Rural Labor Migration: Migrant Network, Information, and Hysteresis
(Preliminary)

by

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Abstract

We investigate a rural household's decision to migrate part or all of its labor to urban areas. Labor migrates only when the expected return passes a hurdle rate that is affected by migration networks. We develop a dynamic model of incomplete information, and characterize the unique pure strategy perfect Bayesian equilibrium. Based on the predictions of the equilibrium, we develop a set of econometric models to estimate the migration decisions. Our results show that more current information helps migration, while the expectation of more information in the future may higher migration.

Key Words: migrant network, strategic delay, information externalities, real options.

With Chinas accession into the WTO, arguably the most significant challenge facing its agricultural sector is the ensuant foreign competition. Without government subsidies, reduced returns to traditional farming will likely put more pressure on the already surplus agricultural labor force. Although subsidies can help alleviate poverty and inequality, fundamentally, especially in the long run, the agriculture sector can only be saved by increasing its own competitiveness. Given the labor surplus and land scarcity, migration of rural labor force to non-agricultural sectors, including migration to urban areas, is an inevitable consequence of or even a necessary condition for a more competitive agriculture.

This paper investigates a rural households decision to migrate part or all of its labor force to urban areas. Different from other production activities such as farming and local off-farm employment, migration is unique in that it incurs significant sunk and fixed costs, including costs of transportation and networking. Networking is especially important: a migrant relies heavily on other migrants from the same area in finding jobs. Further, it takes efforts to join the network, and a migrants network expands as he stays longer in the urban area. Thus, once an individual migrates (and successfully finds a job), he will return to the rural area only after enough income is generated to cover the sunk costs. That is, labor migration hours are typically "chunky."

Expecting that sizable sunk costs have to be incurred to migrate, and facing uncertainty in the earnings and the probability of finding a job, a rural labor may be reluctant to migrate for two reasons: risk aversion and hysteresis. If he is risk averse, uncertainty in the migration income means that the expected utility from migration is lower. But even if he is risk neutral, he may have incentive to wait and gather more information about the potential payoff from migration before committing the sunk costs. Typically, such information may be obtained from others who have migrated, and from the news media.

We first develop a theoretical model to investigate the interaction among migration network, information and hysteresis. In particular, we show that local network reduces migration hysteresis in three ways. First, a larger network provides better starting information for a potential migrant, and more information (or less uncertainty) reduces the hysteresis involved in the migration decisions. Second, to the extent that more future information is generated by other new migrants, a larger local network also implies that there will be fewer labors available who have not migrated, given the fixed total labors. That is, there will be fewer migrants in the future to generate more information. Expecting less future information, a labor is more willing to migrate now. Finally, local network may also raise the expected earnings from migration.

Once a rural labor decides to migrate, i.e., once the hurdle of hysteresis is surpassed, the length of migration (e.g., days in the city) depends on the earnings potential. Here local network again helps to maintain a longer migration period by raising the expected earnings. However, the information service of networks will not affect the migration length significantly.

Based on the theoretical results, we empirically estimate the magnitude and sign of the information and earnings effects of migration networks in decisions about whether or not to migrate, as well as about the length of migration. The data are obtained from a five year (1995 to 1999) survey of farming and migration decisions of about 590 households in 29 villages from 9 provinces. We adopt a two stage estimation procedure, where the first stage estimates the effects of networks on migration earnings, its effect on the length of migration, the variability in the size of the networks, and the uncertainty in migration earnings. In the second stage, we jointly estimate a hurdle model and a migration labor allocation model where the information and earnings effects of networks are separately identified. Preliminary analysis indicates that the both the information and earnings effects of networks are significant. We also study how these effects are influenced by household characteristics, such as education, income, land area, and household size.

Existing literature on labor migration has identified the positive effects of networks on migration (Zhao (1999b), Zhao (1999a), and Zhang, Huang and Rozelle (2002)). But the literature failed to distinguish between the information and earnings effects, and the effects on the hurdle of deciding to migrate and the length of migration. In fact, there are few papers that formally tackle the issue of hysteresis in migration decisions (Epstein (2002) and Bauer, Epstein and Gang (2002)). The contribution of our paper is to develop both theoretical and empirical models to identify these separate effects in China's rural labor migration.

1 A Model of Labor Migration

Consider a village of N agents, and each agent can be in two states: either he is staying in the village, or he has migrated. We call the agent in the first state a farmer and that in the second state a migrant. Let N^a be the number of farmers and N^m the number of migrants, and let $\mathcal{N} = \{1, \ldots, N\}$, $\mathcal{N}^a = \{1, \ldots, N^a\}$, and $\mathcal{N}^m = \{N^a + 1, \ldots, N\}$. Each agent is risk neutral, is endowed with one unit of labor, lives for infinite periods, and has a discount factor $\beta < 1$.

At the beginning of a period, a farmer $i \in \mathcal{N}^a$ can decide either to stay in the agricultural sector or to migrate. The agricultural payoff per unit of labor is $\pi(\theta_i^a)$, where θ_i^a represents the agent's agriculture characteristics such as the amount of land, the crops grown, etc. For simplicity, we take θ_i^a as a scaler with $\pi' > 0$ and $\pi'' < 0$. We also assume that the value of θ_i^a is common knowledge among the villagers.

If the farmer decides to migrate, he can either stay the entire period or part of the period in the urban area. The probability of finding a job in the urban area is p.[1] The expected salary if he finds a job is $w(\theta_i^m)$, where θ_i^m is his "type" or characteristics related to urban employment, such as his education level, his training, etc. Again, θ_i^m is assumed to be a scaler with $w' > 0$ and $w'' < 0$. Thus, if he stays in the urban area for an length of τ, his expected salary income is $pw(\theta_i^m)\tau$. We assume that θ_i^m is the private knowledge of agent i, and other agents hold the common belief that θ_i^m is distributed on $\Theta = [\underline{\theta}^m, \bar{\theta}^m]$ with distribution function $G_0(\cdot)$. The common beliefs about the

[1] For simplicity, we assume that p is constant over time and is independent of the number of migrants from this village N^m. In general p depends on the macro-economic status of the urban economy. A village, being a smaller player in the economy, will only play an negligible role in the urban labor market.

types of different agents are i.i.d.

The cost of living in the urban area is $c(N^m)$ per unit of time, with $c' < 0$ and $c'' > 0$. The cost being a function of N^m represents the role of migration networks: the more people in urban areas from the same village, the lower cost it is to live in those areas. In addition to the cost of living, the farmer has to incur a fixed cost c_0 to migrate: this cost may include the transportation cost, the initial cost of settling down, etc. Thus, if a farmer decides to migrate, and spends τ time period in the urban area, his total cost is $c_0 + \tau c(N^m)$.

In each period, a migrant allocates his time between working in the urban area, τ_i^m, and going back to his village to work in agriculture, τ_i^a, with $\tau_i^m + \tau_i^a = 1$. Here we are allowing the maximum flexibility in a migrant's labor choices. Given reasonable transportation costs, a migrant may decide to work on land, say, during the harvest season, and work in the urban sector after that. Of course, there are also many cases where the migrant could only work in the urban area so that $\tau_i^m = 1$. Let c_1 be the fixed cost of a migrant to go back to work on his land.

We now describe the agents' information structure. At the beginning of period t, a farmer has a belief about p, the probability of finding a job if he migrates. The belief is given by a nonatomic densify function $f_t(\cdot)$ on $[0, 1]$. Further, farmers in the same village share the same beliefs. The beliefs may be based on the media, news from other villages, and most importantly, from observing other migrants in his village.

To describe how migrants provide information to farmers about p, let $f_0(\cdot)$ be the belief that is obtained from sources other than the migrants. For simplicity, we assume that this belief remains the same overtime. In each period, farmers observe how the migrants perform, i.e., whether or not they have jobs in the urban area. Let $\mathcal{N}_t^m$ be the set of migrants at the beginning of period t. Each of them releases a signal s_i, with $s_i = 1$ if migrant i finds a job and $s_i = 0$ otherwise. Obviously, the conditional probability of a signal s, conditional on a particular value of p, is given by $h(s = 1|p) = p$ and $h(s = 0|p) = 1 - p$. Since the probability of a migrant finding a job is independent of others' finding jobs, we know the conditional probability of observing signals $\boldsymbol{s}_t \equiv \{s_i, i \in \mathcal{N}_t^m\}$, is

$$h(\boldsymbol{s}_t|p) = p^{\sum_{j\in\mathcal{N}_t^m} s_j}(1-p)^{\sum_{j\in\mathcal{N}_t^m}(1-s_j)}. \tag{1}$$

Observing these signals, farmers update their beliefs about p in the Bayesian way. Given the prior belief $f_0(\cdot)$ and signals $\boldsymbol{s}_t$, the posterior belief, which is also the starting belief in period t, is given by

$$f_t(p|\boldsymbol{s}_t) = \frac{h(\boldsymbol{s}_t|p)f_0(p)}{\int_0^1 h(\boldsymbol{s}_t|p)f_0(p)dp}, \tag{2}$$

where $h(\boldsymbol{s}_t|p)$ is given in (1).

Thus, if more farmers migrate in period t, remaining farmers expect to obtain more information about p by period $t+1$, as they will observe the signals of the new migrants. Let $\mathcal{N}_t^a \subseteq \mathcal{N}^a$ be the set of farmers at the beginning of period t, $\mathcal{N}_t^n \subseteq \mathcal{N}_t^a$ be the set of farmers who decide to migrate in period t, and $\boldsymbol{s}_t^n = \{s_i, i \in \mathcal{N}_t^n\}$ be their signals, with $s_i \in \{0,1\}$. Then the set of signals at the beginning of period $t+1$ is $\boldsymbol{s}_{t+1} = \boldsymbol{s}_t \cup \boldsymbol{s}_t^n$, and the starting belief at period $t+1$ is

$$\begin{aligned} f_{t+1}(p|\boldsymbol{s}_{t+1}) &= \frac{h(\boldsymbol{s}_t^n|p)f_t(p|\boldsymbol{s}_t)}{\int_0^1 h(\boldsymbol{s}_t^n|p)f_t(p|\boldsymbol{s}_t)dp} \\ &= \frac{h(\boldsymbol{s}_{t+1}|p)f_0(p)}{\int_0^1 h(\boldsymbol{s}_{t+1}|p)f_0(p)dp}. \end{aligned} \tag{3}$$

Thus, the belief in period $t+1$ can be thought of as being obtained either through Bayesian updating with $f_t(\cdot)$ as the prior and $\boldsymbol{s}_t^n$ as the signals, or with $f_0(\cdot)$ as the prior and $\boldsymbol{s}_{t+1}$ as the signals.

The second element in a farmer's information structure is his belief about the types of remaining farmers, θ_i^m, for $i \in \mathcal{N}_t^a$. This belief is important when the farmer forms expectations about how many future signals about p he will obtain if he decides not to migrate in period t. For example, suppose in equilibrium, only farmers with types higher than a threshold will migrate. If the farmer believes that there are many farmers whose types pass this threshold, he may prefer to wait for the many new signals he will receive before deciding to migrate. But if he believes that there are few farmers with types higher than the threshold, the farmer may decide to migrate in this period as waiting will not bring much new information about p. The updating of this belief depends on the strategies of the agents, which will be described later on.

Thus, a farmer's migration decision has two steps: First, he decides whether or not he will migrate, based on his beliefs about p and about the types of the remaining farmers. Due to the fixed cost of migration c_0, a farmer facing much uncertainty but expecting more information about p may decide to wait, even if migration brings higher expected payoff than staying in agriculture. Second, if he migrates, depending on whether he finds a job and his salary level, he decides how much time to allocate to migration (τ_i^m).

Before we formally define the migration game, we first study the second stage decision of a migrant to allocate time between migration and agriculture job. Since he is already in the urban area, the migrant knows his probability of getting a job, p. If he stays, his expected payoff rate is $pw(\theta_i^m) - c(N^m)$. His agricultural payoff rate is $\pi(\theta_i^a)$. In each period, if he has already stayed in the urban area for a length of τ, he will go back to work in agriculture if and only if

$$(\pi(\theta_i^a) - pw(\theta_i^m) + c(N^m))(1 - \tau) > c_1. \tag{4}$$

Thus, a larger migration network will help the migrant stay in the urban area longer. Further, the longer a migrant has already stayed, the more likely that he will stay longer. In summary,

Proposition 1 *A migrant stays longer in the urban area*

(i) as the migrant's type θ_i^m is higher,

(ii) as the migrant's agriculture characteristic θ_i^a is lower,

(iii) as the expected wage in the urban area increases,

(iv) as the farming payoff decreases, and

(v) as the migration network gets larger.

Now we describe the migration game. At each time t, the set of players is the farmers $\mathcal{N}_t^a$, i.e., those agents who have not migrated. The history is comprised of the migration decisions that have occurred so far, i.e., who has migrated and who has not migrated. Let $\mathcal{H}$ be the set of histories, and

$h \in \mathcal{H}$ be a particular history. A player's type is θ_i^m, his private information, and his action space is $\mathcal{A} = \{0, 1\}$, where 0 represents not migrating and 1 represents migration. Player i's behavior strategy $b_i(h, \theta_i^m)$ describes the probability with which he migrates, following history h.

We have already described how agents update their information about the probability of finding a job, p. Now we describe how agents form beliefs about the others' types. Along the equilibrium path, the agents update their beliefs according to Bayes. Let $g_t^i(\theta_i^m)$ be the common belief others hold about the type of agent i. Given i's strategy $b_i(h_t, \theta_m^i)$ and observing i's action $a_i = 0$, or 1, this belief is updated as

$$g_{t+1}^i(\theta_i^m | a_i, h_t) = \frac{[b_i(h_t, \theta_i^m)a_i + (1 - b_i(h_t, \theta_i^m))(1 - a_i)]g_t^i(\theta_i^m)}{\int_\Theta [b_i(h_t, \theta_i^m)a_i + (1 - b_i(h_t, \theta_i^m))(1 - a_i)]dG_t^i(\theta_i^m)}. \quad (5)$$

We look for the symmetric perfect Bayesian equilibrium of the adoption game. Following Fudenberg and Tirole (1993) (Section 8.2.3), we impose the condition that beliefs about the types are updated in the Bayesian way whenever possible, even on paths reached with zero probability. We also assume that the densify functions $g_0(\cdot)$, $f_0(\cdot)$, and $h(\cdot)$ are continuous and bounded above and away from zero. In period $t = 0$, the number of migrants $N_0^m < N$ is given.

Here we briefly sketch the unique symmetric pure strategy perfect Bayesian equilibrium of the adoption game. The existence, uniqueness, and derivation of this equilibrium are provided in the Appendix. We show that other things equal, the relative payoff of migration and staying in agriculture is increasing and concave in an agent's type θ_i^m. Thus, the behavior strategy of a farmer can be represented as follows: given any history h_t, there exists a critical level $\theta_t^{m*}(h_t)$ such that the farmer migrates if and only if $\theta_i^m \geq \theta_t^{m*}(h_t)$. Further, given the same expected probability of finding a job, the more migrants there are in h_t, the lower θ_t^{m*} is, and the more farmers there are in h_t, the higher θ_t^{m*} is. These results are intuitive: higher θ_i^m implies that farmer i receives a higher salary if he migrates. Thus, it is more likely that he will migrate. As more farmers migrate, farmer i has better information about p. Facing the same expected p, he is more willing to migrate if armed with better information. If on the other hand, there are more farmers in h_t, i would expect that more farmers will migrate in the future. That is, by waiting to migrate, he expects more information about p that will be generated by the future new migrants. Thus he is more willing to wait, and less willing to migrate.

In equilibrium, the migration process develops in the following pattern. Facing initial uncertainty about p and about each other's types, all farmers believe that only those with types higher than θ_0^{m*} should migrate. Farmers with such types then migrate. If no farmer types are higher than θ_0^{m*}, no farmers migrate, and they update their belief about each other's type, based on the new information that all types are below θ_0^{m*}. This will generate a new strategy where farmers with types higher than $\theta_{01}^{m*} < \theta_0^{m*}$ should migrate. This process continues until there are farmers who start to migrate.

After some farmers migrate, their career success in the urban area provides information about p. The remaining farmers then update their belief about p, and form a new strategy where types higher than θ_1 should migrate. Depending on the signals about p, θ_1 may be higher or lower than θ_0. For example, if the new migrants fail to find any job, the remaining farmers may believe that p is low, and decide not to migrate. On the other hand, if the signals do not change the expected value of p, or indicate a higher p, some remaining farmers may want to migrate: now they are armed with better information about p, as well as a larger migration network N_1^m. That is, if $\theta_1 < \theta_0$, more farmers will migrate, eventually. If, however, $\theta_1 \geq \theta_0$, no more farmers migrate and there is no updating about farmer types. The migration process stops.

From the equilibrium, we obtain the following Proposition, which also serves as the testable hypothesis in the empirical model.

Proposition 2 *In the symmetric PS-PBE, a farmer is more willing to migrate*

(i) as the initial uncertainty about the probability of finding a job, p, decreases,

(ii) as the farmer's type θ_i^m increases, or as the expected income from migration increases,

(iii) as his agriculture characteristic θ_i^a decreases,

(iv) as the migration network N^m increases, and

(v) as there are fewer farmers remaining in the village (i.e., as he expects less information from new migrants in the future).

Comparing Propositions 1 and 2, we know while the migration decision depends on the initial uncertainty about p and the number of remaining farmers, how long a migrant stays is independent of these factors. The two Propositions also indicate the two roles of networks: it raises the expected payoff from migration, thus promoting both the length of stay and the incentive to migrate. It further helps the incentive to migrate through reducing the uncertainties about the migration payoffs.

2 The Empirical Model

In this section, we set up the empirical model used to estimate the two decision processes: the decision to migrate, and the decision of how long to stay in the urban area once migrated. In particular, we show how an agent responds to uncertainties in the migration payoff, and the role of networks in reducing the uncertainties and in raising migration payoff.

The two stage decisions can be represented by the following sample selection model:

$$
\begin{aligned}
y_i^1 &= \beta^1 X_i^1 + \epsilon^1 \\
d_i &= \begin{cases} 1, & \text{if } y_i^1 > 0 \\ 0, & \text{if } y_i^1 \leq 0 \end{cases} \\
y_i^2 &= \begin{cases} \beta^2 X_i^2 + \epsilon^2, & \text{if } y_i^1 > 0 \\ \text{unobserved}, & \text{if } y_i^1 \leq 0 \end{cases}
\end{aligned}
\tag{6}
$$

where $i = 1, \ldots, N$ indexes the agents, y_i^1 is the latent variable, d_i is the decision variable of migration or no migration, and y_i^2 represents the length of stay in the urban area. Variables X_i^1

and X_i^2 are vectors of explanatory variables, and ϵ^1 and ϵ^2 are jointly normally distributed, with $\text{var}(\epsilon^1) = 1$, $\text{var}(\epsilon^2) = \sigma^2$, and $\text{cov}(\epsilon^1, \epsilon^2) = \rho$.

The first equation in (6) represents the agent's decision to migrate or not, and the latent variable y_i^1 in (6) relates directly to the equilibrium migration condition of the last section. In particular,

$$y_i^1 = \theta_i^m - \theta^{m*}(h).$$

following history h. Thus, X_i^1 should include all variables that affect the migration payoff (e.g., the size of the migration network), the agricultural payoff, the agent's agricultural and migration characteristics θ_i^a and θ_i^m, as well as the uncertainties about the probability of employment.[2] We do not have data on the employment status and the wage level. Instead, we only observe the gross income earned by migrants. Thus, uncertainties in migration income are used in X_i^1.

The last equation in (6) represents the decision of how long to stay in the urban area. As indicated in the last section, variables affecting this decision include the payoffs of migration and agriculture, as well as the network size.

Equation (6) is estimated using the method of maximum likelihood. If agent i does not migrate, we know $y_i^1 \le 0$ or $\epsilon^1 \le -\beta^1 X_i^1$. If agent i migrates and stays in the urban area for a length of τ_i, we know $\epsilon^1 > -\beta^1 X_i^1$, and $\epsilon^2 = \tau_i - \beta^2 X_i^2$. Thus, the log likelihood function is given by

$$\text{Log}(L) = \sum_{i=1}^{N} \left\{ (1 - d_i)\text{Log}[\Phi(-\beta^1 X_i^1)] + d_i \text{Log}[\int_{-\beta^1 X_i^1}^{\infty} \phi(\epsilon^1, \tau_i - \beta^2 X_i^2) d\epsilon^1] \right\}, \tag{7}$$

where $\Phi(\cdot)$ is the Gaussian distribution function, and $\phi(\cdot)$ is the joint normal density function specified following (6).

We do not observe the uncertainties in migration payoff directly. Instead, we adopt Appelbaum and Ullah (1997) and obtain estimates of the payoff uncertainty from an auxiliary estimation. Since farmers in the same village share the same information, the following estimation equation is applied

[2]We do not have data that allow us to estimate the uncertainties about each other's types. Thus we ignore this variable in the estimation equation.

to the village level data:

$$y_j^3 = \beta^3 X_j^3 + \epsilon^3, \tag{8}$$

where y_j^3 is the migration income of village j, and X_j^3 are the variables that influence this income, such as migration network size. The estimated uncertainty in migration income is represented by the square of the fitted error $(y_j^3 - \hat{y}_j^3)^2$.

3 Data and Estimation Results

The data come from a survey by Research Center for Rural Economy in China, conducted since 1986 in 29 provinces covering more than 20,000 households. The data used in our study are from 1995 to 1999, covering 590 households in 29 villages of 9 provinces. In total, we have 2742 observations. Although the data set is a panel of five years, currently we ignore time dependence and treat decisions in each year as independent of other years.

Each household is considered as a single agent. For this agent, we observe the total migration income, the total agricultural income, the household head's education level, the household size, etc. Table 1 presents the summary statistics of the variables used in this study.

Table 2 shows the results of the auxiliary estimation, estimated using OLS. Models 1 and 2 are used to estimate the uncertainties in migration income. The dependent variable is HAVMINC, the average household migration income among migrant households in the village. It is related to the macro-economic environment facing migrants from this village. Since this is the village average migration income, an average migrant may expect to receive this income level. The uncertainty in HAVMINC then represents the uncertainty in the expected income from migration. The estimated uncertainty levels, i.e., the square of the residuals of the dependent variable, are represented as XXX2 and XXX2L. The third moments of the residual are also calculated.

Models 1 and 2 differ in whether the lagged HAVMINC is used as an independent variable.

Using the lagged variable clearly improves the accuracy of estimation, but the model estimates do not seem to be extremely sensitive to the inclusion.

In Models 3 and 4, we estimate the uncertainties in the network size, or the total migrants of the village, EMMIGLAB. In latter models, this uncertainty, together with the uncertainty of HAVMINC, will be used together to represent the information farmers have about the migration payoff. We include this uncertainty for two reasons. First, since the migration network affects the cost of migration and thus the migration payoff, its uncertainty is relevant in the migration decisions. Second, the network itself may represent uncertainties in urban employment that is not captured by the uncertainty in HAVMINC. In Model 4, where the lagged dependent variable is included, a unit root test may be required.

The squared residuals, used as the estimates of the uncertainty levels, are denoted as YYY2 and YYY2L, for the two models.

Table 3 presents results of the maximum likelihood estimation. The provincial dummies are not reported. The three models reported differ in some of the variables used in the estimation of whether or not to migrate. All three models lead to similar estimates for the sign and magnitude of the common variables. For example, education, household size, labor ratio, and male labor ratio all significantly raise the likelihood of migration, as well as the length of stay in urban areas. These results are consistent with the literature. Village income level (INCOMEPPV) and the village level off farm labor ratio (LABOR2RATIO) also significantly and positively affect migration and duration. These variables may indicate that the labor force in a village is better trained in terms of non-agricultural job, and thus help promote migration.

As expected, migration network (EMMIGLAB) positively and significantly affects both decisions. Note that Model 7 used H(EMMIGLAB), the fitted value of EMMIGLAB in the OLS estimation in the previous stage (Model 4). Cropping income (CROPINC) negatively affects the decision to migrate and the migration duration, consistent with our theory.

The village average migration income (HAVMINC) does not significantly affect the decision to migrate. It does significantly and positively affect the duration of stay in urban areas. Its fitted value obtained in Model 2 (H(HAVMINC)), however, does positively and significantly affect the decision to migrate.

It is interesting to note that the total number of farmers, i.e., labors that have not migrated (TOTALLAB), negatively affects the decision to migrate. This result is rather unique in the literature, and is consistent with our equilibrium migration theory. It is consistent with the conjecture that more non-migrant labor force means more potential migrants in the future, and thus more future information. The incentive to migrate is reduced expecting the future information.

Across all three models, uncertainty in migration income (XXX2, or XXX2L) significantly reduces the incentive to migrate. Our results thus confirm the theoretical conjecture that higher uncertainty about migration payoff, or less information, hinders migration. The uncertainty in network size YYY2 or YYY2L is significantly only in Model 5. In that model, it also negatively affects the decision to migrate.

4 Conclusion

In this paper, we developed a dynamic model with incomplete information to study farmers' decisions to migrate and their duration of stay in urban areas. We then formed an econometric model based on the equilibrium migration behavior, and applied the model to rural labor migration data in China. Our results confirm the theoretical predictions that information about migration payoff, migration networks, and higher expected migration income all promote migration. On the other hand, higher non-migration population and higher agricultural payoff reduce the incentive to migrate. Our model highlights the role of migration networks and information.

These results have important policy implications, especially with China joining the WTO. To the extent that networks promote information, and information is important in migration decisions, policies that help the transmission of information about earning potentials will facilitate migration. For example, governments may wish to help establish informal groups based on regions of origin in urban areas. Since networks generate both information and earnings externalities for future migrants, villages may subsidize early migrants, e.g., in the form of insurance and capital allocation. If WTO successfully brings more jobs to urban areas, networks will become even more important in helping facilitate the migration of rural labor.

Table 1: Variable Description and Summary Statistics

Variable Name	Description	Unit	Mean	Std Dev
IFMIG1	whether the household has migrants	1 if yes, 0 otherwise	0.38	0.49
MIGLABORINPUT	household migration labor	labor day	71.88	138.04
HAVMINC	village level hshd migration income	yuan	3779.33	1896.02
CROPINC	household cropping income	yuan	5130.67	4664.73
HAGE	age of head of household	1 if >30, 0 otherwise	0.91	0.28
HHEDUP	education of head of household	years	3.62	1.66
HSIZE	household size		4.24	1.41
SEXRATIO	male labor / overall household labor		0.53	0.20
LABORRATIO	household labor/household size		0.64	0.21
TAX	household tax level	1000 yuan	0.06	0.05
INCOMEPPV	village income level	1000 yuan	1.85	0.92
LABOR2RATIO	village nonfarm labor percentage		0.22	0.14
EMMIGLAB	village total migrant labor	labor	127.48	126.28
TOTALLAB	village total non-migrant labor	labor	810.44	482.57

Table 2: Auxiliary Estimation Results: To Estimate Uncertainties

	Model 1		Model 2		Model 3		Model 4	
Dependent Variable	HAVMINC		HAVMINC		EMMIGLAB		EMMIGLAB	
C	589.234	[.000]	156.49	[.115]	-32.83	[.000]	-28.90	[.000]
LAGHAVMINC			0.44	[.000]				
LAGEMMIGLAB							0.92	[.000]
INCOMEPPV	817.33	[.000]	560.73	[.000]	0.82	[.683]	4.95	[.000]
LABOR2RATIO	-1535.5	[.000]	-884.71	[.000]	99.77	[.000]	44.46	[.000]
TOTALLAB	0.774719	[.000]	0.54	[.000]	0.15	[.000]	0.04	[.000]
EMMIGLAB	2.63276	[.000]	-0.03	[.927]				
PROV2	1094.1	[.000]	521.50	[.000]	-21.89	[.000]	-22.84	[.000]
PROV3	-915.016	[.000]	-61.18	[.578]	-23.53	[.000]	0.68	[.825]
PROV4	1181.36	[.000]	1264.99	[.000]	33.12	[.000]	-7.76	[.018]
PROV5	-166.169	[.358]	141.83	[.294]	12.86	[.145]	6.33	[.141]
PROV6	2711	[.000]	1736.59	[.000]	20.31	[.022]	3.87	[.374]
PROV7	2471.91	[.000]	1343.27	[.000]	-81.49	[.000]	-26.16	[.000]
PROV8	1482.05	[.000]	1548.89	[.000]	59.73	[.000]	-2.20	[.480]
PROV9	-2012.54	[.000]	-470.67	[.018]	24.79	[.006]	17.32	[.000]
R2	0.51		0.74		0.52		0.92	
Residual^2	XXX2		XXX2L		YYY2		YYYL2	
Residual^3	XXX3		XXX3L		YYY3		YYYL3	

P-values in the square brackets.

Table 3: Estimation Results

	Model 5		Model 6		Model 7	
Migration or not						
C	-3.01	[.000]	-2.69	[.000]	-2.71	[.000]
HAGE	-0.10	[.309]	-0.08	[.505]	-0.11	[.346]
HHEDUP	0.07	[.001]	0.08	[.001]	0.07	[.002]
HSIZE	0.22	[.000]	0.21	[.000]	0.22	[.000]
SEXRATIO	0.50	[.001]	0.26	[.130]	0.31	[.075]
LABORRATIO	1.27	[.000]	1.28	[.000]	1.28	[.000]
TAX	-0.02	[.960]	-1.16	[.236]	-1.36	[.163]
INCOMEPPV	0.22	[.000]	0.08	[.100]	0.03	[.622]
LABOR2RATIO	2.01	[.000]	2.02	[.000]	2.22	[.000]
EMMIGLAB	3.35E-03	[.000]	4.04E-03	[.000]		
HAVMINC	-3.57E-05	[.132]	3.69E-05	[.269]		
H(EMMIGLAB)					3.66E-03	[.000]
H(HAVMINC)					1.30E-04	[.003]
CROPINC	-2.71E-05	[.001]	-2.74E-05	[.009]	-2.68E-05	[.010]
TOTALLAB	-3.69E-04	[.000]	-7.17E-04	[.000]	-8.57E-04	[.000]
XXX2	-2.12E-08	[.045]				
YYY2	-9.22E-06	[.026]				
XXX3	2.43E-12	[.102]				
YYY3	3.16E-08	[.157]				
XXX2L			-3.99E-08	[.041]	-4.10E-08	[.036]
YYY2L			1.15E-05	[.234]	5.32E-07	[.958]
XXX3L			-1.15E-11	[.209]	2.21E-12	[.792]
YYY3L			3.17E-08	[.635]	3.70E-07	[.000]

Table 3 continued

	Model 5		Model 6		Model 7	
Length of stay						
C	-659.65	[.000]	-623.90	[.000]	-628.23	[.000]
HAGE	-40.31	[.023]	-36.70	[.066]	-38.90	[.051]
HHEDUP	14.32	[.000]	17.95	[.000]	18.16	[.000]
HSIZE	55.96	[.000]	55.19	[.000]	55.89	[.000]
SEXRATIO	76.37	[.006]	25.50	[.419]	30.89	[.328]
LABORRATIO	322.35	[.000]	314.85	[.000]	314.14	[.000]
TAX	28.93	[.636]	-264.76	[.159]	-266.42	[.156]
INCOMEPPV	34.67	[.000]	17.92	[.039]	16.20	[.054]
LABOR2RATIO	251.93	[.000]	270.09	[.000]	275.16	[.000]
EMMIGLAB	0.45	[.000]	0.44	[.000]	0.34	[.000]
HAVMINC	0.01	[.015]	0.02	[.000]	0.02	[.000]
CROPINC	-3.88E-03	[.022]	-3.34E-03	[.094]	-3.33E-03	[.094]
SIGMA	187.35	[.000]	182.79	[.000]	182.97	[.000]
RHO	0.97	[.000]	0.97	[.000]	0.97	[.000]
LogLikelihood	-6625.51		-5190.5		-5197.11	

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