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Abstract: In this paper, we use the "2002 Chinese Household Income Project Survey" (CHIPS2002) data to examine how heterogeneous social interactions affect the peer effect in the rural–urban migration decision in China. We find that the peer effect, measured by the village migration ratio, significantly increases the individual probability of outward migration. We also find that the magnitude of the peer effect is nonlinear, depending on the strength and type of social interactions with other villagers. Interactions in information sharing can increase the magnitude of the peer effect, while interactions in mutual help in labor activities, such as help in housing construction, nursing and farm work in busy seasons, will impede the positive role of the peer effect. Being aware of the simultaneity bias caused by the two-way causality between social interaction strengths and migration, we utilize "historical family political identity in land reform" as an instrumental variable for social interactions. However, the hypothesis that probit and instrumental-variable probit results are not significantly different is not rejected. The existence of a nonlinear peer effect has rich policy implications. For policy makers to encourage rural–urban migration, it is feasible to increase education investment in rural areas or increase information sharing among rural residents. However, only an increase in the constant term in the regression, i.e. a "big push" in improving institutions for migration, can help rural Chinese residents escape the low equilibrium in migration.

Keywords: labor migration, urbanization; peer effect, social interaction, social multiplier
JEL Classification: J61, O15, R23

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1 Introduction

Rural-to-urban migration and hence urbanization are key symbols of economic development. Especially for developing countries, policies promoting migration from the countryside to cities are structural forces for sustainable growth. However, except for well-known migration-facilitating measures such as infrastructure and human capital investment, are there other policies to promote migration? This encourages us to explore further the determination of labor migration. In this paper, we attempt to answer two questions. First, how does the peer effect—interdependence in decision making—affect the migration decisions of rural residents in China? Second, how do social interactions of different types and frequencies affect the peer effect in migration?

Using CHIPS2002 (2002 Chinese Household Income Project Survey) data, we find strong evidence that the peer effect exists in the outward migration decision in rural China. This finding has two important interpretations. On the one hand, in the presence of the peer effect, other policies, such as increasing the education of rural residents, have larger effects than previous estimates because of the spillover of the peer effect or the so-called social multiplier (Glaeser *et al.*, 2002). On the other hand, however, the rural–urban segmentation policy in China will also limit the equilibrium migration ratio to a low value and thus be harmful for the process of urbanization.

With the recent increasing concern about nonlinearity in the peer effect (Ballester *et al.*, 2006; Calvó-Armengol and Zenou, 2005; Marmaros and Sacerdote, 2006; Patacchini and Zenou, 2008), we also develop a model to incorporate heterogeneous peer effect. In our model, the magnitude of the peer effect depends on within-peer-group social interactions that may consume time during the outward migration decision. Empirically we interact the peer effect with different types of social interaction and obtain some interesting results: higher interaction frequencies in information sharing with other villagers will enhance the magnitude of the peer effect, while higher interaction frequencies in time-consuming local labor exchange activities will reduce the positive role of the peer effect. These findings are consistent with Narayan's (1999) proposition that social capital has two forms: bonding and bridging. While the affluence of bonding social capital (in our context the labor exchange activities) will directly increase the social welfare of a community, more internal communication will, however, make the community close and lowers its members' inclination of outward migration, which is an important way of reducing rural poverty.

The presence of the peer effect implies multiple equilibria in labor migration, either a low-level equilibrium, which our policy simulation shows, or a high-level one. If social interactions of different types and frequencies affect the peer effect in migration, new social policy tools can be utilized to push ahead rural–urban migration and urbanization. Policy makers seeking to encourage outward migration can either increase education or promote information sharing among villagers. However, neither of these two policies can shift the equilibrium to a high-level one even if we combine the two. To achieve a high migration ratio, it is more important to eliminate urban-biased policies and accelerate social integration between rural and urban areas. This is what we emphasize in our paper: the institutional "big-push" in China.

The rest of this paper is organized as follows. Section 2 reviews studies on labor migration in China and empirical strategies for identifying the peer effect. Section 3 establishes a simple model to demonstrate how the peer effect is affected by heterogeneous social interaction strength. Section 4 describes the data and Section 5 presents the econometric model and empirical findings. The social interaction strength may potentially be endogenous because of unobserved family culture or reverse causality; therefore, in Section 6 we use the "historical family political identity in land reform" as an instrument for social interaction strength. Section 7 presents policy simulations, in which we explore the effects of different policies on labor migration equilibrium. The final section concludes.

2 Literature Review

Many empirical studies have explored migration determination. In classical theories, the factors affecting the labor migration decision are a group of individual and family characteristics. In migration studies for China, the classical framework is also applicable. Using cross-sectional data in the Sichuan rural areas, Zhao (1999a; 1999b) finds evidence consistent with findings in other countries: male laborers have a higher probability of outward migration, while aging and more household land area will significantly decrease the probability of migration. Zhu (2002) finds that the income gap between farming and nonfarm activities will affect the migration decision, which is consistent with the Harris–Todaro model. Cai *et al.* (2003) discover that although the income gap between west and east China is greater than that between middle and east China, migration is more prevalent from middle to east than from west to east, which seems to contradict the Harris–Todaro prediction but still can be explained by distance effects.

Recent studies add the role of social networks to the analysis of the migration decision. Munshi (2003) finds that networks play a significant role in helping rural Mexican residents migrate to the US. Mckenzie and Rapoport (2007) argue that with the expansion of migration networks, more poor families can engage in migration, thus reducing rural inequality. Using Chinese data, Zhang and Li (2003) find that rural residents have a higher probability of being employed in the nonfarm activity if their family has social ties outside the village. Bao *et al.* (2007) find that province-to-province migration rates rise with the size of the migrant community in the destination province. Zhao (2003) shows that larger numbers of local experienced migrants will significantly increase the migration probability of villagers in the same village, and she argues this is the result of job information sharing among villagers.

Although findings about the role of social networks extend our understanding of labor migration, all of these empirical studies only consider the peers in one's community as the network that provides information to reduce migration costs. However, as Bauer *et al.* (2002) point out, peers in the community also contribute to herd/peer effects even in the presence of migration networks.[1] To our understanding, the network effect occurs mainly through information sharing within and across social groups, while the peer effect is due to both information sharing and behavior assimilation within group members. In fact, in rural China, villagers form strong social and economic ties in their daily lives, so the behavior of a person would be affected by his or her village peers. Bauer *et al.* (2002) and Araujo *et al.* (2004) find strong evidence that peer effects exist in labor migration from rural Mexico to urban areas and from Mexico to the USA, respectively. In our study, using data from rural China, we further confirm the existence of the peer effect in labor migration. In contrast to Araujo *et al.* (2004), we use regression parameters to simulate the equilibrium rate of migration in China and the effects of different policy instruments available in the model framework such as increasing human capital or promoting job information sharing.

The peer effect is found in many social and economic behaviors, although the terminology differs according to research contexts (see Durlauf (2004) for an exhaustive literature survey). It is not a new idea that people are interdependent in decision making, but empirically constructing the peer group was once formidable because of the lack in subtle microdata. Therefore, the measurement of the peer effect is always at the core of research. Early research only roughly measured the peer effect as the average outcome in a group. For example, Evans *et al.* (1992) defined the class as the peer group and observed the effect of class average education scores on the probability of becoming an unmarried mother. Recent studies used unique data to identify friend networks and thus peer groups (Ballester *et al.*,

[1] Bauer *et al.* (2002) use the terminology "herd effect" to demonstrate decision interdependence. We use the term "peer effect" in the same way.

2006; Calvó-Armengol and Zenou, 2005; Patacchini and Zenou, 2008). Some even used the correspondence frequency to measure friendship distance (Marmaros and Sacerdote, 2006). In our research, we assume people in the same village play with all the villagers, but each individual has a heterogeneous distance from the other villagers. Empirically, we construct the nonlinear peer effect using interaction terms between the peer effect and social interaction frequencies, our measure of social distance. Our work also endogenizes the social distance discussed in Zanella's (2004) theoretical model, which will be shown in Section 3.

Both the peer effect and social interaction frequency can be potentially endogenous. One source of endogeneity is the self-selection in group formation. A reference group may be formed by individuals who share similar characteristics; therefore, it is not the peer effect, but the group characteristics that affect one's decision. If we do not consider the self-selection group formation, the peer effect would be overestimated. However, in our paper, we take the village as one's reference group. The identity as a villager is exogenous and the self-selection problem is alleviated. Another endogeneity bias is associated with social interaction frequency, which could be a result of migration. To account for this, an instrumental variable for social interaction frequency is used in our study.

In summary, our study contributes to the literature in three ways. With the out-of-village network effect controlled for, we first confirm the peer effect in decision making in rural–urban migration in China. Second, we add an interaction term between social interaction strength and the peer effect to examine whether the peer effect is nonlinear. Meanwhile, we use the variable "historical family political identity in land reform" to instrument social interaction strengths. Third, we simulate the effects of policy measurements designed to promote rural–urban migration and discover that only through a "big push" in institutional change can we shift the low-migration equilibrium to a high-level one.

3 A Model of Social Interactions and Peer Effect

Our model is mainly based on network models such as Ballester *et al.* (2006) and simplifies some of their assumptions. We contribute to those models by endogenizing the network connection, which is also termed "social distance" in Zanella (2004).

There are N individuals in a village. The network N = {1, . . . , n} is a finite set of agents. The n-square matrix G of a network g keeps track of the connections in this network. Here, we simply assume each individual is friends with everybody else in network G. We borrow the standard peer effects model with the assumption $g_{ij} = g_{ik} \neq 0$. Ballester *et al.* (2006), Calvó-Armengol and Zenou (2005), and Patacchini and Zenou (2008) discuss more general cases where individuals face different peer networks; however, we dismiss this idea because of the data limitation. Every person in our model has heterogeneous attitudes toward the behavior of peers, thus is a different social distance from the network. That is to say, in matrix G, $g_{ik} \neq g_{jk}$ if $i \neq j$. It also implies that friendship is not a reciprocal relationship. We also set $g_{ii} = 0$.

Using matrix denotation:

$$G = \begin{pmatrix} g_{11} & g_{12}\cdots & g_{1n} \\ g_{21} & g_{22}\cdots & g_{2n} \\ \vdots & \ddots & \vdots \\ g_{n1} & g_{n2}\cdots & g_{nn} \end{pmatrix} = \begin{pmatrix} 0 & g_1\cdots & g_1 \\ g_2 & 0\ldots & g_2 \\ \vdots & \ddots & \vdots \\ g_n & g_n\cdots & 0 \end{pmatrix} = \begin{pmatrix} g_1 & 0\ldots & 0 \\ 0 & g_2\cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & 0\cdots & g_n \end{pmatrix} \begin{pmatrix} 0 & 1\ldots & 1 \\ 1 & 0\ldots & 1 \\ \vdots & \ddots & \vdots \\ 1 & 1\cdots & 0 \end{pmatrix}.$$

Group influence/peer effects are expressed as:

$$\frac{\sum_{i=1} g_{ij} m_j}{\sum_{i=1} g_{ij}} = \frac{g_i}{n-1} \sum_{i=1} m_j = g_i \overline{m}. \tag{1}$$

g_i measures the social distance to the network. The standard peer effect model implies g_i equals a constant; thus, g_i cannot be estimated Here we write $g_i = J + \lambda_i s_i$, with $J, \lambda_i > 0$ to capture the heterogeneous social distances of different individuals to other villagers. J is a constant, while s_i is the individual interaction frequency with other villagers. It is natural to assume that if one person is more involved in the local interaction, the peer effect will be larger.

Because more local interactions s_i will squeeze out the time that can be allocated to outward migration, we standardize s_i and m_i to be continuous and $m_i, s_i \in [0,1]$, and simply assume:

$$s_i + m_i = 1, \tag{2}$$

where 1 is the total time available for migration and social interaction. The utility that individual i obtains from outward migration is:

$$U(m_i) = a + b_i m_i - c m_i^2 + d m_i \sum_{i=1} g_{ij} m_j \Big/ \sum_{i=1} g_{ij}, \tag{3}$$

with $a, c, d > 0$ and $b_i > 0$.

Inserting equations (1) and (2) into (3) we obtain:

$$U(m_i) = a + b_i m_i - c m_i^2 + d m_i [J + \lambda_i (1 - m_i)] \overline{m}. \tag{4}$$

An individual optimizes the time allocated to outward migration work (First order condition):

$$dU(m_i) \big/ dm_i = b_i - 2c m_i + d\overline{m}[J + \lambda_i - 2\lambda m_i] = 0 = G(m_i, \overline{m}). \tag{5}$$

The following second-order condition guarantees an interior solution:

$$\partial G(m_i, \overline{m}) \big/ \partial m_i = -2c - 2d\lambda_i \overline{m} < 0, \tag{6}$$

$$\partial G(m_i, \overline{m}) \big/ \partial \overline{m} = dJ + d\lambda_i - 2d\lambda_i m_i. \tag{7}$$

From the derivation calculus of implicit functions, we obtain:

$$\frac{dm_i}{d\overline{m}} = -\frac{G_{\overline{m}}'}{G_{m_i}'} = \frac{dJ}{-G_{m_i}'} + \frac{d\lambda_i}{-G_{m_i}'} + \frac{2d\lambda_i m_i}{G_{m_i}'}. \tag{8}$$

$\frac{dm_i}{d\overline{m}}$ is the core concept in our paper: the peer effect. Here, it can be decomposed into three parts. $\frac{dJ}{-G_{m_i}{}'} > 0$ corresponds to the standard linear term in the peer effect, and we can see that when the village migration ratio increases, the individual allocates more time to migration work. $\frac{d\lambda_i}{-G_{m_i}{}'} > 0$ represents the positive effect of social interaction on the peer effect. When an individual increases his or her social interaction strength λ_i, the peer effect also rises. $\frac{2d\lambda_i m_i}{G_{m_i}{}'} < 0$ is the third part and it shows that when individual i spends more time in outward migration, the effect of peer behavior decreases. The intuition behind this is that when one spends more time in social interaction, the time constraint on outward migration is more stringent. In summary, equation (8) can lead to two hypotheses: (1) individual migration time is positively related to group mean migration time; and (2) combining terms 2 and 3, social interaction can have either positive or negative effects on the peer effect, depending on the type and frequency of social interaction. Here, "type" means whether social interaction greatly reduces outward migration time. Equation (8) also predicts that social interaction frequency is determined simultaneously with migration, because migration time appears on both sides of the equation. This endogeneity problem will be treated using an instrumental variable in our study.

4 Data Description

The data used in our research are from the 2002 Chinese Household Income Project Survey (CHIP 2002) collected by the Chinese Academy of Social Science. Survey data are from 121 counties, 961 administrative villages, 9200 households and 37,969 individuals. The sampling frame for the survey is a subsample of the official rural household survey conducted by the

National Bureau of Statistics (NBS).[2] The questionnaires were collected in February 2003, the Chinese Lunar New Year when almost all the Chinese including rural migrants return home and celebrated the spring festival together. Therefore, the survey captures information of all members of rural households including outward migrants. The data contain individual information, such as sex, age, education, job status, family information such as family structure, family economic condition and village geography, village population and economic conditions. More importantly, it also includes information on family social interactions with other villagers.

The explained variable "migrants or not" is a 0–1 dummy variable. Defining the migration variable as discrete makes identification possible in the presence of the reflection problem. The reflection problem coined by Manski (1993) is a difficulty in estimating the peer effect. Simply speaking, in a linear model, individual characteristics affect one's decision linearly. The average characteristics and average choice (measurement of the peer effect) are perfectly collinear so that parameters cannot be identified if we control them simultaneously in the regression model. However, Brock and Durlauf (2001) prove that the reflection problem can be avoided in the nonlinear model. Personal characteristics influence the choice nonlinearly in a nonlinear model such as probit or logit, so that they are not linearly correlated if we put them together in the regression model. In our paper, we define the explained variable "migration" as a 0–1 dummy variable, so that the reflection problem is avoided.

In CHIPS2002, individuals reported the days away from their family in a year. Because of the data limitation, we consider the urban areas in China as the only migration destination in our paper and do not differentiate between migration locations. We follow Zhao (2003) and define an individual as a migrant if he or she lives away from home more than 180 days in a

[2] The stratified sampling of the NBS rural household survey followed two steps. First, sample administrative villages were directly selected in each province according to income level, and second, sample households (generally 10) were chosen from each sample village. For details of the sampling framework and sampling method of the CHIP 2002 survey, see Gustafsson, Li, and Sicular (2008).

year. Obviously, leaving family for more than six months in a year does not necessarily mean a person is a migrant. Therefore, we dropped all long-term out-of-village students, as well as the nonfarm employees who work in the township enterprise outside the village, because we have personal job status information. The largest change in our sample is that we only include the working-age population, i.e., observations of male individuals aged 16–60 and females aged 16–55 according to the official definition in China. We also drop observations whose important variables are missing. Finally, we have 16,401 observations.

From the CHIPS2002 questionnaire data, we obtain information on the village population and village migrant numbers. We calculate the village migration ratio using the following equation:

$$village\ migration\ ratio = \frac{no.of\ \ village\ migrants - no.of\ \ family\ migrants}{village\ \ population - \ family\ \ population}. \qquad (9)$$

This is the measure of village peer behavior in our paper. Peer influence should not contain the effects from one's own family, so one's own family is excluded from the village migration ratio. Another advantage of this is that we can have variances in "village migration ratio" among different households. This definition is close to the one used in Zhao (2003), who used the absolute number of migrants in a village to measure the network effects of migration. From her definition, we can interpret the migrant as an information source. When adding one migrant to the village, she will bring one job opportunity to the village. In contrast to Zhao (2003), we use the number of friends and relatives outside the village as a control variable of the household network, and the migration ratio of village peers to capture peer effects. The interpretation of this variable is how the villagers respond to the increase in the village migration ratio. It mainly captures the decision dependence among the villagers. Intuitively, when two villages have the same number of migrants but a huge difference in total population, the residents in the high migration ratio village are more inclined to participate in outward migration because of peer behavior assimilation.

Social interactions between one's family and other villagers are another group of focus variables in our study. Here, we categorize the social interactions into three types: interactions in labor markets, in information sharing and in financial markets. In Chinese rural areas, the market for labor services is still so unfledged that rural residents cooperate a lot in labor-sharing activities. The enlarging rural–urban income gap makes outward migration an effective way of income earning, so rural residents also exchange job information. Moreover, mutual borrowing and lending are a substitute for missing formal financial services in rural areas. In the CHIPS2002 data, a series of questions record the social interaction strengths of a family with their relatives and neighbors, such as “mutual help during busy seasons”, “labor exchange in house building”, “taking care of old persons, sick persons, and babies”, “exchange information on employment”, and “borrowing money”. The answers to these questions are discrete: (1) very frequently, (2) often, (3) just so-so, (4) sometimes, and (5) none/few. We categorize “mutual help during busy seasons”, “labor exchange in house building”, and “taking care of old persons, sick persons, and babies” as the social interactions in the labor market. “Exchange information on employment” is obviously an interaction in information sharing, and “borrowing money” is an interaction in financial markets. We transform each question into a group of four dummy variables with the baseline being “none/few”. On that basis, we interact the social interaction dummies with the village migration ratio (peer effect), and use the interaction terms to capture the nonlinear peer effect.[3]

All the explanatory variables are listed in Table 1, and the basic statistical descriptions are in Table 2. We can see from Table 2 that among the 16,401 rural laborers, 2675 individuals participated in outward migration in 2002, which indicates an overall migration ratio of 16.31%. Even in the basic statistics, we can see some differences between migrants and

[3] We get a total of $5 \times 4 = 20$ interaction terms.

nonmigrants. Fewer women are employed in outward migration, and in the migrants sample, 50.24% individuals are unmarried, compared with 25.21% in the nonmigrants sample. The outward migrants are much younger with an average age of 27.1, lower than the 36.1 years in the nonmigrants' sample. All these explanatory variables are controlled for in our regression model. However, in the regression analysis, we focus on the magnitude and direction of the peer effect and the interaction term between social interaction strength and the peer effect.

5 Regression Model and Result

Based on the theoretical model, we define a latent variable Y^*, thus the latent utility function is:

$$Y_i^* = X_i\beta + g_i\bar{M}_i + \varepsilon_i \,, \tag{10}$$

with:

$$\begin{aligned} M_i &= 1 \ \ if \ \ Y_i^* \geq \alpha_i \\ &= 0 \ \ otherwise \end{aligned} \tag{11}$$

Here M_i represents the migration decision, and equals one if the utility from migration is greater than some subjective threshold disutility for outward migration, which we denote as α_i.

$$\begin{aligned} \Pr(M_i = 1) &= \Pr(Y_i^* \geq \alpha_i) = \Pr(X_i\beta + g_i\bar{M}_i + \varepsilon_i \geq \alpha_i) \\ &= \Pr(\varepsilon_i \geq \alpha_i - X_i\beta - g_i\bar{M}_i) = \Phi(-\alpha_i + X_i\beta + g_i\bar{M}_i) \end{aligned} \tag{12}$$

The marginal effect of the peer effect is $\partial \Pr(M_i = 1) \big/ \partial\bar{M}_i = \Phi' \cdot g_i$, where $g_i = J + \lambda_i s_i$.

We establish the following probit model to explore the determinants of outward migration:

$$P(Y_{ijk} = 1) = \Phi(X_{ijk}\beta + J\bar{M}_{jk} + \bar{M}_{jk} \times \sum \lambda_{st} s_{jkst}) \,. \tag{13}$$

Equation (10) is the determination function of outward migration probability. i, j and k represent the individual, family and village, respectively. X_{ijk} is a vector of individual, family and village characteristics variables. $\bar{M}_{jk}$ is the village migration ratio (excluding one's own family) and it is the measurement of the peer effect that we are mostly concerned with in our paper. s_{jkst} are the dummies of social interactions of a family with their relatives and neighbors, where subscript s denotes s kinds of social interaction and t is the interaction strength. If we do not control for unobservable village characteristics, the parameters are potentially biased. In our regression, we follow Ding and Lehrer (2007) and control the lagged village migration ratio in 1998 to control for unobservable village characteristics. Meanwhile, in the robustness check, we alternatively control the county dummies to see the validity of coefficients.

The regression results are reported in column 1 of Table 3. In Table 3, we include all the interaction terms in the regression and also control for the lagged village migration ratio. We can see from the regression that the coefficient of the peer effect is positive and significant at the 1% level as expected. However, coefficients of interaction terms appear to be divergent: stronger social interactions in labor markets reduce the positive role of the peer effect; by contrast, more interactions in job market information sharing enhance the peer effect. Interactions in financial markets are somehow irrelevant to the role of the peer effect.

To check the robustness of the results, we report different functional form regressions in Table 4. In columns 1 and 2, we control the county dummy instead of the lagged village migration ratio. The distinction is that in column 1 we do not control all the interaction terms that are all included in column 2. The results show that the direction and significance of the peer effect do not change much. In columns 3 to 7, we still control the lagged village migration ratio, but in each regression, we include only one group of interaction terms. From the regression results we can see that in the "exchange information on employment" regression, the magnitude of the peer effect falls significantly, but more interactions in information sharing enhance the peer effect. To check the robustness of whether labor market interactions diminish the effect of peers, we utilize the data in CHIPS2002 that records the exact number of days of mutual help in year 2002. Column 8 shows that more interactions in the labor market decrease the magnitude of the peer effect. All of the above checks confirm the robustness of the regression results in Table 3, so we analyze and interpret the result based on the parameters in Table 3.

The parameter from the probit regression does not represent the true marginal effects of that variable. However, when Stata is calculating the marginal effects, it treats the interaction term as an independent variable, so Ai and Norton (2003) point out that almost all previous empirical studies have incorrectly estimated the marginal effect of the interaction term. In our paper, we have 20 interaction terms and they are all interacted with the peer effect. If we do not correctly calculate the marginal effects of these interaction terms, our interpretation of the peer effect will also be incorrect. We show how to calculate and interpret the marginal effects of the interaction terms in Appendix 1. The marginal effects of parameters are reported in column 2 of Table 3.

What we are primarily interested in is the peer effect. Not surprisingly, we can see that a one percentage increase in the village migration ratio increases the individual probability of outward migration by 0.124%. This is termed a "social multiplier" in the literature (Glaeser *et al.*, 2003). This result has confirmed the existence of the peer effect in the outward migration decision in rural China. However, the positive relationship between the village migration ratio and individual migration probability also indicates the potential danger of outward migration: if village peers are less inclined to migrate because of institutional obstacles such as urban–rural segmentation in China, the negative effects will also be amplified by the social multiplier.

Is the peer effect nonlinear? We know that the role of the peer effect stems from interaction with peers. Intuitively, if one's family is reluctant to interact with other villagers, they will be more separated from their neighborhood and less influenced by village peers.

Being guided by this interpretation, we include the interaction terms of social interaction strength and the peer effect to observe the nonlinearity.

Our empirical findings are very interesting. From Table 3, we can see that the effects of the interaction terms differ among the different social interaction categories. First of all, people who are more willing to share job opportunity information will have a stronger information advantage from social interaction and they are more likely to assimilate with their village peers in the outward migration decision. Interaction in the labor market is the second kind of social interaction we are concerned with. From column 2 in Table 3, we can see that the interaction term of “mutual help during busy season—very frequently” is significantly negative at the 10% level. “Mutual help during busy season—often and just so-so” are insignificant although the coefficients are negative. The coefficient of “mutual help during busy season—sometimes” is positive and significant at the 5% level. All the four interaction terms for “labor exchange in house building” with the peer effect are significantly negative and only the interaction term of the peer effect with “taking care of old persons, sick persons, and babies—sometimes” is significantly negative at the 5% level.

The negative sign of the interaction terms has rich implications. Labor market interactions can have dual effects. On the one hand, they can serve as a way to shorten the social distance between peers and can lead to more binding relationships with peers. On the other hand, labor market interactions can also make the individual’s time constraint more binding. In other words, more interaction in the labor market will increase potential migration time more because of the weaker role of the peer effect. Our findings have supported the above interpretation. When mutual help in the busy season occurs “sometimes”, the time constraint is less tight, so social interaction can enhance the role of the peer effect. If we increase the interaction strength to higher levels, the time constraint would be more binding, so the coefficients become negative but insignificant and then eventually significantly negative. In the other two labor market interactions, “labor exchange in house building” and “taking care of old persons, sick persons, and babies”, the time constraint mechanism is more important, so the coefficients are always negative, only differing in significance level. This is understandable, because “labor exchange in house building” and “taking care of old persons, sick persons, and babies” are long-term and time-consuming activities while “mutual help during busy season” is merely a short-term one. The fact that within-community social interaction may play a negative role in labor migration has previously been neglected in the literature except by Narayan (1999) and Alesina and Giuliano (2007). Narayan (1999) separates social capital into within-community “bonding” social capital and between-community “bridging” social capital. He argues that if a community has higher bonding social capital, it will have higher internal welfare, but they will also lose many outside job opportunities. Alesina and Giuliano (2007) find that stronger family ties can decrease the geographical mobility of individuals. However, social interactions in the labor market are perhaps the spontaneous substitutes of an unfledged labor service market in the rural areas. Therefore, we can expect that with the development of the economy, more and more emerging labor market services will decrease the interactions of rural residents in the labor exchange, thus promoting outward migration.

We also explore the effect of financial market interactions on the peer effect. However, no evidence has shown that financial interaction matters for the peer effect. It seems that the two processes are mutually independent.

All the other coefficients are consistent with the findings in previous studies.

(1) Individual characteristics will significantly affect the migration decision. Women are less inclined to migrate, with a probability that is 4.36% lower than males. Marriage will greatly decrease the probability of outward migration by 11.96%. Age has an inverse U-shaped relationship with the migration probability. A laborer has a maximum migration

probability at the age of 31, and beyond this age the marginal effect of age is negative. All these findings are consistent with existing empirical results. Zhao (2003) finds that all levels of education are insignificant in migration determination, which is in contrast to our result that education levels are all significantly positive with illiteracy as the reference point. However, the influence of education is nonlinear; villagers who receive a junior high school education have the highest probability of migration, 7.17% higher than the illiterate group, while villagers with a primary education have the second-highest probability of migration, 5.33% higher. If a person has a higher education level, the probability of outward migration is moderately higher than the illiterate group. The probability of migration for villagers with a technical school education or higher is 4.63% higher and for senior high school education is 4.82% higher. Our findings seemingly imply that higher education for the rural residents may be at the expense of a lower outward migration probability. For the policy makers, there may exist some “optimal” education level for the purpose of rural–urban migration. However, we need to be cautious about this conclusion: one possible explanation for the nonlinear “education return” is that the higher education receivers have permanently stayed in the city areas after gaining their urban *Hukou* (residence registration), so that they are not included as “migrants” in the rural sample. Another explanation is that better-educated workers are more likely to participate in local nonfarm employment (Zhao, 1999a, 1999b; Liang and White, 1997), which is included as nonmigration in our regression.

(2) Family characteristics also significantly affect the migration decision. For an additional laborer in a family, the individual probability of migration increases by 3.98%. Meanwhile, if a family has more arable land, the probability of outward migration declines because of the labor substitution between local farming and migration work. The family structure can also influence the individual migration decision. Families that have one additional child aged between six and 12 have a 0.99% lower migration probability. One

additional older person does not significantly influence the migration decision because they can be either an effective laborer in the household or a person to be taken care of in rural China. The household social network can also promote labor migration. If one's family has social ties outside the village or has kin as village cadre, the probability of outward migration increases by 1.17% and 1.06%, respectively.

(3) Village geographical characteristics also matter. An increase of village income by 100 RMB yuan increases the opportunity costs of migration and decreases the individual migration probability by 1.01%. People living in the mountainous and hilly areas have a higher probability of migration. These two dummies may have captured unobserved poor living conditions regardless of village income. The distance from a village to the county seat and to the nearest transportation terminal does not significantly influence the migration decision.

6 Historical Class Identity and Social Interaction: An IV Estimation

In our study, because the survey was conducted in February 2003, which was the Chinese Lunar New Year and people always go back to their families for reunion, the data avoid sample selection bias to a great extent. At the same time, we use administrative villages as the focus of our analysis. The formation of village and villager identities is largely exogenous to the individual; thus we also alleviate self-selection of the reference group. Although there may still exist bias in the omission of village characteristics, we attempt to control for the effect of village characteristics by controlling the lagged village migration ratio in 1998, which is used to absorb the unobserved fixed effect of village, historical information and other features of the village.

More importantly, we are concerned with the endogeneity bias associated with social interaction strength among villagers. The unobservable features of the family and village may influence the frequency of social interactions, leading to missing variable bias. The strength of social interactions may not be the cause of migration but the outcome that results in simultaneity bias. Instrumental variables can be used to achieve efficient estimation. However, the problem is that because we decompose these qualitative variables of social interaction into four dummies for each of the five groups in our research, it is impossible to find enough instrumental variables. Our strategy is as follows. First, we change the measurement of household social interaction into a continuous variable. This method is obviously problematic because the value of these variables only represents the relative change, not the change in absolute value. However, it does not impair the robustness of the result. The results in column 1 in Table 5 show that it makes no significant difference in terms of either the coefficient sign or the significance level when using a continuous measurement of household social interaction and interacting it with the peer effect. The signs of the interaction terms of labor market interactions, such as “mutual help during busy season”, “labor exchange in house building” and “taking care of old persons, sick persons, and babies”, are still negative and are different from zero at the 5% significance level. That is to say, families that have a higher level of social interaction in the labor market have a weaker peer effect. The coefficient of the interaction term of information exchange is positive. For the interaction term of “borrowing money”, the result is still insignificant. These results are consistent with our previous findings. We separately put these interaction terms into the regression, and the results are listed in columns 2, 3, 4, 5 and 6 in Table 5). In these results, the interaction term for “borrowing money” is significant at the 10% level. Our other results are still consistent with previous regression results in terms of coefficient signs and significances.

Because the signs and significances of the interaction terms do not change when we include them all in the same regression, we use this functional form and use “historical family political identity in land reform” as an instrument for social interaction strength. In the early days after the founding of the P. R. China, to consolidate fragile state finances and eliminate the "counterrevolutionary forces" hidden in rural areas, Chairman Mao Zedong initiated the Movement of Land Reform in rural areas (from the end of the 1940s to the early 1950s). The families in rural areas were labeled with different political identities, "landlord", "rich peasant", "rich-middle peasant", "lower-middle peasant" and "poor peasant or landless", according to their economic status and the acres of household land. At the same time, the private lands and properties of the "rich peasants" and "landlords" were redistributed to the "lower-middle peasant" and "poor peasant or landless" who had no or only small land ownership. As a result, the once "lower-middle peasant" and "poor peasant or landless" who were at the bottom of the rural society jumped to the top in the reversal of political status, while the "landlords" and "rich peasants" were deprived of their previous political and economic power, and were labeled as "black class". These lifetime-accompanying political identities were important criteria to judge someone in a job, marriage and many other aspects of social life. In our research, we generate a dummy for the family head's father's political identity in land reform. The dummy given to "lower-middle peasant" and "poor peasant or landless" is 0 and 1 otherwise. In politics, "rich-middle peasant" is the class to be combined with "lower-middle peasant" and "poor peasant or landless", but it did not belong to "red class". Sato and Li (2007) study the class identities' role in intergenerational education attainment. Although they have distinguished "middle-rich peasant" from "rich peasant" and "landlords", and use two dummies to control them separately, they discovered that the interaction terms of these political identities and Maoist era are significantly negative. That is to say, during Mao's time both of them had a negative effect, so we group "middle-rich peasant" into the same class as "landlords" and "rich peasants". We believe that, their families being classified as middle-rich, rich peasants and landlords were discriminated against in politics, their social lives and other public services such as education, until the reform and opening up of China. During that long period, families with low political status suffered social separation and retaliation, so these families would reduce their interaction with other peasants. These reductions came not only from subjective motivation but also from social pressure in rural society. Past interaction frequency will influence current household interactions with other villagers. Furthermore, we also argue that the father's political identity following the land reform movement does not influence the individual's current decision regarding outward migration. Indirect evidence is that Sato and Li (2007) discover that distributions of different political identities are nearly the same between migrants and nonmigrants. Thus, we are safe to use "historical family political identity in land reform" as the instrument for social interaction strength. We report our regression results in Table 6.

We use a two-step probit regression that was introduced by Rivers and Vuong (1988). We can see from the first stage regression, except "borrowing money from each other", that the other social interaction variables are strongly negatively influenced by the instrument. For the "mutual help during busy season", the instrumental variable is significant at the 10% level, while for other social interactions, the instrumental variable is significant at the 1% level. The R^2 of the first-stage regression is around 0.67–0.68 for different social interactions. These results validate our assumption that the middle and rich peasants and landlords who suffered past discrimination reduced household current social interaction with other villagers. However, for the results of the second stage, in all regressions using instrumental variables, the Wald exogeneity test shows that the hypothesis that the probit and ivprobit results are not significantly different is not rejected. Therefore, we still use the result in Table 3.

7 Peer Effect and Public Policy

Our empirical results show that the peer effect exists in rural China's labor migration. Furthermore, the peer effect is nonlinear. More interaction in the labor market reduces the strength of the peer effect, while information sharing enhances the peer effect. The existence of a nonlinear peer effect has rich implication for policy makers. Theoretically, the peer effect will lead to multiple equilibria in the economic process. When the mean group behavior outcome is at a low level, the economic process may converge to a low-level equilibrium because of interdependences in decision making; however, when the mean group behavior outcome exceeds some threshold, the economic process will converge to a high-level equilibrium with social interaction (Zanella, 2004). In the context of our paper, China's urbanization would be dampened if there was a low-level equilibrium in rural–urban labor migration. We use the regression parameters in Table 3 to simulate the equilibrium condition in the labor migration decision. Figure 1 reflects the relationship between the village migration ratio and the mean individual migration probability. The horizontal axis represents the village migration ratio and the vertical axis represents the mean individual migration probability. The solid line is the 45 degree line. The dash-dot line, the individual response curve, shows the relationship between individual migration probability and village migration ratio. Here we have only one point of intersection between the individual migration probability curve and the 45 degree line, with a slope less than one that guarantees a stable equilibrium with an average village migration ratio of 8.45%. As the pdf (probability density function) of the probit model is a standard normal distribution and its cumulative distribution function is assumed to be S-shaped, the low-level and high-level equilibriums can be differentiated according to the intersection point between the 45 degree line and the response curve. If the intersection point lies below 50% of the village migration ratio, the equilibrium is a low-level one. In contrast, if it is above 50%, the equilibrium is high level and stable, meaning that any departure within a limited range from the equilibrium will converge to the high equilibrium during dynamic adjustment. From Figure 1, we see that the intersection of the response curve and 45 degree line lies in the lower half of the S curve. That is to say, with the coefficients of the model unchanged, even if an exogenous shock increases the village migration ratio along the response curve, the labor migration ratio still converges to the low-level equilibrium trap under the influence of the peer effect.

Promoting rural-to-urban labor migration is not only beneficial to rural residents, but also to China's economic growth. Thus, our policy design aims to promote labor migration from rural to urban areas. In the following policy analysis, we distinguish policies at three levels and simulate their effects.

The first kind of policy is to move the response curve by changing individual characteristics such as education level. This policy can increase the migration probability but has no impact on social interaction among villagers, and thus does not change the slope of the response curve. Among the variables controlled, only the education level can be largely improved through economic policy. In Figure 2, we assume that policies are to improve the education of the villagers so that all villagers that are illiterate or have a primary school education can have the compulsory junior high school education. From the regression, we have already learned that the enhancement of rural residents' education will increase the probability of outward migration. Figure 2 again shows this result. We find that the individual migration probability curve moves upwards and intersects with the 45 degree line at a higher point where the village migration ratio equals 9.35%. However, it should be noted that the effect of the policy is still limited and the point of intersection resumes the characteristics of a low-level equilibrium.

The second policy is to increase the social interaction that contributes to the peer effect and decrease the social interaction that reduces the peer effect. Graphically, this means rotating the curve anticlockwise while holding the intercept of the response curve constant. Figure 3 shows clearly this case. If we create policies to encourage more extensive interactions among villagers about job information (define the state of "exchange information on employment” as “very frequently”) and at the same time establish a rural labor service market to decrease the interactions on the labor market (we define the state of three dimensions of labor interactions strength as “none/few”, the reference group in the regression specifications), we may find a significant increase in the slope of the migration curve and a higher point of intersection on the 45 degree curve with a corresponding village migration ratio of 12.44%. In addition, we observe from Figure 3 that the individual migration probability curve is S shaped; however, the equilibrium is still at a low level.

What if we combine the above two policies? Figure 4 shows that by altering simultaneously the villagers’ education and their social interactions strength, the combined policy will increase the migration ratio in equilibrium with a corresponding village migration ratio of 14.57%. However, the labor migration equilibrium is still at a low level even if the two policies are implemented together. In other words, new policies should be found to escape the low-level equilibrium of labor migration.

One way to retain the low migration ratio equilibrium is to allow an enlarging of the urban–rural income gap. When the income gap increases continuously, the response curve shifts upward until the intersection becomes a high-level equilibrium. However, the increasingly widened income gap between rural and urban areas is never costless. The urban–rural income gap in China is already very large and the widening of the income gap will threaten economic growth (Wan *et al.*, 2006). To facilitate the transition from a low-level equilibrium of migration to a high-level one, a more important approach is the integration of the urban and rural labor markets through institutional reform, which is also the third kind of policy we could propose to increase labor migration within our analytical framework. Graphically, the policy will further heighten the intercept of the response curve. Although the current migration decision from rural to urban areas is in fact basically a free decision process, the existence of urban–rural segmentation and urban-biased economic policy still exerts extensive discrimination against rural migrants and labor migration is constrained (Chen and Lu, 2008).[4] If we could eliminate this kind of urban-biased economic policy and promote rural–urban social integration, then the expected return of outward migration and thus the probability of outward migration increase. In Figure 5, we conduct a simulation and increase the intercept from –4.6432 to –4.4399, that is, an increase of 0.2033 in absolute value. Combined with the improvement in the rural education level and social interaction, this leads to an equilibrium migration ratio of 50%, which is obviously the threshold point of having a high-level equilibrium of labor migration. If the high-level equilibrium appears in the figure, by relying on the peer effect and social multiplier, a small-scale positive impact to increase the labor mobility can result in the migration ratio converging to an even higher equilibrium. For the transition from a low-level equilibrium to a high-level one, a "big push" in the institutional environment is needed. Policies toward education must be more economic in nature and those targeting the strength of social interaction must be more social in nature, and then the institutional reform will indeed bear more political characteristics.

8 Conclusion

In this paper, we tested the existence and influence of the peer effect on the labor migration decision. Our empirical results suggest the following conclusions. (1) The peer effect exists in migration decision making. (2) The magnitude of the peer effect is nonlinear. Families who are more frequently involved in information sharing can enhance the peer effect, while more interactions in the labor market will reduce the positive effects of peers. Interactions in the financial market do not affect the peer effect. At the same time, we use the instrumental variable method to test whether household endogeneity bias exists. We utilize the "historical family political identity in land reform" as the instrument for social interactions. The ivprobit

[4] In urban areas of China, multiple discrimination policies still exist for rural migrants, for example, management fees collected from rural migrants, lower wages, discrimination in social security, labor protection and education, and even compensation for accidental death.

regression results do not show significant difference compared with the probit results. These findings enrich our understanding of social capital. Labor market interactions diminish the probability of outward migration through the peer effect.

These findings have important policy implications. We calculate the labor migration equilibrium, which results in a low-level equilibrium. Through the policies of increasing education and enhancing the peer effect, we can increase the labor migration ratio. However, neither of these two policies can shift the low-level equilibrium to a high-level one, even if we combine the two. Only through institutional reform, i.e. the elimination of rural–urban labor market segregation policy and promoting social integration, can we change the low-level labor migration equilibrium to a high-level one.

More generally, our findings regarding the peer effect provide a new explanation for the previously unexplained phenomenon in urbanization in the world. From a cross-sectional viewpoint, under population mobility control, China has a low urbanization ratio, only 43.9% at the end of 2006, while some other developing countries appear to have a high level of urbanization given their low degree of industrialization. For example, the urbanization ratio of Brazil in 2003 was 82.9%, and the urbanization ratio exceeds 70% in Africa. Longitudinally, when a country is experiencing rapid industrialization, urbanization accelerates and only 20–30 years are needed to complete the S-shaped process (Northam, 1975). If we consider the role of the peer effect in labor migration, when the mean migration ratio is low, people are more inclined to stay because of decision interdependence, and the migration ratio will increase rapidly after passing a certain threshold.

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Appendix 1: The Marginal Effects of the Probit Model with Interaction Terms

We use the following regression model to derive the marginal effect of the probit model with interaction terms:

$$P(Y_{ijk}=1)=\Phi(X_{ijk}\beta+J\bar{M}_{jk}+\bar{M}_{jk}\times\sum\lambda_{st}s_{jkst})\,. \tag{14}$$

Here s denotes the category of social interaction, s = 1,…,5, t represents the interaction strength, j = 1,…,4. Therefore, λ_{st} is a 1×20 vector. We derive P with respect to M and get:

$$\partial P(Y=1)\big/\partial\bar{M}=\Phi'*(J+\sum\lambda_{st}s_{jkst})\,, \tag{15}$$

where

$$\Phi'=\Phi'(X_{ijk}\beta+J\bar{M}_{jk}+\bar{M}_{jk}\times\sum\lambda_{st}s_{jkst})\,. \tag{16}$$

When all the variables are evaluated at their mean, we obtain the "average" marginal effect of the peer effect. S_{jkst} are dummy variables; we have five groups and each group has five statuses of social interactions, therefore, a total of 5^5 = 3125 marginal effects. It is too complicated to report them in the paper so we follow another approximate routine. First, we control all the social interactions in the baseline (none/few) and then pick out one group and calculate the marginal effect from the changing of only one social interaction strength. So we only need to report 5 × 5 = 25 marginal effects, and the nonlinearity of the peer effect can be considered by changing from the baseline to a specific social interaction strength. To be more specific, we take (0,0,0,0,0) as the baseline and from (15) and (16) we obtain the partial effect for the baseline model as $\Phi'(X\beta+J\bar{M})*J$. We define it as the baseline marginal effect of the peer effect that is reported in the footnote of Table 3.

Every partial effect can be expressed as the departure from the baseline:

$$\begin{aligned}&\partial P(Y=1)\big/\partial\bar{M}\,|_{s\in[1,\cdots,5],t\in[1,\cdots,4]}-\partial P(Y=1)\big/\partial\bar{M}\,|_{s\in[1,\cdots,5],t=0}\\&\quad=\Phi'(X\beta+J\bar{M}+\lambda_{st}\bar{M})*(J+\lambda_{st})-\Phi'(X\beta+J\bar{M})*J\,.\end{aligned} \tag{17}$$

This is the marginal effect of each interaction term compared with the baseline. We report them in column 2 of Table 3.

Table 1: The Variable Definition

Peer effect	village migration ratio	village migration ratio (excluding one's own family) in 2002
Individual characteristics	female	dummy variable, female=1
	age	age
	married	dummy, married=1
	primary school	dummy, if education is primary school, primary school=1
	junior high school	dummy, if education is junior high school, junior high school =1
	senior high school	dummy, if education is senior high school, senior high school =1
	tech school or more	dummy, if education is technical school or college education, tech school or more =1
	communist	dummy, if respondent is communist party member, communist =1
	health very good	dummy, if health is very good, health very good =1
	health good	dummy, if health is good, health good =1
	health so so	dummy, if health is just so so, health so so =1
	health bad	dummy, if health is bad, health bad =1
Family characteristics	household labor force	the number of labor force of a family
	family per capita land	family per capita land
	kids no. under 6	the number of children under age six of a family
	kids no. between 6 and 12	the number of children aging between six and twelve of a family
	elder no. over 65	the number of elders over age 65 of a family
	friends or relatives outside	dummy, if a family has friends and relatives outside village, friends or relatives outside =1
	friends or relatives village cadre	dummy, if a family has friends and relatives as village cadre, friends or relatives village cadre =1
Village characteristics	village mig ratio 1998	village migration ratio in 1998
	distance to nearest transportation terminal	the distance from village to a nearest transportation terminal, unit: kilometers
	distance to the country seat	the distance from village to the county seat, unit: kilometers
	village per capita income	village per capita income, unit: hundred Yuan
	mountain area	dummy, if a village locates in the mountain area, mountain area =1
	hill area	dummy, if a village locates in the hill area, hill area =1
Social interaction with other villagers	info very frequently	dummy, if "exchange information of employment" is "very frequently"", information very frequently =1
	info often	dummy, if "exchange information of employment" is "often", information often =1
	info just so so	dummy, if "exchange information of employment" is "just so so", information just so so =1
	info sometimes	dummy, if "exchange information of employment" is "sometimes", information sometimes =1
	borrow very frequently	dummy, if "borrowing money" is "very frequently", borrow very frequently =1
	borrow often	dummy, if "borrowing money" is "often", borrow often =1
	borrow just so so	dummy, if "borrowing money" is "just so so", borrow just so so =1
	borrow sometimes	dummy, if "borrowing money" is "sometimes", borrow sometimes =1
	help very frequently	dummy, if "mutual-help during busy season" is "very frequently", help very frequently =1
	help often	dummy, if "mutual-help during busy season" is "often", help often =1
	help just so so	dummy, if "mutual-help during busy season" is "just so so", help just so so =1
	help sometimes	dummy, if "mutual-help during busy season" is "sometimes", help sometimes =1
	housing very frequently	dummy, if "labor exchange in house-building" is "very frequently", housing very frequently =1
	housing often	dummy, if "labor exchange in house-building" is "often", housing often =1
	housing just so so	dummy, if "labor exchange in house-building" is "just so so", housing just so so =1
	housing sometimes	dummy, if "labor exchange in house-building" is "sometimes", housing sometimes =1
	care very frequently	dummy, if "taking care of old person, sick person, and babies" is "very frequently", care very frequently =1
	care often	dummy, if "taking care of old person, sick person, and babies" is "often", care often =1
	care just so so	dummy, if "taking care of old person, sick person, and babies" is "just so so", care just so so =1
	care sometimes	dummy, if "taking care of old person, sick person, and babies" is "sometimes", care sometimes =1

Table 2: Statistical Description of Variables

	Full sample 16401		Migrants 2675		Non-migrants 13726	
Variable	Mean	s. d.	Mean	s. d.	Mean	s. d.
Individual Characteristics:						
female	0.4459	0.4971	0.3727	0.4836	0.4602	0.4984
age	34.6344	12.4495	27.1166	8.34829	36.09952	12.5880
married	0.6993	0.4586	0.4501	0.4976	0.7479	0.4343
primary school	0.2649	0.4413	0.1806	0.3847	0.2813	0.4496
junior high school	0.5033	0.5000	0.6191	0.4857	0.4807	0.4996
senior high school	0.1321	0.3386	0.1140	0.3179	0.1356	0.3424
tech school or more	0.0659	0.2481	0.0789	0.2696	0.0634	0.2437
communist	0.0710	0.2568	0.0303	0.1714	0.0789	0.2696
health very good	0.2408	0.4276	0.2834	0.4507	0.2325	0.4224
health good	0.6281	0.4833	0.6624	0.4730	0.6214	0.4851
health so so	0.0983	0.2978	0.0422	0.2012	0.1093	0.3120
health bad	0.0253	0.1571	0.0093	0.0962	0.0284	0.1662
Family Characteristics:						
household labor force	2.7678	1.2718	3.3544	1.2583	2.6534	1.2427
family per capita land	2.0937	2.3302	1.6258	1.7300	2.1849	2.4196
kids no. under 6	0.1818	0.4285	0.2011	0.4534	0.1780	0.4234
kids no. between 6 and 12	0.3354	0.6014	0.2819	0.5630	0.3458	0.6081
elder people no. over 65	0.1806	0.4535	0.1966	0.4794	0.1775	0.4482
friends or relatives outside	0.5726	0.4947	0.5922	0.4915	0.5688	0.4953
friends or members village cadre	0.2240	0.4169	0.2456	0.4305	0.2198	0.4141
Village Characteristics:						
distance to the country seat	25.2382	21.6849	27.1437	20.3367	24.8668	21.9194
distance to nearest transportation terminal	5.4653	8.3177	5.3916	7.9651	5.4797	8.3849
village per capita income	2.3886	1.3957	2.1802	1.1521	2.4292	1.4349
village mig ratio 1998	0.0882	0.0786	0.1204	0.0814	0.0819	0.0764
mountain area	0.2187	0.4134	0.2426	0.4287	0.2140	0.4102
hill area	0.3436	0.4749	0.4426	0.4968	0.3243	0.4681
Peer effect:						
village migration ratio	0.1703	0.1474	0.2297	0.1533	0.1588	0.1434
Social Interaction Strength:						
info very frequently	0.0465	0.2106	0.0587	0.2351	0.0442	0.2054
info often	0.1722	0.3776	0.2213	0.4152	0.1627	0.3691
info just so so	0.2855	0.4517	0.2916	0.4546	0.2844	0.4511
info sometimes	0.2077	0.4057	0.2041	0.4031	0.2084	0.4062
borrow very frequently	0.0546	0.2271	0.0557	0.2294	0.0543	0.2267
borrow often	0.2043	0.4032	0.2146	0.4106	0.2023	0.4017
borrow just so so	0.3539	0.4782	0.3555	0.4788	0.3536	0.4781
borrow sometimes	0.2407	0.4275	0.2497	0.4329	0.2389	0.4264
help very frequently	0.1138	0.3176	0.0983	0.2978	0.1169	0.3213
help often	0.2198	0.4141	0.2329	0.4228	0.2173	0.4124
help just so so	0.3057	0.4607	0.2662	0.4420	0.3134	0.4639
help sometimes	0.1890	0.3915	0.2034	0.4026	0.1862	0.3893
housing very frequently	0.1289	0.3351	0.1372	0.3441	0.1273	0.3333
housing often	0.2647	0.4412	0.2632	0.4404	0.2650	0.4413
housing just so so	0.2543	0.4355	0.2265	0.4187	0.2597	0.4385
housing sometimes	0.1748	0.3798	0.1836	0.3872	0.1731	0.3783
care very frequently	0.0434	0.2037	0.0434	0.2037	0.0433	0.2036
care often	0.1172	0.3217	0.1133	0.3170	0.1180	0.3226
care just so so	0.2197	0.4140	0.1940	0.3955	0.2247	0.4174
care sometimes	0.2199	0.4142	0.2508	0.4336	0.2138	0.4100

Table 3: Probit Regression Result (Discrete Social Interactions)

Dependent Variable: Migrant or not (Migrant=1, Non-migrant=0)

Variable	Coef.	Standard Error	Marginal Effects	Variable	Coef.	Standard Error	Marginal Effects
Peer effect							
village migration ratio	0.9437***	0.2142	0.1240				
Interactions of Peer effect with Social Distance							
mig ratio×info very frequently	1.3444***	0.2768	0.3605	mig ratio×help just so so	-0.1156	0.1663	-0.0241
mig ratio×info often	1.0975***	0.1822	0.2829	mig ratio×help sometimes	0.3640**	0.1744	0.0828
mig ratio×info just so so	0.6296***	0.1663	0.1500	mig ratio×housing very frequently	-0.5927***	0.2209	-0.1124
mig ratio×info sometimes	0.4208**	0.1731	0.0967	mig ratio×housing often	-0.7206***	0.1843	-0.1331
mig ratio×borrow very frequently	-0.3484	0.3161	-0.0693	mig ratio×housing just so so	-0.8320***	0.1808	-0.1503
mig ratio×borrow often	-0.0794	0.1999	-0.0166	mig ratio×housing sometimes	-0.3045*	0.1854	-0.0611
mig ratio×borrow just so so	-0.0465	0.1842	-0.0098	mig ratio×care very frequently	-0.3638	0.2927	-0.0722
mig ratio×borrow sometimes	-0.0058	0.1847	-0.0012	mig ratio×care often	-0.1947	0.2074	-0.0399
mig ratio×help very frequently	-0.4086*	0.2399	-0.0804	mig ratio×care just so so	-0.3052**	0.1551	-0.0612
mig ratio×help often	-0.0443	0.1780	-0.0094	mig ratio×care sometimes	-0.0611	0.1481	-0.0129
Individual, Household and Village Characteristics							
Married	-0.6018***	0.0492	-0.1196	kids no. under 6	-0.0483	0.0336	-0.0082
Age	0.1999***	0.0113	0.0037	kids no. between 6 and 12	-0.0583**	0.0249	-0.0099
age squared	-0.0032***	0.0002	----	elder people no. over 65	0.0376	0.0283	0.0064
Communist	-0.1642**	0.0674	-0.0254	Friends/relatives outside	0.0694**	0.0303	0.0117
health very good	0.2367	0.2136	0.0436	Friends/relatives vil. cadre	0.0612*	0.0350	0.0106
health good	0.1650	0.2126	0.0273	dist. nearest trans. terminal	0.0008	0.0017	0.00013
health so so	-0.0398	0.2188	-0.0066	dist. country seat	0.0004	0.0007	0.00006
health bad	-0.0396	0.2406	-0.0066	vil. per capita inc.	-0.0592*	0.0318	-0.0101
primary school	0.2868**	0.1191	0.0533	vil. per capita inc. squared	0.0011	0.0041	0.0002
junior high school	0.4200***	0.1186	0.0717	mountain area	0.1751***	0.0392	0.0317
senior high school	0.2517**	0.1236	0.0482	hill area	0.1996***	0.0330	0.0354
tech school or more	0.2388*	0.1283	0.0463	mig_1998	1.8111***	0.2557	0.3081
household labor force	0.2339***	0.0114	0.0398	intercept	-4.6432***	0.2976	----
family per capita land	-0.0723***	0.0076	-0.0123				
Pseudo R2	0.2274						
Log likelihood	-5635.632						
Number of obs	16401						

Note: *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels respectively. Standard Errors are in parentheses. Age on migration probability has an inverse-U shape relationship. The marginal effect is 0.0340-age*0.00109. In the above table, we report the marginal effect when age equals 34.6, the mean age in the sample. Health may also have impact on the migration probability, if we put the continuous health variable instead of the discrete ones in the regression function, healthier people have higher probability of out migration.

Table 4: Robustness Check

Dependent Variable: Migrant or not (Migrant=1, Non-migrant=0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer effect								
village migration ratio	0.4981*** (0.1172)	0.9520*** (0.2172)	0.4940*** (0.1699)	0.8977*** (0.1864)	0.8519*** (0.1651)	1.2050*** (0.1737)	0.9119*** (0.1498)	1.6387*** (0.2495)
Interaction of Peer effect with Social Distance								
mig ratio×info very frequently		1.0535*** (0.3125)	0.5411** (0.2264)					
mig ratio×info often		0.8087*** (0.2005)	0.6857*** (0.1638)					
mig ratio×info just so so		0.3906** (0.1828)	0.2086 (0.1475)					
mig ratio×info sometimes		0.0203 (0.1874)	0.2099 (0.1604)					
mig ratio×borrow very frequently		-0.4191 (0.3499)		-0.4039 (0.2740)				
mig ratio×borrow often		-0.1632 (0.2172)		-0.1553 (0.1797)				
mig ratio×borrow just so so		-0.0805 (0.1994)		-0.1933 (0.1682)				
mig ratio×borrow sometimes		-0.1461 (0.2009)		0.0029 (0.1734)				
mig ratio×help very frequently		-0.2238 (0.2667)			-0.3949* (0.2035)			
mig ratio×help often		0.0978 (0.1982)			-0.0995 (0.1572)			
mig ratio×help just so so		-0.0274 (0.1825)			-0.2604* (0.1511)			
mig ratio×help sometimes		0.2676 (0.1871)			0.3172* (0.1655)			
mig ratio×housing very frequently		-0.4879* (0.2508)				-0.4780** (0.1898)		
mig ratio×housing often		-0.7891*** (0.2036)				-0.5292*** (0.1618)		
mig ratio×housing just so so		-0.6856*** (0.1976)				-0.7533*** (0.1579)		
mig ratio×housing sometimes		-0.2664 (0.2008)				-0.1212 (0.1712)		
mig ratio×care very frequently		-0.4098 (0.3211)					-0.2532 (0.2475)	
mig ratio×care often		-0.3779* (0.2279)					-0.1377 (0.1905)	
mig ratio×care just so so		-0.4567*** (0.1700)					-0.4412*** (0.1396)	
mig ratio×care sometimes		-0.3589** (0.1593)					-0.0273 (0.1371)	

mig ratio×Days of Bang Gong in 2002								-0.1235*** (0.0145)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual, family and village characteristics	Y	Y	Y	Y	Y	Y	Y	Y
County Dummy	Y	Y						
Village migration ratio 1998			Y	Y	Y	Y	Y	Y
Pseudo R2	0.3014	0.3058	0.2227	0.2215	0.2225	0.2233	0.2220	0.1884
Log Likelihood	-5010.543	-4979.187	-5670.543	-5678.630	-5671.875	-5666.078	-5675.126	-1964.986
Number of obs	15730	15730	16401	16401	16401	16401	16401	10200

Note: *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels respectively. Standard Errors are in parentheses.

Table 5: Probit Regression Result (Continuous Social Interactions)

Dependent Variable: Migrant or not (Migrant=1, Non-migrant=0)

	(1)	(2)	(3)	(4)	(5)	(6)
Peer effect						
village migration ratio	1.0708*** (0.2207)	0.3115* (0.1785)	1.0135*** (0.1918)	1.0705*** (0.1772)	1.2136*** (0.1797)	0.9946*** (0.1665)
Interaction of Peer effect with Social Distance						
exchange info.×village migration ratio	0.3309*** (0.0502)	0.1720*** (0.0432)				
borrow money×village migration ratio	-0.0448 (0.0550)		-0.0847* (0.0483)			
mutual help×village migration ratio	-0.10098** (0.0478)			-0.1055*** (0.0411)		
labor house×village migration ratio	-0.1747*** (0.0475)				-0.1514*** (0.0410)	
take family×village migration ratio	-0.1199** (0.0504)					-0.0993** (0.0441)
Individual, household and village characteristics	Y	Y	Y	Y	Y	Y
Village Migration Ratio 1998	Y	Y	Y	Y	Y	Y
Pseudo R2	0.2254	0.2223	0.2215	0.2217	0.2222	0.2216
Log Likelihood	-5650.8732	-5672.8737	-5679.2534	-5677.4899	-5673.9726	-5678.2423
Number of obs	16401	16401	16401	16401	16401	16401

Note: *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels respectively. Standard Errors are in parentheses.

Table 6: Two Stage IV-Probit Regression

Dependent Variable: Migrant or not (Migrant=1, Non-migrant=0)

	(1)	(2)	(3)	(4)	(5)
			Second Stage Result		
Instrumented Variable					
exchange info.×village migration ratio	-0.1243 (0.9095)				
borrow money×village migration ratio		-1.3099 (10.5597)			
mutual help× village migration ratio			-0.3044 (3.0132)		
labor house× village migration ratio				-0.1936 (1.5264)	
take family× village migration ratio					-0.0636 (0.5211)
Peer effect					
village migration ratio	1.0751 (2.3854)	4.4746 (29.6344)	1.6139 (8.4403)	1.3231 (4.5365)	0.8983 (1.1984)
Individual, family, village characteristics	Y	Y	Y	Y	Y
Village Migration Ratio 1998	Y	Y	Y	Y	Y
			First Stage Result		
			Instrumented Variable		
	exchange info.×village migration ratio	borr money ×village migration ratio	mutual help×village migration ratio	labor housing×village migration ratio	take family×village migration ratio
Instrument: family political identity	0.1411*** (0.0232)	0.0098 (0.0209)	0.0425* (0.0242)	0.0843*** (0.0243)	0.2471*** (0.0229)
Number of obs	16240	16240	16240	16240	16240
Log likelihood	-7606.5787	-5965.8738	-8328.9546	-8401.6227	-7455.0887
Wald test of exogeneity					
Prob > chi2	0.7447	0.9134	0.9468	0.9803	0.9478

*, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels respectively. Standard Errors are in parentheses.

Figure 1: Simulation of Labor Migration Equilibrium

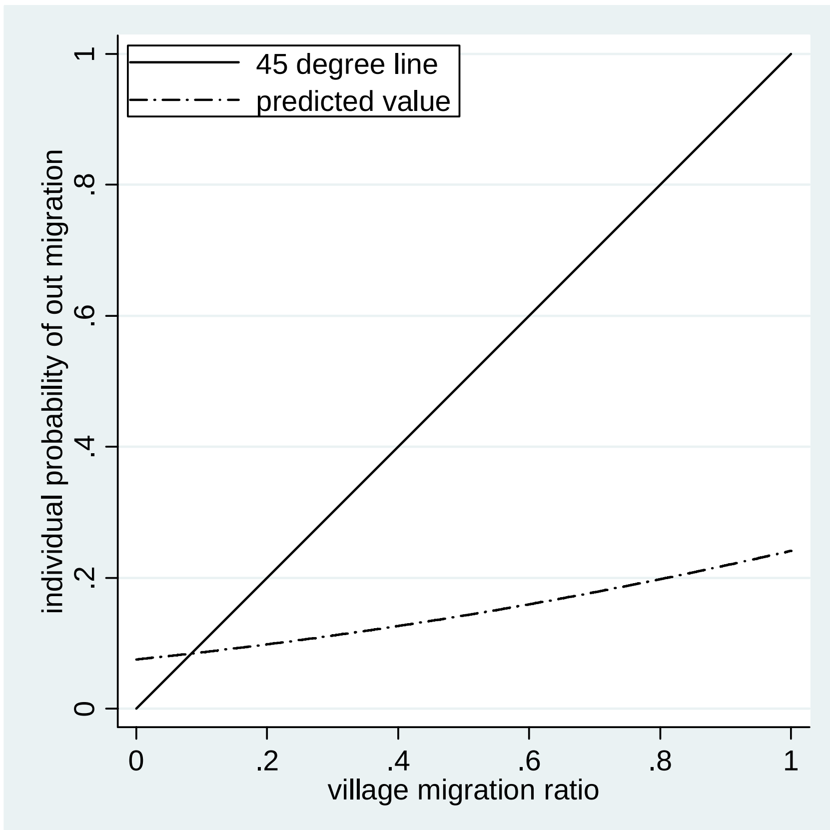

Figure 1 shows the relationship between village migration ratio and mean individual out migration probability (simulation parameters are from table 3). When the two values equal (cut the 45 degree line), it is the equilibrium migration ratio. As shown in the graph, the equilibrium migration ratio is 8.45%.

Figure 2: Policy Effect: Increasing Educational Level

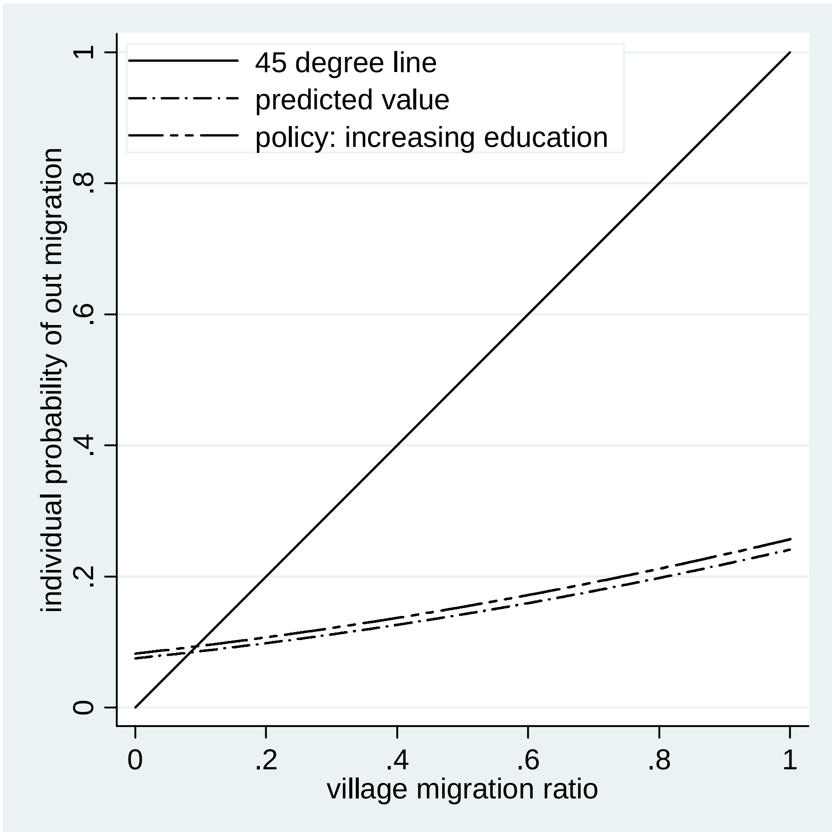

Figure 2 shows the policy effect of increasing education investment on out migration decision. We assume every sample individual receives at least nine year compulsory education (junior high school level). The equilibrium migration ratio increases to 9.35%.

Figure 3: Policy Effect: Increasing Pro-Peer Effect Social Interaction

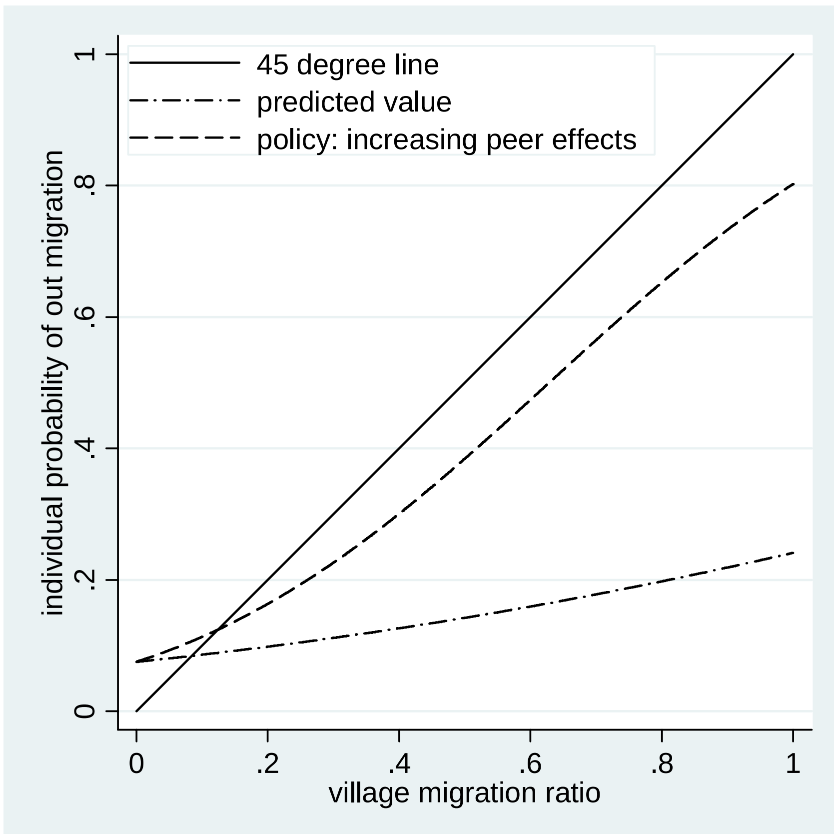

Figure 3 demonstrates the policy effect of increasing pro-peer effect social interaction on migration decision. In here, we control the information sharing interaction at “very frequently” while set the three labor market interactions at “none/few”. The intuitive policy measures are establishing formal job information broadcasting institution and labor service enterprises in rural areas. For such policies, the equilibrium migration ratio reaches 12.44%.

Figure 4: Policy Effects: Increasing Educational Level and Pro-Peer Effect Social Interaction

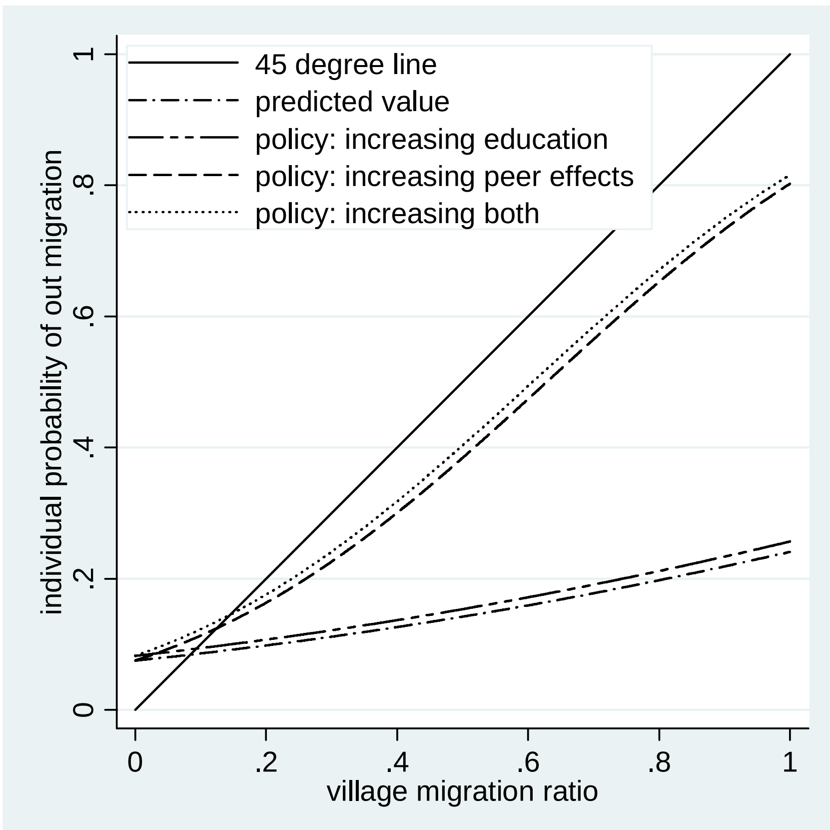

Figure 4 combines Figure 2, 3 and additionally shows the overall policy effect of increasing both education level and pro-peer effect social interaction. The combining policy will lift up equilibrium migration ratio to 14.57%.

Figure 5: Policy Effect: Institutional "Big Push" in Rural-Urban Integration

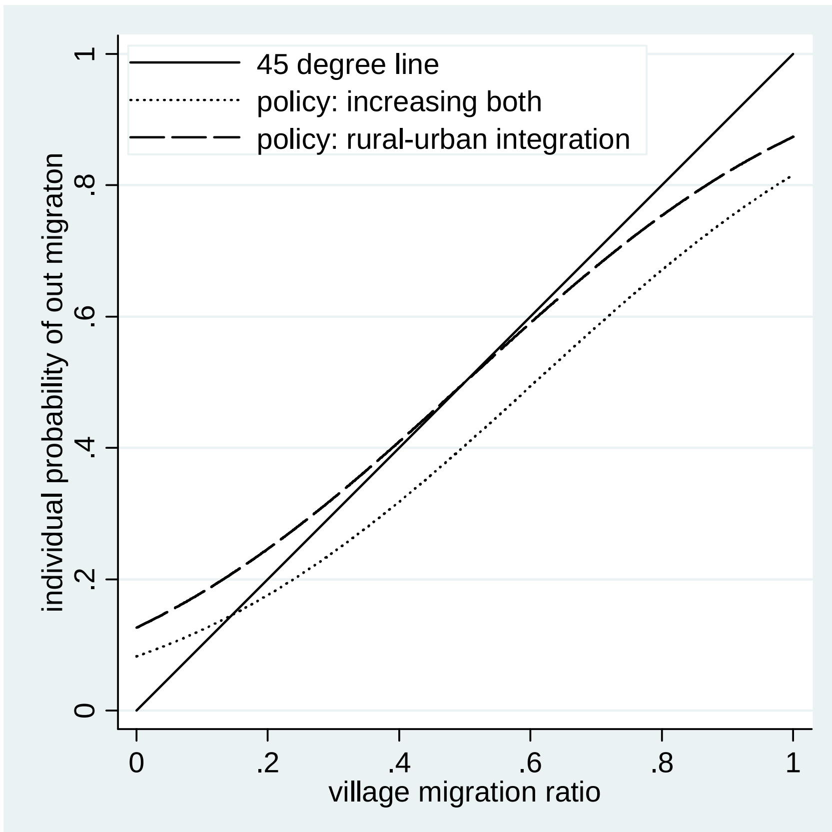

Figure 5 shows the effect of rural-urban labor market integration on out migration decision (long dash line). Though in our framework we do not have explicit parameters to measure the extent of labor market discrimination against rural migrants, we increase the intercept term, which is exogenous and homogenous to every sample individual and thus can represent the "institutional change", to demonstrate the effect of market integration. We increase intercept from -4.6432 to -4.4399 and the equilibrium migration ratio reaches 50%.