	-0.069	0.257
STUS	0.249	-0.405	0.642** (1.900)	0.180
AREA	---	---	---	---
CASH	-0.311	-0.017	-0.030	0.605** (1.831)
<b>Community characteristics</b>				
INC	-1.078** (0.340)	0.100	-0.141	-1.035*** (0.355)
DISC	0.931** (2.537)	-0.354	-0.525	0.094
RDLS	-1.926*** (0.146)	-0.371	-0.763	-1.197*** (0.302)
<b>County economic development level</b>				
GVIO	-0.225	-0.262	0.203	-0.649*** (0.522)
Constant	0.085	-0.015	0.485	2.791***
Test statistics				
Likelihood ratio tests	Chi-Square=344.775*** (df=56)			
Nagelkerke R <sup>2</sup>	0.529			
Correct predictions	69.0%			

**Notes:** OR = Odds ratio. Definitions and values of the variables are given in the notes for Table 1. <sup>a</sup> The reference category is HV. <sup>b</sup> The reference category is o. <sup>c</sup> The reference category is 3. <sup>d</sup> The reference category is Wuxi. \*Significant at  $\alpha = 0.10$ ; \*\*significant at  $\alpha = 0.05$ ; \*\*\*significant at  $\alpha = 0.01$ .

likelihood is that laborers are working far from their home villages, whereas the higher that INC is, the higher the likelihood is that laborers are working near their home villages. In particular, each 1 km increase in the distance to the nearest county increases the likelihood that laborers have chosen HT by 153.7% over choosing HV.

As well, each 1 Yuan increase in community per capita net income decreases the likelihood that laborers have chosen HT and OHP by 66.0% and 64.5%, respectively. Notably—and inconsistent with hypothesis H16 but consistent with previous research (Liu et al. 2014)—the greater that RDLS is, the higher the likelihood is that laborers work in nearby areas. In particular, compared with selecting HV, each 1 m increase in the degree of relief of a village's land surface decreases the likelihood that laborers have chosen HT and OHP by 85.4% and 69.8%, respectively. This result might ensue because as RDLS increases, part of the labor force is consumed engaging in agriculture (it is more difficult to use machinery effectively when farming in mountainous areas; therefore, this type of farming typically relies more on people). In addition, the greater RDLS (which indicates, to a certain extent, that villages are at a higher altitude, are more remote and are more closed), the more limited the employment information is regarding whether higher income can be obtained by migrant workers elsewhere. Thus, migrant workers may be more likely to work nearby because employment information might be effectively transferred to nearby regions.

In terms of county economic conditions, consistent with H17 and with previous research (Liu et al. 2014), the higher the GVIO is, the higher the likelihood is that laborers are working in nearby areas. In particular, compared with laborers who have chosen to work in HV, a 1 Yuan increase in GVIO decreases the likelihood that laborers have chosen OHP by 47.8%.

#### 4 Conclusions and Implications

By combining household data and employment information from 329 households in a representative survey of the Three Gorges Reservoir area, we divided the work locations of rural laborers into HV, HT, HC, HP and OHP.

Then, we constructed multinomial logistic regression models to assess the effects of individual, household, and community characteristics—as well as county development level—on the migration decisions of rural laborers. We arrived at two main conclusions:

(1) In general, laborers tend to migrate to employment locations far from home with high economic benefits. The proportions of rural migrant workers who migrate to HV, HT, HC, HP and OHP are 9.89%, 8.37%, 5.89%, 15.40% and 60.46%, respectively.

(2) Migrant workers' personal characteristics, household characteristics, and community characteristics—in addition to the economic development level of their counties—have significant effects on their choice of employment location. Regarding individual characteristics, rural migrant workers who are older, have higher education levels, have received agricultural skills training and have found non-farm employment by themselves are more likely to work in nearby areas. Meanwhile, the higher the amount of WOM, the higher the likelihood is that laborers are working far from their home villages. Additionally, GEN and SKI had no significant effect on the choice of migrant workers' employment location.

With respect to household characteristics, the higher the values of LAB, CHI, STUS and CASH are, the higher the likelihood is that laborers are working far from their home villages, whereas the higher the number of OLD is, the higher the likelihood is that laborers are working in nearby areas. In addition, AREA had no significant effect on laborers' choice of employment location. As for community characteristics, the higher that INC is, the greater that RDLS is and the farther that DISC is, the higher the likelihood is that laborers are working in nearby areas. As for the county economic development level, the higher that GVIO is, the higher the likelihood is that laborers are working in nearby areas.

In addition to its two main conclusions, this study also has several implications that are described in the following paragraphs.

The study contributes to the literature by improving our understanding of out-migration in rural China, particularly from the typically impoverished mountainous areas. The particular contributions of this study are found in the

construction of an index system and the use of a multinomial logistic regression model. In terms of the design of the index system, this study extracted the general factors that affect the employment location choices of migrant workers on the basis of a literature review. Then, under the guidance of human capital theory and social network theory, we further explored whether TAR, CHA, WOM and RDLS affect migrant workers' choice of employment location. Our findings might have some implications for future studies. In terms of research methods, this study constructed multinomial logistic regression models to assess the effects of individual, household, and community characteristics—in addition to assessing the economic development level of particular counties—on the migration decisions of rural laborers. The multinomial approach employed here is more suitable for the study of rural out-migration. Moreover, the use of a 30 m DEM in the Three Gorges Reservoir area and GIS analytical tools to obtain RDLS was another contribution of this study.

Additionally, this study highlights several avenues for further research.

First, this study is relevant only to mountainous areas, which may be a limitation. Thus, research should be undertaken to examine differences in rural out-migration between mountainous, upland and plains regions.

Second, on the one hand, the basic theory of this research is "push-pull" theory, but the indicators used in this study focus more on the "push" aspect due to data limitations. Little attention has been given to the "pull" aspect (we only focus on the attraction of wages in working locations for migrant workers, which is another limitation of the study), and additional quantitative exploration of this aspect should be undertaken in future studies.

On the other hand, we think that the influence mechanisms of EDU, GEN, WOM, AREA and other indicators found in this study on laborers' employment location selection decisions should be combined with the results found in similar studies, and these indicators should be further tested, particularly with dynamic panel data, on other study areas in the future.

Third, this study is based on an analysis of cross-sectional data. However, if we wish to fully

capture the nuances of rural out-migration and development, we must conduct research based on dynamic panel data. Thus, we intend to undertake this type of research in future studies.

Fourth, this study mainly adopts the quantitative analysis method (multinomial logistic regression model) to explore the influencing factors of laborers' employment location selection decisions, and the lack of information from the laborers' qualitative interviews is undoubtedly one of the regrets and the insufficiencies of the study. We hope that in future studies, a qualitative analysis can be combined with a quantitative analysis to reveal the transfer mechanisms at play in laborers' employment decisions and their influencing factors from both qualitative and quantitative perspectives.

Fifth, the results of this study can provide a reference for various government departments when formulating and implementing relevant policies. For example, laborers who have received non-agricultural training prefer to work far from HV, whereas those who have received agricultural training prefer to work near HV. Government departments might organize relevant agricultural and non-agricultural training for farmers based on this finding to help guide the outflow of migrant workers. Meanwhile, the government should improve the infrastructure and support the development of rural communities and small businesses to increase the local transfer of surplus labor in communities.

Additionally, the government should encourage prestigious and valuable workers who have the ability to integrate migrant laborers who do similar work in the same city, town or community to form work groups (wage clusters) based on kinship and geopolitical relationships. Such wage clusters can lead laborers to share employment information and to provide emotional support for one another, which would further increase household income and enhance these households' ability to withstand external market risks. This policy implication is based not only on the conclusions of this study, i.e., that migrant workers are more likely to choose cities outside their home region with higher economic benefits when they have more relatives and friends to work with, but also on the practical issue that many laborers from the same village may be dispersed in

the same city (such as Wuxi County and Tianyuan BaoPing Township in Wuhan, where a large

number of young workers participate in construction demolition work).

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