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Migration and Local Off-farm Working in Rural China

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Abstract: The paper analyzes the decision-making of rural Chinese households with three alternatives: stay exclusively on farm, take local off-farm jobs, and migrate. Based on a survey of rural Chinese households, we extend the dynamic discrete choice model of Wooldridge (2002a,b) to a trichotomous setting and apply it to a five-year panel study. We observe statistically significant state dependence between the current period response and decisions of the previous time period. We also conclude that education, household size, and social networks play important roles in job-location decision-making of rural Chinese households.

Key words: Labor Migration, Local off-farm working, Random Effect, Multinomial Logit, Rural China

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Introduction

A dilemma China faced on its route to sustainable development is how to absorb the large number of surplus agricultural labors with a delicate balance of efficiency and social fairness. More efficient agricultural production will create a large pool of unemployed labors and possibly social instability. Continuing with conventional agricultural production technology that employs a large percentage of the rural labor force would, however, hinder China's development. An alternative strategy is to permit the surplus labors to move out of the agricultural sector. Rural labors have been migrating and taking local off-farm activities to seek non-farming income[1]. Treating the decision-making process of rural households as a stochastic process, Mohapatra, Rozelle and Huang (2003) studied the evolution of modes of production (including farming, non-farm activities, working in an enterprise, and migration) in rural China during 1990s. They found a systematic pattern emerging in different modes of production across space and time.

With an estimate of more than 100 million[2] internal migrants (most from rural to urban areas), labor migration no doubt is a serious concern for Chinese policy makers and researchers. Migrant labors have brought and are bringing tremendous changes to China's economy. They are building skyscrapers, preparing foods and providing domestic services in the cities. In the villages where these migrants come from, the remittance is an important component of the rural revenue. However, labor migration has been treated cautiously by Chinese officials, largely due to the social imbroglio it caused (Murphy 2002; Hare 2002). Urban and suburban areas have been troubled by increasing crime rates associated with higher population mobility. The fact that young and better-educated individuals compose the largest portion of migrants concerns agricultural researchers. They believe rural out-migration leaves aged and less educated workers in the villages and working on farms, which may adversely affect agricultural production efficiency. Previous studies noted the importance of the decision of rural households to engage in local off-farm activities—or leaving the farm, in addition to migrating—leaving the villages (Tuan, Somwaru, and Diao 2000; Song and Knight 2003).

While some researchers focus on the population that takes local off-farm jobs or migrate (Knight, Song, and Jia 1999; Hare 2002; Roberts 2001), this paper explores the possible determinants of migration based on a survey of rural Chinese households. Following Huffman (2001), which listed "choosing agriculture", "migration" and "off-farm work" as employment choices for rural households, we model Chinese rural households as having three choices: staying on the farm exclusively, staying in the village but partially engaging in local off-farm activities, and at least one household member working outside the home region for a certain period. Hence, we extend the work-choice to trichotomous outcomes. This brings us advantage over the typical dichotomous choices migration (Zhao 1999b; Zhao 2001; Yao 2001). The sample provides more extensive information, such as village characteristics, than that of Tuan, Somwaru, and Diao (2000). Furthermore, we need to note that the usual pooled estimate (with or without fixed effects) for a panel data set ignores the initial condition problem and likely to be biased when the current decision is affected by that of the previous periods (Heckman, 1981). Conditional on the initial value and the observed value of explanatory variables, the approach of Wooldridge (2002b, p493), which leads to a random effects multinomial logit model, is applied to household decision with presence of dynamic state dependence.

This article organizes as following. The second section reviews the literature. The dataset and our propositions are described in section 3. Econometric model is explored in section 4 and we present our results in section 5. The last section concludes this article.

Literature Review

Factors that may affect the decision-making of Chinese households include household and village characteristics. Household characteristics, i.e., education and household size, determine the labor supply and its quality. Village characteristics reveal the information infrastructure and possibly local labor demand. Zhao (2001) concluded the migration decisions were affected by local village attribute. Characteristics of migration destinations are important as well. However, as Zhao (2001) observed that transportation cost is less a concern for the majority of the migrants, most of the rural population in China probably face quite similar migration labor demand due to the high mobility of migrating population, which leads to the conjecture that all migrants face similar choice of destinations after control for migration networks. We follow the literatures on rural migration that omitted destination characteristics (Tuan, Somwaru, and Diao 2000; Zhao 2001). We focus on these factors in this study but understand that other factors may play a role in the decision process. Following the usual practice, we assume that the random disturbance terms catch their effects.

Education

Based on data from ten counties randomly chosen from all over China and surveyed in 1993, Parish, Zhe, and Li (1995) concluded that the returns to education remain modest in rural China as the rural labor market begun to emerge. Zhao (1999b) concluded that negative relationship exists between schooling and the probability of a family having at least one member as a migrant worker in Sichuan for 1995.

However, Tuan, Somwaru, and Diao (2000) suggested that young and well-educated generation are better prepared to work outside agriculture. They concluded that higher education and/or secondary school training develops the skills needed for non-agricultural activities. Zhang, Huang, and Rozelle (2002) found education increases the likelihood of an individual participating in the off-farm labor force, finding job when he/she is unemployed and receive higher pay. They suggested that investments in rural education are desperately needed to improve agricultural productivity and facilitate the demographic and economic transition of the rural area, which is necessary for the economic development of China.

Using data collected from farm households in a central Chinese county in 1995, Hare (2002) applied an ordered probit model to examine the wage and job location outcomes of rural migrants. He found that an individual's education, especially at low levels of schooling, has a positive impact on the earning of the migrants. Hare suggested that reducing the legal and other institutional barriers that would otherwise impede migration, public investments in human capital and infrastructure, are desirable to achieve efficiency and equity outcomes in labor market.

Based on a 1993 sample of migrants in Shanghai, Roberts (2001) found that illiterate migrants are more likely to engage in farming in rural area of Shanghai while individuals who completed more than junior middle school were less likely to choose farming. Rozelle et al. (1999) surveyed 200 Chinese villages and found that younger and relatively well-educated rural residents are more inclined to migrate. Knight, Song, and Jia (1999) studied migration from the perspective of the migrants, enterprises employing migrants, and government. They found that migrants deem vocational training to be very important even if they would reap the benefits only later. Restructuring the rural education system might benefit the rural human capital accumulation and economic development processes.

Household size

Tuan, Somwaru, and Diao (2000) claimed that large households are more likely to have one or more members working as migrants. Zhao (2001) and Zhao (1999a) obtained similar result. She concluded that migrants are more likely to be single young male from families with more labor, less land and fewer dependents.

Migration and Off-farm Activities Network

Roberts (2001) found that region of origin played an important role in sorting of rural labor migrants among occupations and sectors, which suggests the importance of network in migration. Zhao (2001) found positive and statistically significant effects of migrant networks (measured by the number of early migrants from the village in her study) on the probability of migration. Similar result was presented in Hare (2002) where the network is measured by village proportion of households with previous migration experience. It is natural to extend their result to local off-farm activities.

Data and Propositions

The Data

The data set for our study is part of a large comprehensive survey conducted by Research Center for Rural Economy (RCRE) since 1986 in 29 provinces across China, covering over 20,000 households. The survey shows slight attrition over time. The survey was discontinued in 1992 and 1994 for financial reasons.

The original data set spans the time period 1986 to 1999. However, the survey questionnaire before 1995 lacks information on migration. Therefore we dropped these observations. The final data set for this study contains 591 farm households living in 29 villages from 9 provinces in China over 1995 to 1999.

Benjamin, Brandt, and Giles (2001) described the sampling for this data set as being conducted by provincial offices under the Ministry of Agriculture. Each provincial research office first selected equal numbers of three types of counties: upper, middle and lower income; then chose a representative village in each county. Forty to 120 households were randomly surveyed within each village. Village officers and accountants filled out a survey form on general village characteristics every year. Information collected from those surveys is used to control for the structure of the local economy and differences in the share of productive assets controlled by private and collective sectors. Monetary variables are in real term with 1986 as the base year.

Table 1 summarizes the household and village characteristics across the five-year period. Most of the sample means do not vary much over time. Education achieved is measured as the average schoolings of the labor force in the household. Village non-farm labor percentage is calculated as the ratio of the number of labor not exclusively on farm to that of overall labor in the village. No obvious trend exists for this index. Table 2 compares these characteristics of the households making different choices. Households engaged in full time farming tend to have lower average years of schooling of labor force. Mean household size is larger for the latter two groups. The extent they differ on these indexes from the group choosing full-time farming is far greater than the difference between them. The groups choosing migration are residing in villages having a higher percentage of non-farm labor, which suggests the effect of social networks.

Propositions

Since the structural model of discrete choice has been laid out in the literature for a quite long time, we can use the reduced model directly without any confusion or discontinuity, see, i.e., the example provided in Wooldridge (2002a).

We are concerned about the effect of education, household size and social network. Huffman (1979) suggested that human capital is an important factor determining whether member of a household would take a non-farm job. The intuition is that improved human skills, e.g., formal schooling, vocational training, and experience, shift the wage offer or labor demand curve. It is expected that households engaged in off-farm working might have larger coefficient of education measure in their indirect utility function than that of those stayed exclusively on farm. Therefore the difference should be positive and we expect a positive sign of the coefficient for the average years of schooling of household labor[3]. Note that we treat education as a household characteristic and use the initial period average schooling as a proxy. This is an innocuous simplification since education, especially the average years of schooling across labor force, do not vary over such a short period (five years). Assuming it is time-varying may introduce perfect collinearity.

Proposition 1: *Different levels of initial period average years of schooling increase the likelihood of a household to have at least a member engaging in off-farm working and/or migrate.*

Second, large household size indicates more labor supply. In rural China, the family planning policy permits households to have a second child if the first-born is a girl. Family planning policy is less strictly enforced in areas with higher density of ethnic minority and remote areas. These facts, along with the tradition of living together with the elderly, ensure that household size varies across China. It also varies across time due to newborns and marriages.

Proposition 2: *Large household size increases the likelihood of a rural household not staying exclusively on the farm.*

Social networks play an important role in pursuing off-farm opportunities (Zhao 2001). Percentage of non-farm working labors in the village is a natural choice for the proxy of social network. Households may obtain information regarding off-farm working from the village neighborhood. Note we did not distinguish migration and non-farm working in constructing this ratio due to data availability.

Proposition 3: *The percentages of labor engaged in non-farm activities in the village increases the likelihood of a household engaging in off-farm working.*

The last but probably most important issue is the dynamic state dependence of the decision-making on job location of the rural Chinese households. It is straightforward that a household engaged in non-farm working is more likely to do so in the next time periods since household members have experience of non-farm working and better access and/or utilization of relevant information.

Proposition 4: *The decision of the previous time period(s) affects the response of current year.*

We will construct testable hypothesis based on these propositions in next section.

Econometric Model

Researchers used different econometric models to study migration and off-farm working, e.g. hazard rate model (Huffman and Feridhanusetyawan 2003), ordered probit (Hare 2002), and two-stage estimation (Zhu 2002). Multi-nominal logit model is one of these widely used (e.g., Parish, Zhe, and Li 1995; Roberts 2001). With the presence of the dynamic state dependence, we extend the model of Wooldridge

(2002a) to three-alternative setting with a random effect multinomial logit and estimate it based on the five-year panel.

Dynamic Dependence in Discrete Choice Model

Three approaches, dynamic programming, semi-parametric, and parametric, have been used in the literature to incorporate and estimate the state dependence when fitting discrete choice model to a panel data set.

Rust (1987, 1997, 2000) incorporated dynamic programming into discrete choice model for panel data set. Rust (1988) proposed the nested fixed-point algorithm to produce the conditional maximum likelihood estimates. He formulated it as a problem of statistical inference while explicitly accounted for the unobserved heterogeneities. Rust (1997) analyzed how the U.S. social security and Medicare insurance system affects the labor supply of older males in the presence of incomplete markets for loans, annuities, and health insurance with the dynamic programming model. However, the computation of this model is a burden when there are multiple state variables. Furthermore, the transition nature of Chinese economy raises doubt on the applicability of dynamic programming.

The second approach is the semi-parametric models proposed by Honoré and Kyriazidou (2000), which used an identification strategy based on the conditional MLE. They showed how to estimate the parameters in the unobserved effects logit model with a lagged dependent variable and strictly exogenous explanatory variables without making distributional assumptions about the unobserved effects. This approach is consistent but do not generally converge at the usual square root of N rate and the discrete explanatory variables such as time dummies must be ruled out. Neither is it possible to estimate the average partial effects (Wooldridge 2002a).

The third is the parametric approach discussed in Wooldridge (2002a). The primary problem faced by parametric approach is how to handle initial conditions. Wooldridge (2002a) summarized three methods. The simplest is to ignore the randomness of initial response, which in essence is an over-strong assumption that the initial response is independent of unobserved heterogeneity. A better way is to model the initial condition as random variable with certain distribution. However, this evokes the question of "which distribution should we use". Some authors used a steady-state distribution but it is unlikely when there is obvious trend, especially in transitional economies. The third is a method proposed by Wooldridge (2002a; 2002b, p493), which models the distribution of unobserved effects conditional on the initial value and any exogenous explanatory variables. Note that fixed effects model which treats the individual effects as parameters to be estimated is not preferred in the dynamic panel setting (Heckman, 1981).

Wooldridge (2002a) proposed to use $h(\boldsymbol{c} \mid \boldsymbol{y}_0, z; \boldsymbol{\alpha})$ rather than $f(\boldsymbol{y}_0 \mid \boldsymbol{c}, z; \boldsymbol{\alpha})$ to catch the dependence between $\boldsymbol{c}$ and $\boldsymbol{y}_0$. Specify a density of $(\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T)$ conditional on z and $\boldsymbol{c}$, which is noted as $f(\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T, \mid z, \boldsymbol{c}; \boldsymbol{\delta})$. The $f(\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T, \mid z, \boldsymbol{c}; \boldsymbol{\delta})$ is integrated against the density $h(\boldsymbol{c} \mid \boldsymbol{y}_0, z; \boldsymbol{\alpha})$ to obtain the conditional density of $(\boldsymbol{y}_{i1}, \boldsymbol{y}_{i2}, \ldots, \boldsymbol{y}_{iT})$ given z and $\boldsymbol{y}_0$, which can be used in an MLE estimation.

State Dependence in Three-Alternative Discrete Choice Model

Wooldridges (2002a,b) presented example of random effects probit model with two alternatives. For a three-alternative decision problem we have:

$$f(\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_T} \mid \mathbf{y}_0, \mathbf{z}, \boldsymbol{\theta}) = \int_{R^3} f(\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_T} \mid \mathbf{y_0}, z, \mathbf{c}; \boldsymbol{\delta}) h(\mathbf{c} \mid \mathbf{y_0}, \mathbf{z}_i; \boldsymbol{\gamma}) d\mathbf{c}$$

where $\mathbf{y_1}$, $\mathbf{y_2}$, …, $\mathbf{y_T}$, $\mathbf{y_0}$ are 3×1 vectors with values of (0, 1) indicating whether the alternative is chosen or not. $\mathbf{c}$ is a vector of random effects for different alternatives, i.e., $\mathbf{c}=\{c_1, c_2, c_3\}$. Following Chamberlain's (1980) approach to static probit model with unobserved effects and condition on $\boldsymbol{y}_{i0}$ as Wooldridge (2002a), we assume independence between the random component of $\mathbf{c_1}$, $\mathbf{c_2}$, and $\mathbf{c_3}$ and specify $h(\mathbf{c}_j|\mathbf{y}_0, z_i; \gamma)$ as a normal distribution: $\mathbf{c_j} \sim N(\psi_j + \mathbf{y}_{i0}\xi_{0j} + \mathbf{z}_i\xi_j, \sigma_{aj}^2)$. It is equivalent to $c_j = \psi_j + \mathbf{y}_{i0}\xi_{0j} + \mathbf{z}_i\xi_j + a_{ij}$, where $a_{ij} \sim N(0, \sigma_{aj}^2)$ and independent of $(\boldsymbol{y}_{i0}, z_i)$. We also assume that the random effect is additive to the indirect utility function, i.e.:

$$V_{ijt} = \mathbf{z}_{it}\boldsymbol{\delta}_j + \gamma_{2j} y_{i2,t-1} + \gamma_{3j} y_{i3,t-1} + c_{ij} + \varepsilon_{ijt} \tag{4.1}$$

which can be rewritten as:

$$V_{ijt} = \mathbf{z}_{it}\boldsymbol{\delta}_j + \gamma_{2j}y_{i2,t-1} + \gamma_{3j}y_{i3,t-1} + \psi_j + \mathbf{y}_{i0}\boldsymbol{\xi}_{0j} + \mathbf{z}_i\boldsymbol{\xi}_j + a_{ij} + \varepsilon_{ijt} \tag{4.2}$$

By the usual assumption of Weibull distribution of the disturbances, we have the conditional probability as:

$$\text{Prob}(Y_i = j \mid \mathbf{y_0}, \mathbf{z}, \mathbf{c}; \boldsymbol{\delta}) = \frac{e^{\mathbf{z}_{it}\boldsymbol{\delta}_j + \gamma_{2j}y_{i2,t-1} + \gamma_{3j}y_{i3,t-1} + \psi_j + \mathbf{y}_{i0}\boldsymbol{\xi}_{0j} + \mathbf{z}_i\boldsymbol{\xi}_j + a_{ij}}}{\sum_{j'=1}^{3} e^{\mathbf{z}_{it}\boldsymbol{\delta}_{j'} + \gamma_{2j'}y_{i2,t-1} + \gamma_{3j'}y_{i3,t-1} + \psi_{j'} + \mathbf{y}_{i0}\boldsymbol{\xi}_{0j'} + \mathbf{z}_i\boldsymbol{\xi}_{j'} + a_{ij'}}} \qquad \text{for } j = 1,2,3.$$

Normalize it based on the first choice, we have:

$$\text{Prob}(Y_i = 1) = \frac{e^{a_{i1}}}{e^{a_{i1}} + \sum_{j'=2}^{3} e^{\mathbf{z}_{it}\boldsymbol{\delta}_{j'} + \gamma_{2j'}y_{i2,t-1} + \gamma_{3j'}y_{i3,t-1} + \psi_{j'} + \mathbf{y}_{i0}\boldsymbol{\xi}_{0j'} + \mathbf{z}_i\boldsymbol{\xi}_{j'} + a_{ij'}}}$$

$$\text{Prob}(Y_i = j) = \frac{e^{z_{it}\delta_{j'} + \gamma_{2j'}y_{i2,t-1} + \gamma_{3j'}y_{i3,t-1} + \psi_j + \xi_{0j}y_{i0} + z_i\xi_j + a_{ij}}}{e^{a_{i1}} + \sum_{j'=2}^{3} e^{\mathbf{z}_{it}\boldsymbol{\delta}_{j'} + \gamma_{2j'}y_{i2,t-1} + \gamma_{3j'}y_{i3,t-1} + \psi_{j'} + \mathbf{y}_{i0}\boldsymbol{\xi}_{0j'} + \mathbf{z}_i\boldsymbol{\xi}_{j'} + a_{ij'}}} \qquad \text{for } j = 2,3.$$

We have the following likelihood function:

$$f(\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T \mid \mathbf{y}_0, \mathbf{z}, \boldsymbol{\theta}) = \int_{R^3} \prod_i \prod_j \{[\Pr(Y_{ij} = 1)]^{y_{ij}}\} \bullet h(\mathbf{c} \mid \mathbf{y}_0, \mathbf{z}; \boldsymbol{\gamma}) d\mathbf{c}$$

Note that $\boldsymbol{\delta}_j, \boldsymbol{\gamma}_j, \psi_j, \boldsymbol{\xi}_{0j}, \boldsymbol{\xi}_j$ are the difference of the original parameters and the parameters for the baseline alternative (exclusively working on farm). However, we did not normalize the a_{ij} s for the convenience of estimation, which we go into details in next section. We can explicitly control on observed heterogeneity, i.e., education. The distribution of $\mathbf{c_1}$, $\mathbf{c_2}$, and $\mathbf{c_3}$ can be specified as $N(\psi_j + \mathbf{y}_{i0}\xi_{0j} + \mathbf{z}_i\xi_j + \mathbf{x}_i\pi, \sigma_{aj}^2)$, in which **x** is the measure of education and π is the coefficient to be estimated.

This model then can be estimated as random effects multinomial logit model. We can test the null hypothesis that there is no random effects by restricting the variances of the random components to zero.

We examine the state dependence by testing γ_2 and γ_3 jointly equal to zero. Inference on the exogenous variables can be tested by asymptotic *t*-test or likelihood ratio test.

Note that in this dynamic panel analysis, the household-specific variables that do not vary over time cannot be included. We use the household size since other variables do not vary much over the four-year period. We use the logarithm of the village non-farm working ratio as a proxy of the social network. Hence we focus on education, labor supply and social network for this dynamic study. This reduces the burden of computation since we need to include the values for the four years of any variable in z_i and estimate the coefficients for the last two alternatives. Adding one policy variable will force us to add about ten unknown parameters to maximize over.

Let $z_{it} = \begin{pmatrix} \text{household size} \\ \ln(\text{village non-farm working ratio}) \end{pmatrix}$ and $\delta = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix}$, the propositions can be re-formulized as the standardized testable hypothesis:

Hypothesis 1: $\pi_2=\pi_3=0$, *which means that increasing average years of schooling has no effect on the likelihood of a household to engage in off-farm working*.

Hypothesis 2: $\delta_{12}=\delta_{13}=0$, *larger household size has no effect on the likelihood of a rural household staying exclusively on farm.*

Hypothesis 3: $\delta_{22}=\delta_{23}=0$, *the percentage of labor engaged in non-farm activities in the village has no effect on the likelihood of a household engaging in off-farm working.*

Hypothesis 4: $\gamma_{22}=\gamma_{23}=\gamma_{32}=\gamma_{33}=0$, *There is no state dependence between the present response and the response of previous period(s).*

Estimation and Results

Estimation

We can normalize the intercepts of the three alternatives as the difference of the original random component and the disturbance of the baseline alternative, i.e., $a'_{i2}=a_{i2}-a_{i1}$, $a'_{i3}=a_{i3}-a_{i1}$. However, this means that they are no longer independent to each other. We can use SAS PROC NLMIXED to estimate the random effect multinomial logit model but the computation is a burden as Malchow-Møller & Svarer (2003) claimed. In this study, we used the mixed logit code developed by Train et. al. (1999) to estimate the random effects multinomial logit, which requires the random components are independent to each other. Therefore, we do not normalize the random component.

Train's code produces maximum simulated likelihood estimates. Lee (1992) and Hajivassiliou and Ruud (1994) provided the asymptotic distribution of the maximum simulated likelihood estimator. The estimator is consistent and asymptotically normal under regularity conditions. Revelt and Train (1998) pointed out that the simulated probability is an unbiased estimate of the true probability. However, the logarithm of the simulated probability with fixed number of repetitions is not an unbiased estimate of the logarithm of the true probability. This introduces certain levels of bias but it proved to be decreasing as we increase the number of repetitions (Train, et. al, 1999; MacFadden and Train 2000).

Computation of the marginal effects of this model involves the integration over the possibility density function of extreme value distribution and normal distribution. Close form of marginal effects is not easy to obtain thus we turn to simulation. We are interested in the change of the predicted probability due to change of exogenous variables, i.e., $E\{P_k(x',\widehat{\beta}) - P_k(x,\widehat{\beta})\}$, where $\widehat{\beta}$ is the estimated parameters. *x'* is the original value plus an increment, i.e., one percent or one unit of the measurement. The expectation can be consistently estimated by $\frac{1}{n_1}\sum_i \frac{1}{n_2}\sum_j [P_k(x',\widehat{\beta}^i,\hat{c}^j) - P_k(x,\widehat{\beta}^i,\hat{c}^j)]$, where $\widehat{\beta}^i$ is a draw from the estimated asymptotic distribution of $\widehat{\beta}$. $\hat{c}^i$ is a draw from the normal distribution with the parameters generated from $\widehat{\beta}^i$.

Results

Table 3 summarizes the coefficient estimates of the random effects multinomial logit model of fitted on the panel data set. Tests of state dependence and random effects are presented in Table 4. Table 5 provides simulated probability changes due to the change of schoolings and village percentage of non-farm labor. Table 6 gives the simulated probabilities of choosing the three alternatives when given the initial and the last period choices.

We conclude that a household is more likely to have members as migrants if the household has a high level of average schooling of household labor at the initial period. The conclusion is consistent with the theory of Huffman (1991) and findings of previous studies on rural Chinese households, e.g., Tuan, Somwaru, and Diao (2000). It is interesting that the simulated effects of increasing education on the probability choosing the local non-farm working is negative though statistically insignificant. This is likely attributable to the fact that there are more opportunities and higher pay for the educated labor as migrants. As to the measurement of education, while Yang (1997) and Chen, Huffman and Rozelle (2003) found that the highest education attained is better than other measures in their production studies, the average schoolings is preferred here. Intuition is that the decision of production is collectively made but the decision to pursue a non-farm job rely more on the schoolings of individuals. Household head education is least relevant here, which is supported by our estimation result.

The simulated probability change when there is a change of village percentage of non-farm labors show that availability of social networks increases the likelihood of rural households taking non-farm jobs but there is no statistically effect on migration choices. We conclude that village-level non-farm labor ratio affect the decision-making of a household in the dynamic setting. Rural Chinese household is less likely to stay exclusively on the farm not only because that there are more people taking non-farm jobs in the village than other villages but also because that there are increasingly more people in the village taking non-farm jobs than the past, which in essence reduced the effect of unobserved heterogeneity. Furthermore, our model has controlled for the effects of previous responses. Note that the percentage of off-farm labor in the village are not correlated to the previous household response since the percentage is calculated based on village-level survey while we only sampled a portion of the households in the village.

We found that household size does affect the job-location decision in the dynamic setting. Controlling for the effect of the previous decisions, increasing household size makes the household more likely to pursue non-farm working than to stay exclusively on farm.

Based on the estimation result, we conclude that there is strong dynamic state dependence between current response and that of the previous time period. The intuition is that households had at least a member working off-farm in the local last year is more likely to do so this year. Similarly, a household that has at least one member who migrated last year is more likely to have at least a member to migrate this year. The experience and information accumulated during the previous time periods helps them to make judgment over job-location decision and even perform better in this period. The coefficients also revealed that the previous experience as migrate labor improves the likelihood of both taking local off-farm job and migrating, while the extent for the latter option is larger; and the experience of taking local off-farm job improves the likelihood of leaving the farm, with slightly inclination to take local off-farm job. We performed likelihood ratio test and found that we cannot accept the null that there is no dynamic state dependence after controlled for the unobserved heterogeneity. The likelihood ratio test of no-state dependence yields a test statistics of 92.44 distributed as chi-square with degree freedom of 4.

We test the hypothesis whether the random terms can be ignored or not by restricting the variances of the random term as zero. We reject the null that the random terms have zero variance. The test statistics are presented in Table 4, as well as the test of state dependence.

We also present the simulated probability prediction for 1999 when varying the initial and last period decision and fixing the other exogenous variables as the value in the original dataset. We found that it is less likely that household stay on exclusively on farm if its initial choice and last period choice are taking non-farm working. Interestingly, migrate labor seems more likely come from these households with experience of local non-farm working, which implies that the experience of local non-farm working maybe beneficial for the migrate working. Household with initial decision of migration are more likely to take local non-farm working. They are probably found themselves are not fit for migrate working or accumulated a fortune to stay in the local.

Conclusions

Based on a recent household survey data set, this paper analyzes determinants of the decision of rural Chinese households on whether to stay exclusively on farm, take local off-farm jobs or migrate. We add to the literature a dynamic three-alternative discrete choice model as well as a migration study on China that included an additional choice of local off-farm working. We confirmed results that migrants more likely came from households having more labor and better education.

Networks not only play an important role in household's decision on migration as previous studies found Zhao (2001), but also on choosing local off-farm jobs. Even after controlling the effect of previous decision, the percentage of village non-farm labors is increasing the likelihood of a household to have some local non-farm activities. Social network does help rural household to gather information about the new environment and be familiar with new production mode. We also find that average schooling of household labor is increasing the likelihood of a household to engage non-farm working in the dynamic setting. The results of random effects multinomial logit model show that there does exist strong state dependence. Human capita acquired during off-farm working improves the likelihood of obtaining a non-farm job opportunity later.

The policy implications from this study are obvious. First, in order to move labor out of agricultural sector, China may invest more on the education of rural population. Second, the effect of social networks for non-farm work suggests better information availability may help to transform rural China. Both private and public sectors can be involved to construct an improved information infrastructure. Lastly, the effect of household characteristics may help agencies to target certain household in carrying out relevant projects, e.g., large households with more male labors should be kept updated with changes of labor market. Efforts should be made to improve large households' access to information about labor market and relevant vocational training.

Further studies will be benefited by field surveys with more extensive information. We might be able to explore potential nesting structure when more alternative-specific and individual-specific information are available.

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[1] Many rural Chinese households engage in off-farm activities, e.g. employment in TVE (town and village enterprise), transportation, construction, small business and services. However, they are classified as rural household since they still engage in agricultural production in varying extensity. It is well accepted that off-farm activities has been an important part of Chinese rural economy (Parish, Zhe, and Li, 1995; Rozelle et al., 1999).

[2] Johnson (2002) projected that inter-provincial migration during the 1990s involved somewhere between 16 million and 39 million people. The number for overall internal migration including these within province is much larger, e.g. *Migration News* June 1994 issue estimated there are 100 million internal migrants (Migration News 1994). Estimates for 1995 are about 154 million rural people engaged in off-farm activities (Rozelle et al., 1999) and 120 million (Bhattacharyya and Parker 1999).

[3] Yang (1997) argued that there are collective decision-making processes, e.g., the household member with highest education may play an important role since he is likely to have better chance to access and utilize information. He claimed that the appropriate measure of the human capital stock for the Chinese rural household might be highest education achieved by any household member. However, the highest education achieved has less variation in the five-year period than the average years of schoolings, especially when we incorporate the fixed effects or dynamic state dependence. We use the average schoolings of the labor force in this study instead.

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Table 1. Household / Village Characteristics of the 5-year Panel

	1995	1996	1997	1998	1999
Observations	482	482	482	482	482
Village Income Level (1000 Yuan)	1.703	1.973	1.951	1.848	1.793
	(0.685)	(0.832)	(0.780)	(1.111)	(0.844)
Education Achieved (Year)	3.397	3.434	3.454	3.642	3.741
	(1.656)	(1.624)	(1.607)	(1.583)	(1.614)
Household Size	4.317	4.297	4.295	4.218	4.201
	(1.370)	(1.371)	(1.331)	(1.392)	(1.351)
Land Per Capita (Mu)[4]	2.285	2.293	2.257	2.286	2.190
	(1.767)	(1.896)	(1.866)	(1.905)	(1.905)
Village non-farm Labor Percentage	0.486	0.453	0.465	0.465	0.456
	(0.255)	(0.268)	(0.272)	(0.272)	(0.261)

Table 2. Characteristics of Three Types in the 5-year Panel

	Full-time Farming	Local off-farm Activities	Migration
Observations	421	1179	328
Education Achieved (Year)	3.010	3.617	4.108
	(1.640)	(1.526)	(1.657)
Household Size	4.076	4.234	4.546
	(1.581)	(1.232)	(1.454)
Land Per Capita (Mu)	3.632	2.533	2.114
	(3.625)	(1.757)	(1.179)
Village Income Level (1000 Yuan)	2.073	1.875	1.717
	(0.835)	(0.933)	(0.839)
Village non-farm Labor Percentage	0.305	0.508	0.516
	(0.260)	(0.261)	(0.192)

Table 3. Random Effect Multinomial Logit Model

	Local Off-farm Working (j=2)	Migration(j=3)
Constant	-1.488**	-3.163***
	(0.646)	(0.788)
State Dependence (γ_2)	1.778***	1.428***
	(0.366)	(0.475)
State Dependence (γ_3)	1.025**	2.913***
	(0.428)	(0.473)
Average years of Schoolings	0.249***	0.157**
	(0.062)	(0.079)
Household size	0.224	0.504***
	(0.157)	(0.252)
Ln(Village Non-farm Labor Percentage)	0.629***	1.929***
	(0.157)	(0.513)
1997 Dummy	0.328	0.752***
	(0.233)	(0.287)
1998 Dummy	0.474*	0.005
	(0.249)	(0.339)
1999 Dummy	1.100***	1.597***
	(0.258)	(0.319)
y_{0a}	2.099***	1.111**
	(0.512)	(0.554)
y_{0b}	1.200**	1.457**
	(0.557)	(0.643)
Z_i		
	Omitted	Omitted
Random Term variance estimate of the baseline alternative $var(a_1)$	1.223***	
	(0.280)	
Random Term variance estimate $var(a_j)$	0.764***	0.314
	(0.267)	(0.613)

Note: 1)* indicates the parameter is significant at 10% significance level, ** for 5% and *** for 1%. 2) Reference group is the stay exclusively on farm.

Table 4: Likelihood Ratio Test for State Dependence/Random Effect

H_0	Hypothesis	Ln(lik)	λ	D.F	Critical Value[5]	Inference
H0: γ_{22}=γ_{23}=γ_{32}=γ_{33}=0,	No State Dependence	-1111.70	92.44	4	13.28	Reject
H1: Negation		-1065.48				
H0: a_1= a_2= a_3=0,	No Random Effect	-1075.55	20.14	3	11.34	Reject
H1: Negation		-1065.48				
H0: π_1= π_2=0,	No Random Effect	-1074.54	18.12	2	9.21	Reject
H1: Negation		-1065.48				

Table 5: Simulated Marginal Effects

+% Probability	+1 Avg. year of Schoolings	+ 1% Avg. year of schoolings	+0.01 ln(vlg. non-farm labor ratio)	+1% ln(vlg. non-farm labor ratio)
Change of Prob. Of choosing Alternative 1	-0.0008	-0.0145	-0.0038	-0.0007
	(0.0002)	(0.0035)	(0.0009)	(0.0004)
% Change of Prob. Of choosing Alternative 1	-0.0109	-0.1702	-0.0269	-0.0081
	(0.0028)	(0.0398)	(0.0065)	(0.0020)
Change of Prob. Of choosing Alternative 2	-0.0003	-0.0041	0.0050	0.0014
	(0.0003)	(0.0046)	(0.0016)	(0.0005)
% Change of Prob. Of choosing Alternative 2	-0.0021	-0.0287	0.0582	0.0117
	(0.0023)	(0.0391)	(0.0210)	(0.0041)
Change of Prob. Of choosing Alternative 3	0.0010	0.0186	-0.0012	-0.0007
	(0.0003)	(0.0055)	(0.0014)	(0.0004)
% Change of Prob. Of choosing Alternative 3	0.0027	0.0558	-0.0011	-0.0017
	(0.0008)	(0.0163)	(0.0045)	(0.0011)

Table 6: Simulated Probabilities for 1999

(P_1, P_2, P_3)	y_0=1	y_0=2	y_0=3
y_{t-1}=1	0.42 (0.04)	0.20 (0.04)	0.19 (0.05)
	0.17 (0.04)	0.19 (0.05)	0.48 (0.07)
	0.42 (0.04)	0.61 (0.05)	0.33 (0.06)
y_{t-1}=2	0.18 (0.03)	0.07 (0.01)	0.07 (0.02)
	0.13 (0.04)	0.12 (0.02)	0.39 (0.06)
	0.69 (0.05)	0.82 (0.02)	0.54 (0.06)
y_{t-1}=3	0.25 (0.06)	0.10 (0.03)	0.09 (0.02)
	0.24 (0.05)	0.24 (0.04)	0.56 (0.04)
	0.51 (0.06)	0.66 (0.05)	0.35 (0.04)

[4] 1 Mu=1/15 Hectare

[5] The critical values correspond to 1 percent level of significance.