9-2015

Social network, intra-network education spillover effect and rural–urban migrants' wages: Evidence from China

Chunchao Wang
Jinan University - China

Chenglei Zhang
Jinan University - China

Jinlan Ni
University of Nebraska at Omaha, jni@unomaha.edu

Social Network, Intra-network Education Spillover Effect and Rural-urban Migrant Wages: Evidence from China

ABSTRACT: This study examines the determinants of rural-urban migrant wages, paying special attention to the intra-network education spillover effect of the migrants' social network in China. Using the new migrant sample of Rural Urban Migration in China (RUMiC) 2009 survey data, we find that the migrants' social network does have a significant impact on their own earnings. In particular, we find evidence that there exists an education spillover effect of the migrants' social network, which indicates that the education level of the migrants' social network has a significant positive effect on their earnings. We also find that the education spillover effects differ with gender. The results are robust after considering the potential problem of endogeneity.

Key words: Social network; Education spillover effect; Earnings of rural-urban migrants
JEL classification: J61, O15, R23

1. Introduction

Social networks play an important role in an individual's occupational turnover, wage premium and job access as shown by research in developed economies (Calvo-Armengol and Jackson, 2004, 2007; Loury, 2006; Caliendo et al., 2010; Cingano and Rosolia, 2012; Schmutte, 2015). During the past decades of urbanization in China, social networks (called "Guanxi" in Chinese) have become an important resource to migrants in job seeking, income upgrading, and integration (Bian, 1994; Zhang and Li, 2003; Wang et al., 2014; Wang et al., forthcoming). The Chinese hukou system that does not allow free labor mobility makes a natural social network in a village (Vendryes, 2011). Since the 1980s, these social networks have helped Chinese farmers who have migrated to the city seeking non-agriculture jobs. Existing research has documented the direct influence (offering information, providing financial aid, recommending a job) of the social network on migrant wages (Mortensen and Vishwanath, 1994; Bian, 1997; Lin, 1999; Ye and Zhou, 2010; Caliendo et al., 2010; Dong, Huang and Tang, 2014; Wang et al., forthcoming). More work needs to be done on the indirect influence such as social learning/network spillover effects.

This paper studies the intra-network education spillover effect[1] among closely related migrant workers to examine whether there exists a human capital externality among a migrant's social networks. Using rural migrant worker sample data in the 2009 Rural Urban Migration in China (RUMiC) survey, the paper makes an overall inspection of the roles that

[1] Generally, peer effect is divided into two categories: endogenous effect (outcome to outcome) and exogenous effect (endowment to outcome). Most previous research (Fitzgerald et al., 2012; Burke and Sass, 2013; Sacerdote, 2001) focus on the outcome to outcome effect (someone may be influenced by a peer's behavior or achievement); however, fewer studies (Calvo Armengol et al., 2009) pay attention on the endowment to outcome effect (a peer's attributes may affect someone's own achievement). This paper mainly refers to the latter one including peers among individuals' closely related persons. However, this paper focuses on the individuals' closely related persons that differs from typical peers in relationships although the two cohorts have overlapping contents.

social networks play on the wage increase of migrant workers. In particular, we study the intra-network education spillover effects within the social network represented by the three closest related persons. We find that social network members have substantial direct effects on the wage increment of migrant workers, which can be divided into direct influence such as monetary help, and indirect influence such as social learning or spillover effect. Furthermore, we also find that the social network of migrant workers has significant human capital externality on their monthly wages. That is, those whose closest related persons have a higher education level tend to get higher wages, and this effect significantly differs with gender.

Our paper differs from the existing research in several ways. First, to the best of our knowledge, this paper is the first one focusing on intra-social network education spillover effect in China using micro-level data. We use the attribute-outcome network effects that focus on the intra-network human capital externality spillover effect. This differs from previous research that mostly focused on outcome-outcome peer effects (Moretti, 2002, 2004; Sousa, 2013; Liu 2008; Angrist, 2014). Our model setup avoids potential spurious results due to endogenous issues because the related person's education is determined by his own family background and not affected by migrant income. Second, the detailed micro survey data set on rural to urban migrants allows us to further study the mechanism of how this network on human capital externality works. We find the direct channel through which a migrant's social network may influence their economic outcome. More importantly, we find the indirect effect, such as social learning spillover, where interpersonal communication usually leads to information, knowledge and benefit exchange within the social relations network.

The paper is structured as follows. We first review the related literature in section 2.

Section 3 presents the data and descriptive statistics results. Section 4 introduces the empirical framework. Section 5 carries out the empirical results, conducts the robustness inspection, and then gives further evidence for the mechanism analysis. The conclusion follows in the final section.

2. Literature Review

2.1. Social network

The social network is referred to as “weak ties" through which information transfer plays an important role in the process of job hunting (Granovetter, 1973). [2] Granovetter (1985) further points out those human economic activities are embedded in the social network, and Lin (1999) defines these embedded resources in social network as social capital. Based on previous network theory, Bian (1997) calls the social network “strong ties” that play a vital role on the income of network parties.

Some research has shown that the social network plays an important role in the decision-making, economic returns and other aspects through social resource, social rule and social impact. Lin (1999, 2008) studies the direct causal effects of the social network from the angle of social resources strategies. From the perspective of social rules, Coleman (1988) and Putnam (1995) emphasize that the social network is a specific structural organization that regulates individuals in specific network architecture, and produces some peer pressure on the members within that network. Furthermore, peer pressure can result in incentives to network members. Social learning mainly comes from the spillover effect of human capital among the interior network members. Through familiarity, individuals are more likely to

[2] Social network can be broadly categorized into “weak ties” and “strong ties”. However, Granovetter (1973) highlighted the importance of weak ties, hence, the definition of social network usually can be narrowed into “weak ties” accordingly.

work hard and thus the spillover effect on other internal personnel within the social network improves the productivity of the related parties and thus increases income.

The literature provides diverse ways for us to understand how social networks function. However, it is a challenge for researchers to define the structure and size of the social network accurately. A key concept of an individual's social network is that the closest relationships play important roles in their behaviors. Therefore, in this paper, we regard the closest related persons as the representatives to analyze the possible impact on individual income payment.

2.2. The education spillover effect

Previous literature has shown positive education spillover effect. Moretti (2004) indicates that overall education levels of citizens are able to cause positive spillover effects to individuals. Using the community data, Sousa (2013) finds that the average level of education in the immigrant community has a positive effect on the individual's self-employment. Using data at the enterprise level, Battu *et al*. (2003) and Moretti (2002) find that the average education level of the workers has a positive impact on the productivity of individual workers. These studies find that the overall education levels of the residents in cities and workforces within the same enterprise help to increase the productivity and then affect their income outcomes. In that case, are there any similar education spillover effects at the individual level not only from peers but also from the social network? Furthermore, the research on peer effect in relevant literature shows that the peer cohort does affect their individual behaviors and economic returns in many aspects. However, the individual's social network from the peer effect is not exactly equal to its cohort (i.e. one's friend may not live or work together with him/her). Thus, besides the impact of information transfer and direct help from the social network, is there any indirect intrinsic pathway that has an impact on the individuals?

Our paper examines the above issues by emphasizing the intra-network education spillover effects. Along with previous studies, we find that the impact on the individual's social network analysis mainly focuses on the level of resource provision and reciprocal help. In particular, some close friends from a long distance but communicating frequently, may have an education spillover effect. As mentioned in the introduction, Chinese society features a "human society" and "relational society", and this type of "relation" is a central element in daily economic activities, especially in rural areas and in migrant communities. The majority of migrant workers follow their relatives or fellow villagers when leaving rural areas to work in cities. They are more inclined to be social with people from their home village/province. This kind of social relation, either on the household level or village level, has a great impact on the migrant's employment or earnings in the city. Therefore, the study of social network effects requires the combination of the migrant's own characteristics and that of their closely related persons. Our analysis relating the individual's level of education with their income is not yet included in the literature.

The education spillover effect potentially comes from two channels in the social network. One is from social learning within a specific social network. Chinese rural-urban migrant workers usually work in similar industries and workplaces because of their homogeneity of skill and education levels. In this case, migrants are more likely to learn skills from their village friends. Social learning is a significant channel to improve workers' skills and thus productivity, resulting in increased income. The other channel is most likely from social impact in the long run. This impact results from gradual contagious connections (some research also calls it peer effect) within the social network. If a related person has a relatively higher level of education, they are more likely to disseminate efficient information or knowledge to other members of the network. This may affect an individual's skill level in the long term.

The next two sections empirically study the migrant's social network influence, especially the intra-spillover effect that is based on the education level of the closest relatives, friends or peers. In the regression analysis, we analyze the impact that social network's quantity has on migrants' wages. We then focus on the quality, exploring the intra-network educational spillover effects among the migrant's social network.

3. Data

The data are from the RUMIC survey (2009), conducted by the Australian National University, Beijing Normal University and the Institute for the Study of Labor (IZA). We focus on the new samples of the migrant families in 2009, which were selected from the sampling frame designed by the group. It covers nine provinces and 15 cities, both urban and the rural, including Shanghai (the main metropolitan), Guangzhou, Shenzhen and Dongguan (eastern areas of Guangdong province), Nanjing and Wuxi (eastern areas of Jiangsu), Hangzhou and Ningbo (eastern areas of Zhejiang), Wuhan (central area of Hubei province), Hefei and Bengbu（central areas of Anhui), Zhengzhou and Luoyang (central areas of Henan), Chongqing (western area) as well as Chengdu (central area of Sichuan). The majority of the floating population in China is integrated into the above cities (the designs and investigation details of the floating population sampling frame can refer to Kong (2010).

The original data contain 3,422 migrant families. We select only the individual's (the head of household) answers to the questionnaires for this study, since we are concentrating on migrant workers rather than migrant families. After dropping missing data of the main variables, we get a common sample with 2,828 observations. We further drop six observations that have a local urban household registration, and 15 that have a non-local urban household registration. We focus on rural-urban migrants in this study, so we only keep individuals who have a rural hukou and thus drop an additional 21 observations that have non-rural household registration. Finally, we have 2,807 observations of migrant workers in this research.

The questionnaire mainly investigates migrant worker information on workers aged 16 and above including personal basic information (i.e. sex, age, marital status, education level and training), employment information (i.e. working time, occupational experience, if changed jobs after working outside of the rural, average monthly wage income, current work unit properties, current working industry, city, job, etc.), as well as the social interaction (i.e. the number of people greeted in the Chinese New Year, the basic information of the person who was closest to their family or did favors for them during the past year).

Table 1 presents the descriptive statistics analysis of migrant workers in our sample that involves their individual basic characteristics, human capital, employment information and social interaction. As we can see, the average monthly income is about 1,805 Chinese Yuan, which contains the various bonuses and subsidies to rural migrant workers but excludes the wages earned from their part-time job or other channels. What we need to point out is that the salary has not been adjusted for possible offered meals and accommodation by the employers.

The migrant workers have to spend a portion of their income on housing and daily meals due to sustainable living and working, and this ratio of spending may vary among migrant workers. Therefore, we control for this by adding a dummy variable that denotes whether meals or accommodation is offered.

[Insert Table 1 around here]

The social network section in Table 1 summarizes four alternative measurements for migrant's social network: the total number of persons who were greeted by a single migrant, the number of greeted relatives, the number of greeted friends and the number of greeted people who have performed a favor for the migrant in the past year. These measurements go beyond the previous literature that use the number of persons who were greeted by a single migrant in the Chinese New Year to represent the magnitude of one's social network. As we can see, on average, each migrant greeted approximately 23 persons, among which both relatives and friends account for nearly a half (the number of greeted relatives is 11 while greeted friends is 13). When we turn to the helpers' effects, the number is reduced to four. However, the above processing cannot represent the social network thoroughly and thus cannot reflect how social network members help each individual.

Therefore, we further adopt a nominative approach that is a widely used survey method in the field of social network to measure one's network using the closest persons. In the survey, five people are nominated by "who gave you a direct help on your work and daily life or who has the closest relationship with you in the past one year", and the five nominees are ranked according to the relative importance by the nomination. By using this nominative method, some key information is easily accessible for the five relevant persons such as basic personal characteristics information, education, work status, residence, etc. And, most importantly, the interactions between the migrant and his/her five closest related persons are also available. Due to missing data for the fourth and fifth person in the related network, we only use the closest three persons to represent a migrant's specific social network in order to conduct our investigation.

Table 2 summarizes the descriptive statistics of the three closest persons of the migrant worker. We find that the three closest persons are mainly friends (close to 50%) and relatives (about 30%). As to the help that a related person gave to the migrant worker, 90 percent of received help from their three closest persons, while only 10 percent did not. Seventy percent of the help was indirect help such as spiritual and/or psychological in nature, while a smaller proportion of help was direct help, such as money and gifts. On the other hand, from the education and residence condition of the three closest persons, their average education level is almost at the same level as the migrant worker (the majority are in the junior school graduate level), while more than half of the related persons live near the migrant worker and a smaller proportion of related persons live far away, in rural areas or other provinces.

[Insert Table 2 around here]

In order to study the education spillover effect of the migrant worker's social network, we take the years of education gap between the three closest persons and the migrant worker as the key independent variable.[3] The descriptive statistics data suggest that, there are minor differences between the education level of the three closest related persons and the migrant worker. On average, the related person's years of education are greater than that of the

[3] Actually, the coefficients of using the education gap between the migrant and his/her closest related person or just using the closest related person's education are the same when the migrant's education is controlled. However, in order to exhibit the spillover effect, we still use the "gap" term in the empirical section.

individual migrant worker. The following section makes a concrete estimate as to the intra-network education spillover effect among the social network represented by the three closest related persons of the migrant worker.

4. Econometric Methodology

The econometric model follows the extended mincer model in the literature (Manski, 1993). We use different key independent variables to denote the quantity and quality of a migrant's social network in the specifications. First, a simple regression is run to check the social network's influence on income by using the number of the migrant's relatives, friends and helpers, which are often used in the social network literature. Then we proxy a migrant's social network's quality as their three closest related persons' education levels to seek evidence on whether there exists a human capital externality among the migrant's social network. That is:

$$\ln income = \alpha_1 + \beta_1 \vec{X}_1 + \beta_2 \vec{X}_2 + \varepsilon_1 \tag{1}$$

$$\ln income = \alpha_2 + \beta_1 \vec{X}_1 + \beta_2 \vec{X}_2 + \beta_3 \vec{S}_1 + \varepsilon_2 \tag{2}$$

$$\ln income = \alpha_3 + \beta_1 \vec{X}_1 + \beta_2 \vec{X}_2 + \beta_3 \vec{S}_2 + \varepsilon_3 \tag{3}$$

Equation (1) is the classic wage regression model in which the dependent variable is the logarithm of the monthly wage income of the migrants. X_1 is the vector of a migrant's individual characteristics including age, gender, marital status, education level and health state. Vector X_2 represents migrant's work-related characteristics such as working experience, whether training was received, working hours, current occupation, working city, and whether offered meals and accommodation, etc. Equation (2) adds a vector S_1 that denotes the individual's total social network, which is the number of people to whom a migrant sent greetings to in the last Chinese New Year, including relatives, friends and those from whom a migrant received help. Specifically, we focus on the third equation for substituting vector S_1 with S_2, which is the three closest persons to the migrant to represent their social network. We use the education gap between these three persons and that of the migrant to measure the intra-social network educational spillover effect which may exist within a migrant’s social network.

Our model setup has some advantages over other literature in social network that often encounter an endogenous problem. First, the social network of the individual is defined as friends who are not other observations in the regression. That is, each observation in the regression reports three friends who are not other observations in the regression. This avoids the situation of a traditional peer effect where each individual that we consider comes from the group observations, which leads to an endogenous issue as the same people whose outcome showed up on the left-hand side of the equation also showed up on the right-hand side as part of someone else's network.

Second, our model is set up from attribute (education) to the outcome (income) and this differs from most previous research (Liu, 2008; Han and Li, 2009; Giacomo and Michele, 2013) that examines an individual’s social network outcome, such as a peer’s economic attainment, on his economic attainment (outcome-on-outcome). A migrant’s social network may influence his/her outcome and a migrant’s outcome may also have a reflective impact on his/her social network, the so called reflection problem by Manski (1993) and Angrist (2014). As Angrist (2014) denotes, the outcome-on-outcome peer effect is vacuous due to the endogenous issue. Hence, we try investigating the social network spillover effect by focusing on the endowment-to-outcome model. Here we address a migrant's closest related persons' human capital levels, instead of their economic or social outcomes. We argue that one's friends' or relatives' education levels cannot be influenced by their friends or relatives, it's a predetermined attribute.[4]

However, our methodology faces a selection problem. As we discussed above, migrants cannot influence their social networks' human capital level, but they can choose their friends. We tackle this selectivity in two ways that are commonly used in micro-econometrics. First, we do a propensity score matching analysis based on a migrant's observable characteristics. By doing so we can solve the selectivity problem caused by observable attributes. Second, there may be some unobservable attributes or endowments, so we conduct IV estimation by finding three valid instrument variables for the endogenous gap. We use migrant's school performance, the admission age for primary school, and the proportion of migrant workers in the hometown to instrument the gap term.[5] By doing so, we eliminate the problem of selectivity and endogeneity.

5. Results

5.1 The direct effect of social network on the monthly income

Table 3 presents the OLS estimate results. Column (1) estimates from the classic Mincer wage model that focuses on the return of education, training and working experience. Column (2) reports the estimation results from an extended Mincer wage model by adding

[4] Some may argue that a friend's education are not exogenous, for if their friendship/relationship forms before they come to work, a friend's study choice may be affected by his/her choice. Here we think this situation does exist, however it may not influence our analysis: we are aiming at estimating the intra-network education spillover effect among the migrant's social network, and we hope for a bigger gap between the migrant and his/her related person; the bigger the gap is, the better the results are. Therefore, the existence of the situation mentioned above may lead to a smaller gap, in this perspective, it does no harm to our later result concerning the impact of education gap between the two related persons. We still cautiously use IV to solve this problem for an unbiased result though this problem does not seem serious.

[5] We instrument gap1, gap2 and gap3 with the same instruments, respectively, in the empirical section.

work-related variables. Column (3) further controls occupation based on the model in column (2). As we can see, a migrant's age, years of education, health state, tenure and working hours per week are all having a positive significant effect on monthly income. The results also show that males significantly earn more than females. These findings are consistent with existing literature (Zhang and Li, 2003; Ye and Zhou, 2010; Wang et al., 2014). Most of the rural-to-urban migrants do not have a high education background and no more than half of them participated in a training program.[6] Thus, they are engaged in low-skilled activity and income heavily depends on their health state and weekly working time.

[Insert Table 3 around here]

Columns (4)–(6) consider the social network's effect. The total number of persons that a migrant greeted within the last Chinese New Year has a positive effect on monthly income but not significant. While the number of greeted relatives does not have a significant impact on income, the number of friends and helpers effect are both significant and positive. We further divide the sample into sub-samples to run two separate regressions. Column (7) reports the results of the sub-sample where the migrant found his current job through the social network (i.e., offering job information, introducing a job) while column (8) presents the results of the sub-sample where the migrant found jobs by themselves. The results show that to those who find a job through the social network, the impact of the total number of greeted persons' on income is significant, while to those who find their job by themselves, the total number of greeting persons' impact on income is not significant. In other words, the quantitative effect of the social network only shows up through a direct channel, like offering

[6] Table 1 shows the mean years of education at only 9.59.

information, introducing a job, etc. However, there may be some potential qualitative effect of the social network that we cannot observe, like the intra-network education spillover effect.

5.2 The intra-network education spillover effect on the monthly income

This section exams the education spillover effect by conducting the regression of education gap between the three related persons and the migrant on migrant monthly income. Previous empirical analyses indicate that there is a social network effect on income. However social network is a structure more than a resource (Lin, 2008), and how it influences an individual is through multiple channels and may be complicated. By using the migrant's three closest related persons, we run the regression on the education gap between the migrant and each of them first, and then on the average gap of the three to see whether there exists an intra-social network educational spillover effect. The reason that we use the education gap instead of the three persons' education is that a self-selection problem may exist. Though the self-selective bias cannot be solved completely, the gap variable is more random than the related person's education itself.[7]

Table 4 reports the regression results. Columns (1)-(3) in Table 4 indicate that the education gap between each of the three closest persons and the migrant has a positive significant effect on monthly income. Column (4) presents the estimates of the effect of the average education gap on monthly income and the result indicates a significant positive effect on a migrant's monthly income. To get a robust result we also consider the education phase

[7] As for the possible multicollinearity between the education gap and the migrant's education, we need not to care too much about for two reasons. First, based on John Fox (1991), the multicollinearity only affects the significance of the results but the estimates are also unbiased. Second, we do a VIF test for the regression and we find that a strong multicollinearity of gap and education doesn't exist (the mean VIF coefficient if 5.06 and the VIF coefficient of gap1 and education are 1.25 and 1.73, respectively).

rather than years of education. There are four phases (i.e., primary schooling, middle schooling, high schooling, and college schooling) of education experience. Variable average2 represents the gap of education phase between the three closest persons and the migrant. The results are consistent with the previous finding that a migrant's social network does have a human capital externality to their monthly wages. The results add new micro evidence on human capital externality at the macro level (Moretti. 2004; Sousa, 2013). In the next section, we look at how the social network effect differs with gender.

[Insert Table 4 around here]

5.3 Gender differences of intra-network education spillover effect

This section tests whether a gender difference exists in a migrant's intra-network spillover effect. The male and female usually show different properties in many ways such as risk taking (Charness and Gneezy, 2012), return to education (Li, 2003) and peer influence (Han and Li, 2009). Table 5 presents the regression results for male and female migrants respectively.[8] This spillover effect tends to be more significant for males than for females. The results contradict previous findings that returns to education for women are higher than for men (Han and Li, 2009, Li, 2003). However, the two types of effects differ in impact mechanisms. The spillover effect we emphasize here lies in social learning. Since education spillover effects come from relatively long-run learning, the female migrants are more cautious in connecting with friends outside of their hometowns than males (Charness and Gneezy, 2012).

[Insert Table 5 around here]

[8] Only the estimates of key variables, say, gap1, gap2 and gap3 are presented in Table 5, and other control variables that appear in Table 4 are also controlled.

5.4 Endogeneity test

5.4.1 Propensity score matching: considering the selection problem

The potential problem with the above econometric analysis is twofold. The first issue is the reflection problem or two-way causality, i.e., a migrant's social network may influence their outcome and a migrant's outcome may also have reflective impact on their social network. In this study, we use the migrant's social network attributes but not the outcomes, to exam the intra-network education spillover. This relieves the problem of outcome-outcome two-way causality as the major formation of one's social network based on education in school that happened before earning a wage. The second issue is the self-selection problem based on observable or unobservable characteristics. It is possible that people who earn a high income tend to make friends with those whom earn a high income or have a high level of education. We therefore use the Propensity Score Matching (PSM) method to deal with this.

The PSM method was first developed by Rosenbaum and Rubin (1983) and we apply this method to tackle the possible self-selection problem in our study. First, a Propensity Score (PS) is calculated that measures the extent of matching of the treatment group and the control group in multi-dimensions. The treated groups are those where the related person's education level is higher than the migrant's (the education gap is greater than 0), while the control groups are others. The formation of friendship may be based on life experience (education experiences and working experiences) and character attributes (characters). Migrant workers may choose friends based on observable characteristics (i.e., age, gender, marital status, education, occupation, etc.) and on unobservable characteristics (disposition, habit, etc.).

Thus, we do the match by considering both observable characteristics and proxies of the unobservable characteristics. The observable characteristics include age, gender, marital status, education background, working experience and occupation. The unobservable characteristics use the proxies such as personality (extrovert or introvert), risk taking, willpower (feel that can overcome the difficulties) and trust (feel that most people are trustable). We use three widely used methods that are Nearest-Neighbor Matching, Radius Matching and Kernel Matching.[9]

[Insert Table 6 around here]

The results are presented in Table 6. The ATT values mean the average effect of treatment on the treated. A positive ATT means that the migrant's related person's education is higher than himself, otherwise ATT is negative. Most ATT values are positive, which implies that, after controlling for the problem of self-selection, there exists intra-network education spillover of a migrant's social network.

5.4.2 IV estimation

This section conducts a robust test for the potential unobservable attributes that may correlate to the individuals' selection of related persons. The previous section uses the PSM method that can help to identify the spillover effect. However, it cannot get an accurate coefficient of the spillover effect as it cannot tackle the problem of treatment effects. Therefore, in this section, we use the instrumental variables approach to further mitigate the potential omitted variable bias that may arise from unobserved factors being correlated with the selection. The IV approach allows us to obtain consistent estimates when the education

[9] The ATT values for pre-treated and the matching test results are not presented in table 6. As for the matching test, most variables' bias values after matching are below 5 while a very few variables are not (variable experience is 10.3).

gap is endogenous or measured with errors.

The IVs that we use are a migrant worker's school performance, admission age of primary school and the proportion of migrant workers in the home village. These variables are exogenous to the dependent variable, but are closely related to the endogenous independent variables. The high education school performance could affect the person's income, however the majority of rural-to-urban migrants work in low-skilled industries, which is not relevant to their school performance prior to working. Meanwhile, those well performing students always tend to make friends with those with good performance as well. Admission age of primary school should have no correlation with one's earning but it may affect the education gap between a migrant and his peers.[10] Finally, the proportion of migrant workers in the hometown is exogenous to the monthly income of the migrant. Liu (2008) finds that in rural areas human capital externalities have a discouraging effect on rural-urban migration, which shows evidence that the rural area's ratio of migrants is negatively correlated with its average human capital level. In other words, if the migrant comes from a rural area, his formal education level has a larger probability of being lower than his related person. Therefore, the migration ratio of the migrant's home countryside is exogenous to a migrant's monthly income, but may correlate with the gap between the migrant and his related person.

In summary, we believe the three instruments we chose are valid and can help to identify the setting. Table 7 reports IV regression results. The results indicate that, everything else being equal, the larger the gap between the migrant and their related person, the higher the

[10] For example, if one goes to primary school at seven, one year later than normal, his peers at the same age may be in high school when he is just graduating from primary. This increases the education gap between the migrant and his peers.

monthly wage the migrant will earn. The F statistics of the first stage of each regression are all above 10, indicating that the instruments pass the weak instrument test and the Sargan statistics of over identification test shows that the setting is not over identified.

5.5 Some further findings about the influential mechanism

The previous section documented robust evidence that an intra-network education spillover effect of a migrant's social network exists. This section further investigates the channels that the social network effects on the related persons. As we discussed in Table 3, the channels could be a direct help such as monetary or other indirect influence such as human capital spillover. To do so, we divide the sample into several sub-samples by the type of relationship (relative vs. non-relative), the type of help (psychological vs. monetary), the distance (near vs. far) and the type of contact frequency (frequent vs. not frequent).

Table 8 presents the results of sub-sample regressions by relatives and non-relatives. Three closest related persons mainly consist of relatives and friends, and we thus divide them into relative vs., non-relative. The results indicate that the education spillover effect is more significant among the non-relative network than that of the relative network. However, when looking into some detailed descriptive statistics about a migrant's three related persons, we find that (1) a migrant tends to communicate with his relatives network through the financial channel, while interacting with the non-relatives network through the emotional perspective; [11] and (2) most of the relatives live in the countryside while most of non-relatives live in the same city or same community.[12] This indicates that the significant differences may not come from the differences of relatives or nonrelatives, but may be caused

[11] 59.3% relatives offered psychological help to the migrant while 74.19% nonrelatives offered psychological help during the past year.

[12] 30.22% relatives live in the countryside while only 10.53% nonrelatives live in the countryside.

by ways of interaction. Thus, we do another three regressions to get the evidence.

[Insert Table 8 around here]

Table 9 reports the results by the type of help the migrant received. The results indicate that the intra-network education spillover effect is only significant when the migrant received psychological help, which denotes that the spillover effect relies on this kind of mental communication, not through monetary help. Table 10 presents the estimates that whether the living distance to related person affects the spillover effect. “Live near” means that the related person lives in the same city or community while “live far away” means that the related person lives in the countryside or other province (see Table 10). The regression results indicate that the intra-spillover effect is significant only when the related person lives not far away from the migrant. Table 11 presents the estimates that whether the frequency of the migrant contact to the related person affects the spillover effect. We define the contact “frequently” if the migrant contacts his related person every day or at least one time each month. We define “not frequently” if the migrant does not contact the related person in a year or longer. The results show that gap effect is only significant among migrants who contact their related person frequently.

[Insert Table 9 around here]

[Insert Table 10 around here]

[Insert Table 11 around here]

In sum, the intra-network education spillover effect does exist among migrants who are living and working closer, interacting more frequently and deeply with their social network members. Direct help like offering information or introducing a job may increase the migrant's economic attainment, but this influence is instant and one-time and this influence does not need a long time live-together social network. However, social learning needs more time and more interaction. Thus the results in Table 8 through Table 11 adds further evidence that apart from the direct influences, there does exist intra-network education spillover effect among the migrant's social network.

6. Conclusion

This paper presents the social network spillover effect on an individual's monthly income. The intra-network is represented by the three closest related persons of the migrant. Using micro-level survey data, we find that (1) a migrant worker's social network's higher education is beneficial to their economic earnings, (2) there does exist an intra-network education spillover effect among a migrant worker's social network, and (3) the intra-network education spillover effect is more significant for males than females.

We further exam the channels of this intra-network education spillover effect. The evidence shows that the related person's education level for those who have a frequent relationship with the individual migrant worker has a positive spillover effect on the migrant worker's income. In addition, the spillover effect of education is correlated with the specific communication process between migrant workers and their interacting persons: this spillover effect will be more significant when migrant workers have a closer social distance[13] and physical distance, as well as psychological or spiritual communication. Compared with the direct effect, this inner effect based on spiritual interaction probably can improve the productivity of migrant workers in the long time, and thus increase their earnings.

[13] There are different meanings about "social distance" in diverse research fields, here we define it as the frequency of interaction between migrants and their related persons, relative to "physical distance".

References

Angrist, D. Joshua, 2014. The perils of peer effects. *Labour Economics* 30, 98-108.

Battu, H., Belfield, C.R., Sloane, P.J., 2003. Human capital spillovers within the workplace: evidence for great Britain. *Oxford Bulletin of Economics and Statistics* 65, 575-594.

Bian, Y., 1994. Guanxi and the allocation of urban jobs in China. *The China Quarterly*, 140: 971-999.

Bian, Y., 1997. Bringing strong ties back in: Indirect ties, network bridges, and job searches in China. *American Sociological Review*, 366-385.

Burke, M. and Sass, T.R., 2013. Classroom peer effects and student achievement. *Journal of Labor Economics*, 31(1), 51-82.

Caliendo，M., R. Schmidl and A. Uhlendorff, 2010. Social networks, job search methods and reservation wages: evidence for Germany, German Institute for Economic Research, Discussion Paper.

Calvo-Armengol A. and M. O. Jackson, 2004. The effects of social networks on employment and inequality. *American Economic Review*, 94 (3): 426-454.

Calvo-Armengol A. and M. O. Jackson, 2007. Networks in labor markets: wage and employment and inequality. *Journal of Economic Theory*, 132 (1): 27-46.

Charness, G., Gneezy, U., 2012. Strong evidence for gender differences in risk taking. *Journal of Economic Behavior & Organization* 83, 50-58.

Cingano, F. and A. Rosolia, 2012. People I know: Job search and social networks. *Journal of Labor Economics*, 30 (2), 291-332.

Coleman, J.S., 1988. Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120.

Dong, Z., Huang, D., Tang, F., 2014. Information disclosure and job search: evidence from a social networks experiment. *Applied Economics Letters* 21, 293-296.

Fitzgerald, A., Aitzgerald,N. and Aherne,C., 2012. Do peers matter? A review of peer and/or friends' influence on physical activity among American adolescents. *Journal of Adolescence*, 35(4), 941-958.

Giacomo,D Giorgi and Michele Pellizzari, 2013. Understanding social interactions: evidence from the classroom. *The Economic Journal* 124, 917-953.

Granovetter, M., 1985. Economic action and social structure: the problem of embeddedness. *American Journal of Sociology*, 91 (3), 481-510.

Granovetter, M.S., 1973. The strength of weak ties. *American Journal of Sociology*, 1360-1380.

Han, L., Li, T., 2009. The gender difference of peer influence in higher education. *Economics of Education Review* 28, 129-134.

Fox, J., 1991. *Regression diagnostics: An introduction*. Sage.

Kong, S. T. 2010. Rural-urban migration in China: survey design and implementation. In X. Meng, C. Manning, L. Shi, & T. N. Effendi (Eds.), *The great migration: rural-urban migration in China and Indonesia* (pp. 135-150). Edward Elgar Publishing.

Li, H., 2003. Economic transition and returns to education in China. *Economics of Education Review* 22, 317-328.

Lin, N., 1999. Social networks and status attainment. *Annual Review of Sociology,* 25, 467-487.

Lin, N., 2008. A network theory of social capital. *The handbook of social capital*, 50-69.

Liu, Z., 2007. The external returns to education: evidence from Chinese cities. *Journal of Urban Economics* 61, 542-564.

Liu, Z., 2008. Human capital externalities and rural–urban migration: evidence from rural China. *China Economic Review* 19, 521-535.

Loury, L. D., 2006. Some Contacts are More Equal than Others: Informal Networks, Job Tenure and Wages. *Journal of Labor Economics*, 24 (2): 299-318.

Manski F. Charles, 1983. Identification of endogenous social effects: the reflection problem. *The Review of Economics Studies* 60, 531-542.

Moretti, E., 2002. Human capital spillovers in manufacturing: evidence from plant-level production functions. *National Bureau of Economic Research*.

Moretti, E., 2004. Workers education, spillovers, and productivity: Evidence from plant-level production functions. *The American Economic Review* 94, 656-690.

Mortensen, D. T., Vishwanath, T., 1994. Personal contacts and earnings: It is who you know! *Labour Economics* 1, 187-201.

National Bureau of Statistics of China, 2014. 2013 National Economic and Social Development Statistics Bulletin of People's Republic of China. http://www.stats.gov.cn/tjsj/zxfb/201402/t20140224_517970.html.

Putnam, R.D., 1995. Bowling alone: America's declining social capital. *Journal of Democracy* 6, 65-78.

Rosenbaum, P. R., Rubin, D. B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 41-55.

Sacerdote, Bruce, 2001. Peer Effects with Random Assignment: Results for Dartmouth Roommates. *The Quarterly Journal of Economics* 116 (2),681-704.

Schmutte, I. M., 2015. Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics* 33 (1), 1-32.

Sousa, L., 2013. Community determinants of immigrant self-employment: human capital spillovers and ethnic enclaves. *US Census Bureau Center for Economic Studies Paper* No. CES-WP-13-21.

Vendryes, T., 2011. Migration constraints and development: Hukou and capital accumulation in China, *China Economic Review*, 22 (4), 669-692.

Wang, C., Lao, H. and Zhou, X., 2014. The impact mechanism of social networks on Chinese rural-urban migrant workers' behaviour and wages. *The Economic and Labour Relations Review*, 25(2): 353-371.

Wang, C., Zhou, X. and Zhang, C., forthcoming. The impact of social capital on wages of rural migrants and its gender difference in China. *Journal of Macromarketing*. online, December 1, 2014, doi: 10.1177/0276146714561064.

Ye, J and Zhou, Y., 2010. The transfer of social capital and the income of migrant worker -evidence on the survey of migrant workers in Beijing. *Management World* (in Chinese) October: 34-46.

Yue, Z., Li, S., Jin, X., Feldman, M. W., 2013. The role of social networks in the integration of Chinese rural–urban migrants: a migrant–resident tie perspective. *Urban Studies*

50, 1704-1723.

Zhang, K.H., Song, S., 2003. Rural–urban migration and urbanization in China: Evidence from time-series and cross-section analyses. *China Economic Review* 14, 386-400.

Zhang, X. and Li, G., 2003. Guanxi matter to nonfarm employment? *Journal of Comparative Economics* 31 (2): 315-331.

Table 1

Definition of variables and summary statistics

	Definition	Mean(standard deviation)
Dependent variable		
Monthly income	Total monthly income, including pension and bonus but excluding part-job earnings(*yuan)*	1805 (2090)
Lincome (Log month income)	Natural logarithm of monthly income	7.34 (0.51)
Social network		
Persons	Number of total persons greeted in Chinese Spring Festival in various ways	23.8 (25.1)
Relatives	Number of relatives among the total persons	10.7 (11.5)
Friends	Number of friends among the total persons	12.6 (17.4)
Helpers	Number of people who had helped you in the past 12 months among the total persons	3.7 (5.1)
Average education	Average education of the three closest relation persons in the past 12 months	9.67 (2.63)
Individual characteristics		
Education	Years of education	9.59 (2.55)
College	=1 for college graduates and above, =0 for others	0.075 (0.26)
High school	=1 for high school graduates including vocation high school, =0 for others	0.32 (0.47)
Middle school	=1 for middle school graduates, =0 for others	0.50 (0.50)
Primary school	=1 for primary school graduates, =0 for others	0.10 (0.30)
Age	Age in years	29.8 (10.1)
Male	=1 for males, =0 for females	0.66 (0.47)
Married	=1 for whom married, =0 for whom unmarried	0.49 (0.50)
Health	Varies from 1 to 5 which 1 means has poor health and 5 means has excellent health	4.19 (0.73)
Performance	Varies from 1 to 5 which 1 means the worst and 5 means the best	3.21 (0.70)
Personality	=1 for those relatively extroversive, =0 for those relatively introversive	0.33 (0.47)
Work-related characteristics		
Turnover	=1 for those have changed work since coming out, =0 for those are not	0.38 (0.49)
Work time	Average work time in a week(*hour)*	60.70 (16.22)
Training	=1 for those received training, =0 for those not	0.29 (0.45)
Tenure	Working years for primary job	4.39 (4.36)
Experience	Years since coming out	8.73 (6.68)
Self-employed	=1 for those who are self-employed, =0 for those are not	0.18 (0.38)

Note: 1.Some dummy variables which are also very important are not listed above. They are Occupation, Catering, Accommodation, City, Company size.

2. Data source: RUMiC 2009.

Table 2

Descriptive statistics of three closest relation persons

	Definitions	Descriptive Statistics
Relationship		
Relationship1	Relationship with relation person 1	Relatives (33.6%), Friends (47.7%), Others (18.7%)
Relationship2	Relationship with relation person 2	Relatives (31.0%), Friends (47.8%), Others (21.2%)
Relationship3	Relationship with relation person 3	Relatives (27.6%), Friends (48.4%), Others (12.0%)
Interaction		
Type of help1	Received what kind of help from person 1	Financial (31.92%), Psychological (69.32%), Daily affairs (11.71%), No help (4.32%)
Type of help2	Received what kind of help from person 2	Financial (34.62%), Psychological (73.64%), Daily affairs (10.68%), No help (4.66%)
Type of help3	Received what kind of help from person 3	Financial (21.45%), Psychological (70.38%), Daily affairs (10.40%), No help (7.34%)
Frequency1	Frequency of contact with person 1	At least once a week (63.48%), At least once a month (57.75%), At least once a year (6.69%), Hardly ever (0.57%)
Frequency2	Frequency of contact with person 2	At least once a week (57.75%), At least once a month (34.49%), At least once a year (7.10%), Hardly ever (0.65%)
Frequency3	Frequency of contact with person 3	At least once a week (56.44%), At least once a month (33.17%), At least once a year (9.65%), Hardly ever (0.74%)
Moneyout1	Money/gifts/banquet given to person 1	Yes (30.6%), No (69.4%)
Moneyout2	Money/gifts/banquet given to person 2	Yes (26.6%), No (73.4%)
Moneyout3	Money/gifts/banquet given to person 3	Yes (25.6%), No (74.4%)
Moneyin1	Money/gifts/banquet received from person 1	Yes (30.0%), No (70.0%)
Moneyin2	Money/gifts/banquet received from person 2	Yes (25.5%), No (74.5%)
Moneyin3	Money/gifts/banquet received from person 3	Yes (24.2%), No (75.8%)
Individual characteristics		
Education1	Relation person 1's years of schooling	Mean(9.96), Deviation(3.14)
Education2	Relation person 2's years of schooling	Mean(9..63), Deviation(3.20)
Education3	Relation person 3's years of schooling	Mean(9.58), Deviation(3.22)
Residential_place1	Relation person 1's residential place	Countryside (16.77%), Same community (33.86%), Same city (29.48%), Same province (9.70%), Other province (10.19%)
Residential_place2	Relation person 2's residential place	Countryside (18.66%), Same community (30.97%), Same city (28.80%), Same province (9.11%), Other province (12.47%)
Residential_place3	Relation person 3's residential place	Countryside (17.99%), Same community (29.79%), Same city (29.95%), Same province (9.74%), Other province (12.54%)

Data source: RUMiC 2009.

Table 3

The effect of social network on the monthly income

	(1) lincome	(2) lincome	(3) lincome	(4) lincome	(5) lincome	(6) lincome	(7) lincome	(8) lincome
persons				0.000809*			0.00105**	0.000820
				(0.000447)			(0.000468)	(0.000716)
relatives					-0.00105			
					(0.00128)			
friends					0.00190***			
					(0.000523)			
helpers						0.00492*		
						(0.00226)		
age	0.0507***	0.0407***	0.0399***	0.0399***	0.0402***	0.0403***	0.0276***	0.0454***
	(0.00625)	(0.00572)	(0.00561)	(0.00560)	(0.00558)	(0.00563)	(0.00784)	(0.00793)
age2	-0.000753***	-0.000632***	-0.000608***	-0.000606***	-0.000611***	-0.000611***	-0.000433***	-0.000676***
	(0.0000853)	(0.0000774)	(0.0000751)	(0.0000750)	(0.0000747)	(0.0000752)	(0.000105)	(0.000104)
tenure	0.0415***	0.0347***	0.0325***	0.0326***	0.0328***	0.0325***	0.0279***	0.0331***
	(0.00618)	(0.00582)	(0.00593)	(0.00591)	(0.00594)	(0.00590)	(0.00726)	(0.00901)
tenure2	-0.00113***	-0.000906***	-0.000908***	-0.000917***	-0.000924***	-0.000914***	-0.000556	-0.00106***
	(0.000272)	(0.000250)	(0.000249)	(0.000248)	(0.000250)	(0.000248)	(0.000377)	(0.000333)
experience	0.00175	0.00490**	0.00406*	0.00404*	0.00403*	0.00401*	0.00297	0.00543*
	(0.00229)	(0.00216)	(0.00208)	(0.00207)	(0.00207)	(0.00207)	(0.00209)	(0.00327)
married	0.00335	0.00486	0.000761	0.00350	0.00787	0.00418	0.00619	-0.00203
	(0.0253)	(0.0238)	(0.0231)	(0.0231)	(0.0230)	(0.0230)	(0.0290)	(0.0349)
gender	0.159***	0.155***	0.120***	0.118***	0.116***	0.119***	0.124***	0.110***
	(0.0188)	(0.0180)	(0.0213)	(0.0211)	(0.0212)	(0.0212)	(0.0250)	(0.0303)
training	0.0801***	0.0660***	0.0673***	0.0658***	0.0650***	0.0644***	0.0223	0.0995***
	(0.0193)	(0.0183)	(0.0176)	(0.0174)	(0.0174)	(0.0173)	(0.0210)	(0.0268)
health	0.0499***	0.0362***	0.0382***	0.0378***	0.0382***	0.0385***	0.0273**	0.0412**
	(0.0125)	(0.0121)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0133)	(0.0175)
education	0.0304***	0.0243***	0.0212***	0.0206***	0.0204***	0.0206***	0.0137**	0.0246***
	(0.00415)	(0.00400)	(0.00419)	(0.00424)	(0.00421)	(0.00419)	(0.00471)	(0.00649)
worktime	0.00318***	0.00416***	0.00382***	0.00384***	0.00384***	0.00379***	0.0000628	0.00542***
	(0.000957)	(0.00101)	(0.00123)	(0.00124)	(0.00123)	(0.00123)	(0.000805)	(0.00187)
catering		Yes	Yes	Yes	Yes	Yes	Yes	Yes
accommodation		Yes	Yes	Yes	Yes	Yes	Yes	Yes
city		Yes	Yes	Yes	Yes	Yes	Yes	Yes
occupation			Yes	Yes	Yes	Yes	Yes	Yes
constant	5.601***	5.898***	5.772***	5.762***	5.760***	5.758***	6.387***	5.430***
	(0.127)	(0.127)	(0.131)	(0.131)	(0.131)	(0.132)	(0.163)	(0.182)
Observations	2807	2807	2807	2807	2807	2807	1233	1574
Adjusted R^2	0.146	0.266	0.300	0.301	0.303	0.302	0.398	0.298

Notes: 1. "Yes" represents that dummy variables catering, accommodation, city and occupation are controlled.

2. Numbers in parentheses are standard deviation. ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level;

Table 4

The effect of intra-network education spillover effect on the monthly income

	(1) lincome	(2) lincome	(3) lincome	(4) lincome	(5) lincome
gap1	0.00671**				
	(0.00280)				
gap2		0.00817**			
		(0.00376)			
gap3			0.0146***		
			(0.00519)		
average1				0.0152**	
				(0.00588)	
average2					0.0209**
					(0.0104)
age	0.0383***	0.0376***	0.0268***	0.0258***	0.0268***
	(0.00569)	(0.00708)	(0.00910)	(0.00919)	(0.00909)
age2	-0.000583***	-0.000560***	-0.000427***	-0.000410***	-0.000420***
	(0.0000759)	(0.0000940)	(0.000120)	(0.000121)	(0.000120)
tenure	0.0332***	0.0322***	0.0417***	0.0398***	0.0402***
	(0.00586)	(0.00843)	(0.0105)	(0.0107)	(0.0105)
tenure2	-0.000980***	-0.000886**	-0.00119***	-0.00111**	-0.00108**
	(0.000246)	(0.000375)	(0.000440)	(0.000439)	(0.000433)
experience	0.00477**	0.00526*	0.00836**	0.00806**	0.00782**
	(0.00213)	(0.00274)	(0.00334)	(0.00345)	(0.00343)
married	0.000195	-0.0145	-0.0206	-0.0164	-0.0234
	(0.0235)	(0.0292)	(0.0370)	(0.0377)	(0.0376)
gender	0.119***	0.112***	0.0868**	0.0891**	0.0960***
	(0.0212)	(0.0278)	(0.0331)	(0.0338)	(0.0339)
training	0.0701***	0.0786***	0.110***	0.111***	0.112***
	(0.0176)	(0.0219)	(0.0270)	(0.0270)	(0.0270)
health	0.0352***	0.0358**	0.0236	0.0281	0.0296
	(0.0116)	(0.0142)	(0.0171)	(0.0176)	(0.0175)
education	0.0259***	0.0269***	0.0317***	0.0321***	0.0359***
	(0.00437)	(0.00552)	(0.00805)	(0.00779)	(0.00817)
worktime	0.00367***	0.00463***	0.00618***	0.00633***	0.00600***
	(0.00123)	(0.00170)	(0.00230)	(0.00231)	(0.00229)
catering	Yes	Yes	Yes	Yes	Yes
accommodation	Yes	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes	Yes
occupation	Yes	Yes	Yes	Yes	Yes
constant	5.771***	5.710***	5.731***	5.699***	5.705***
	(0.129)	(0.166)	(0.216)	(0.215)	(0.209)
Observations	2682	1739	1143	1116	1137
Adjusted R^2	0.312	0.296	0.310	0.307	0.304

Notes: 1. “Yes” represents that dummy variables catering, accommodation, city and occupation are controlled;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level;

3. There existing some missing observations about migrant’s relation persons’ education, and the number of missing observations varies when we use the education level to replace years of schooling. So the observations in column (4) slightly differ with those in column (5), and this difference doesn’t affect out results.

Table 5

Gender difference of intra-network education spillover effect

	(1)Male lincome	(2)Female lincome	(3)Male lincome	(4)Female lincome	(5)Male lincome	(6)Female lincome	(7)Male lincome	(8)Female lincome
gap1	0.00739**	0.00582						
	(0.00358)	(0.00425)						
gap2			0.00954*	-0.00372				
			(0.00507)	(0.00589)				
gap3					0.0166**	0.00712		
					(0.00707)	(0.00640)		
average1							0.0164**	0.00158
							(0.00734)	(0.00941)
constant	5.925***	5.688***	5.846***	5.677***	5.747***	5.700***	5.740***	5.711***
	(0.163)	(0.257)	(0.211)	(0.294)	(0.292)	(0.345)	(0.285)	(0.352)
Observations	1763	919	1170	569	797	346	782	334
Adjusted R^2	0.283	0.373	0.270	0.378	0.289	0.465	0.283	0.464

Notes: 1. Only key variables are reported here, same other control variables in table 4 are controlled but not present due to the space limitation;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.

Table 6

Results propensity score matching

	gap1>0		gap2>0		gap3>0	
	ATT value	t-value	ATT value	t-value	ATT value	t-value
Nearest neighbor matching	0.0722	2.95	0.0601	2.00	0.119	3.17
Radius matching	0.0766	3.24	0.0403	1.37	0.0976	2.78
Kernel matching	0.0766	3.25	0.0396	1.29	0.106	2.88

Notes: 1.ATT values for control group not presented here due to the space limitation;

2. t-value>1.96 means the results are significant at the level 5%.

Table 7

Results of IV estimation

	(1) lincome	(2) lincome	(3) lincome
gap1	0.0703*		
	(0.0390)		
education	0.0615**		
	(0.0247)		
gap2		0.0986**	
		(0.0454)	
education		0.0780***	
		(0.0288)	
gap3			0.103*
			(0.0545)
education			0.0780**
			(0.0320)
F statistics of first stage	18.61	12.02	16.54
sargan statistics	0.15	0.85	0.43
Observations	2682	1739	1143

Notes: 1.The other control variables in table 4 are controlled but not presented due to space limitation.

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.

Table 8

Spillover effect of relatives and non-relatives

	(1) relatives	(2) non-relatives	(3) relatives	(4) non-relatives	(5) relatives	(6) non-relatives
gap1	0.00505	0.00749*				
	(0.00416)	(0.00391)				
gap2			-0.00528	0.0154***		
			(0.00695)	(0.00452)		
gap3					0.0142	0.0154***
					(0.0110)	(0.00554)
constant	5.646***	5.932***	6.133***	5.672***	5.501***	5.816***
	(0.248)	(0.146)	(0.368)	(0.192)	(0.505)	(0.216)
Observations	894	1788	535	1204	310	833
Adjusted R^2	0.314	0.351	0.325	0.364	0.356	0.406

Notes: 1. The other control variables in table 4 are controlled but not presented due to the space limitation;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.

Table 9

Spillover effect categorized by different type of helps received from the relation persons

	(1) psychological help	(2) financial help	(3) psychological help	(4) financial help	(5) psychological help	(6) financial help
gap1	0.00724**	0.00883*				
	(0.00337)	(0.00484)				
gap2			0.00898**	0.00403		
			(0.00401)	(0.00725)		
gap3					0.01000**	0.0191
					(0.00481)	(0.0105)
constant	5.739***	5.850***	5.693***	5.809***	5.823***	5.943***
	(0.157)	(0.232)	(0.184)	(0.325)	(0.233)	(0.445)
Observations	1871	852	1287	428	809	244
Adjusted R^2	0.350	0.312	0.355	0.261	0.389	0.351

Notes: 1. The other control variables in table 4 are controlled but not presented due to the space limitation;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.

Table 10

Spillover effect categorized by living distance

	(1) live near	(2) live far away	(3) live near	(4) live far away	(5) live near	(6) live far away
gap1	0.00763**	0.00846				
	(0.00379)	(0.00649)				
gap2			0.00517	0.00471		
			(0.00557)	(0.00692)		
gap3					0.0231***	0.00744
					(0.00852)	(0.00697)
constant	5.894***	5.166***	5.778***	5.520***	5.769***	5.443***
	(0.155)	(0.335)	(0.213)	(0.361)	(0.289)	(0.369)
Observations	1705	977	1048	490	681	462
Adjusted R^2	0.333	0.355	0.316	0.315	0.330	0.331

Notes: 1.The other control variables in table 4 are controlled but not presented due to the space limitation;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.

Table 11

Spillover effect categorized by contact frequency

	(1) frequently	(2) not frequently	(3) frequently	(4) not frequently	(5) frequently	(6) not frequently
gap1	0.00623*	0.00895				
	(0.00332)	(0.00872)				
gap2			0.00984**	0.0210		
			(0.00433)	(0.0155)		
gap3					0.0190***	0.0270**
					(0.00627)	(0.0132)
constant	6.084***	5.713***	5.778***	6.005***	6.087***	5.511***
	(0.145)	(0.525)	(0.213)	(0.192)	(0.294)	(0.377)
Observations	2495	187	1610	129	1022	121
Adjusted R^2	0.428	0.364	0.316	0.445	0.459	0.330

Notes: 1.The other control variables in table 4 are controlled but not presented due to the space limitations;

2. Numbers in parentheses are standard deviation, ***statistically significant at the 1% level; ** statistically significant at the 5% level; *statistically significant at the 10% level.