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Child Migration and the Health Status of Parents Left Behind

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Child migration and the health status of parents left behind

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Abstract

I investigate the causal effect of child migration on the health status of their parents left behind. I mainly focus on the respondents who are more than 50 years old and have only two children to simplify the situations of child migration. Using 2010 wave of China Family Panel Studies (CFPS), I employ propensity score matching method to correct the problem of self-selection and evaluate the causal effect of having migrant children on the health status of the elderly left behind. Results show that, in the case of one child migrating for work, child migration has no impact on the health status of their parents. As the substitutive relationship exists among child siblings, the child staying at home would provide more support to their parents and cancel out the impact of child migration. The incentive of free riding for migrant children is very strong, which reduces the benefit of remittances for the elderly.

Journal of Economic Literature Classification Numbers: D13, F24, I12, O15
Keywords: Self-selection, Migrant children, Health status, Free riding, Propensity score matching

1. Introduction

With the development of the economy, the economic inequality between eastern coastal areas and western inland areas in China is increasing and is becoming the main reason that young members of the labor force migrate to eastern coastal cities such as Beijing and Shanghai. Moreover, the acceleration of urbanization and the development of transportation systems are not negligible factors influencing the migration of young

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cohorts. Although out-migration facilitates the increase in economic growth, it also induces a great number of elderly people to be left behind. The issue of how to deal with elderly people who are left behind has attracted the interest of policymakers and economists. Because the social security systems in China are weakly developed, the elderly mainly depend on support from their adult children, including financial support, physical support, and emotional support. However, because the existence of a registration system limits access to health resources or other public resources for the elderly from emigrant areas, it is difficult for the elderly to accompany their adult children to eastern coastal cities (He & Ye, 2009). Child migration may reduce the provision of economic support (short-term) and physical and emotional support (long-term) for the elderly who are left behind, and thus may cause a deterioration of health status for frail parents. Because child migration prevails in many developing countries, such as China, a growing number of researchers are interested in the relationship between child migration and the health status of parents left behind.

Many previous studies have documented this topic. Marcus, Ruth, and Tobias (2015) and Kuhn, Everett, and Silvey (2011), provide some positive evidence that child migration increases the health status of the elderly left behind. Antman (2010), Antman (2016), Adhikari, Jampaklay, and Chamratrithirong (2011), Lian, Li, and Huang (2014), and Tse (2013) focus on the negative impacts of child migration, including physical health and mental health. Although researchers are interested in the causal effect of child migration on the health status of the elderly left behind, the endogeneity of child migration may contaminate estimation results. Thus, the main methodological obstacle of this topic is the issue of how to deal with the endogeneity of child migration. One of the causes of endogeneity is positive self-selection based on health status. This kind of self-selection may introduce some positive biases into the estimated results. For example, if child migration is positively selected based on the health status of adult children and their parents, unobservable common genetic or regional food culture factors that are positively associated with health status may induce some biases in the comparison between parents of migrants and those of non-migrants (Antman, 2016). If researchers cannot adequately control for positive self-selection, nonexperimental estimates will tend to overstate the household-level benefits of having members migrate (Gibson, Mckenzie, and Stillman, 2011). Certainly, the problem of simultaneity or reverse causation for adult migration may also exist. This is especially true for poor households, because they do not have sufficient economic resources to guarantee medical expenditure for their frail parents, and the decline of parents' health status forces adult children to migrate to obtain additional funds for medical services.

As discussed, the question of how to deal with the endogeneity problem of child migration is the core issue of this topic. Most previous studies try to make causal inferences using the instrumental variable (IV) method to correct the endogeneity bias of child migration. With the development of econometric analysis, propensity score matching (Kuhn et al., 2011) and FEIV (individual fixed effects and instrumental variables estimation, Antman (2011)) are also applied to control the endogeneity of migration. Especially by using a propensity score to match the treatment and control groups, researchers can conduct a quasi-experiment to deal with the issue of self-selection regarding child migration.

In the economics literature, remittances, as a potential channel to influence the health status of the elderly left behind, has attracted significant attention (Gibson et al., 2011; Marcus et al., 2015). Many previous studies indicate that remittances can increase the disposable income of the elderly and lead to improvements in diet or an increase in medical expenditure, which may potentially benefit the health status of the elderly (Adhikari et al., 2011; Marcus et al., 2015). On the other hand, some previous studies indicate that child migration may not increase the disposable income of the elderly left behind and may even lead to a reduction in household income per capita (Gibson et al., 2011). With the number of migrant children increasing, it has become more difficult to identify this potential channel.

Although intergenerational transfers from children to parents are considered the cultural norm of filial piety, in exchange, the elderly are expected to provide grandchild care for the migrants' children (Cong & Silverstein, 2011). By providing grandchild care, adult migrants can optimize their potential earnings and send more remittances to their parents (i.e., the elderly's decision to provide grandchild care services can be seen as a strategic investment with an expectation that children will reciprocate). This is consistent with the analysis of children as investment goods (Cochrane, 1975). If the burden of grandchild care exceeds the benefit of remittances, the decline of the health outcomes of the elderly may negatively influence child migration. Certainly, the provision of grandchild care services is also an altruistic act by the elderly for the betterment of the children of their progeny, and this hypothesis may temper the exchange process (Cong & Silverstein, 2011).

In addition to remittances and the provision of grandchild care services influencing the health status of the elderly left behind, the living arrangements of the elderly are very important factors for studying the problem of child migration. Per Connelly & Margaret (2016), the elderly who are alone in a village are most at risk, while those living with other non-migrant adult children are much less affected by migration. At the same time, informal social security networks of families are robust despite high opportunity costs, and they shield elderly people from some of the negative social consequences of large-scale child migration. Particularly in the context of developing countries, social security networks are weakly developed. The elderly are mainly dependent on support from their adult children. Consequently, child migration behavior may be conditioned on the cooperation of non-migrant children (Stohr, 2015). It is necessary to highlight the potential importance of including information on nonresident family members when studying the relationship between elder care requirements and the labor supply decisions of adult children (Giles & Ren, 2007).

With the increase of child migration and an aging population, researchers increasingly emphasize the causal effect of child migration on the health status of the elderly. Using diverse indicators such as self-reported health, BMI, depression, and ADL to evaluate the health status of the elderly left behind may help us detect other potential channels of child migration. Controlling for the endogeneity of child migration is another important issue. Although some previous studies use an IV design to deal with the endogeneity of child migration, most IVs do not satisfy the two criteria of IV analysis. It is necessary to find suitable IVs for child migration or use other econometric analysis techniques to correct the endogeneity bias, such as panel data analysis and propensity score matching (Antman, 2011; Antman, 2016; Kuhn et al., 2011). Furthermore, health investments, including smoking and drinking, are also considered to provide a potential channel for child migration to influence the health status of the elderly left behind. In the future, this channel should be addressed in an empirical analysis.

This paper examines the causal effect of child migration on the health status of parents left behind. As the number of migrant children increases, it is difficult to control all associated variables from migrant children. Thus, I mainly focus on respondents having two children to relieve the bias from adult children as much as possible. Using the 2010 wave of the China Family Panel Studies (CFPS), I employ the propensity score matching method to correct the issue of self-selection and evaluate the relationship between having migrant children and the health status of parents aged 50 and above who are left behind. According to our estimated results, in the case of one child migration, child migration has no impact on the health outcome of the elderly.

The remainder of this paper is arranged as follows. Section 2 introduces the hypotheses. Section 3 describes my econometric strategy. Section 4 introduces the data used in this study. Section 5 presents my empirical results, and section 6 shows the results of robustness check. Section 7 concludes the paper.

2. Hypothesis

Chen & Yoshida (2017) constructs a simple theory framework to explain the relationship between child migration and the health status of the elderly. The health status of the elderly is determined by the provision of informal care and formal care. The increases of wage for adult children benefit the health status of their parents. However, with the increase of children's number, it becomes difficult to detect this channel. And the existing of free riding behavior will also influence the relationship between child migration and the health status of the elderly. If migrant child is free riding on the behavior of providing informal care service, child migration may not influence the health status of the elderly. To obtain convincing evidence, I focus on the respondents having two children to reduce the potential bias from children.

Hypothesis: in the case of one child migrating for work, child migration would not influence the health status of the elderly left behind. According to Chen & Yoshida (2017), the elderly would benefit from child migration by receiving more remittances. However, in the case of one child migrating for work, the incentive of free riding for migrant child is very strong, because the other child would provide more informal care services. Thus, the health status of the elderly would not be influenced by child migration.

3. Data

3.1 Data source

The data used in this study comes from the CFPS. This longitudinal survey is a nationally representative sample of 14,960 families, including twenty-five provinces in Mainland China and designed and conducted by the Institute of Social Science Survey (ISSS) of Peking University. It adopts a stratified three-stage cluster sample design and uses administrative units and measures of socioeconomic development as the main stratification variables (Xie, Qiu, & Lu, 2012). The CFPS covers a wide range of topics, from the information of family structure to the information of individuals' attributes. CFPS collects the information of child migration including migrant places, whether transfers are provided to parents, whether grandchild care is provided for migrant children, and the health status of the elderly, and thus provides an opportunity to examine the impact of child migration on the health status of parents left behind. I use the baseline of CFPS to examine the effect of child migration, and respondents aged over 50 years are used in this study. I delete some respondents due to missing values of key variables. I also exclude some respondents having obviously incorrect information, such as a negative number of age. The statistical analysis software used is Stata/SE 14.

3.2 Outcome of health status

Table 2 shows the descriptive statistics of the full sample of data used in this study. I use self-reported health status to evaluate the health condition of parents left behind. Because the alternatives are defined as “1 Healthy,” “2 Fair,” “3 Relatively unhealthy,” “4 Unhealthy,” and “5 Very unhealthy,” the options are ordinal categories. It is unsuitable to treat self-reported health status as a continuous variable. Thus, I recode health outcome as a dichotomous variable, which is assigned a value of one if the respondent chooses “1 Healthy,” and otherwise zero. This new dependent variable is called “Health dummy”.

3.3 Pretreatment variables

CFPS collected affluent information associated with non-coresident children including the reasons for leaving home (1. study away from hometown; 2. out-migration for work; 3. monk; 4. visit friends or relatives; 5. in prison; 6. military service; 7. abroad; or 8. others). Consequently, I can use these details to construct child migration dummy variables. Because the number of migrant children increases, it is difficult to control all associated variables from migrant children. Thus, I mainly focus on the respondents having two children to relieve the bias from adult children as much as possible.

I construct two dummy variables to represent the compositions of child migration. Child migration 1 is assigned a value of one if the first child migrates for work and the second child stays in the hometown. Child migration 2 is assigned a value of one if the first child stays in the hometown and the second child migrates for work. By using the compositions of child migration status, I examine the substitutable relationship among child siblings. If this kind of substitutable relationship exists, the other siblings would provide support to their parents instead of their migrant sibling, and the health status of the elderly may not be negatively influenced by child migration.

Because remittances represent the main potential channel influencing the health status of the parents left behind, I try to consider the money transfers from children to their parents. Because only a few respondents give the exact amount of money transfer, I use a dummy variable to represent whether adult children give some money to their parents. Per Gibson et al. (2011), child migration does not always benefit the households. Especially at the beginning of migration, it is necessary to pay a huge cost to migrate, including transaction fees and the risk of unemployment. Therefore, child migration may reduce disposable income and adversely influence the health status of parents. To control this effect, I use a binary variable to stress whether the elderly parents provide money to their children.

For adult children, if they can receive some grandchild care from the elderly parents, they will have a chance to work outside and optimize their earning potential. For elderly parents, the decision of providing grandchild care services can be seen as a strategic investment with an expectation that their children will reciprocate or visit them more often. Certainly, it is possible that the burden of taking care of grandchildren would exceed the benefit of remittances, inducing a decline in health status for elderly parents. Accordingly, I construct a dummy variable to represent whether the elderly parents provide some grandchild care services for their grandchildren.

Regarding the characteristics of the elderly, I control for age (Age) and the quadratic form of age (Age squares/1,000) to capture the nonlinear trend. The male dummy is measured dichotomously: the variable takes the value of one for a male respondent and zero for a female respondent. We also control for household registration (Hukou dummy: agricultural=1 and non-agricultural=0) using a binary variable. Educational attainment is described by a binary variable indicating whether the respondents obtain a junior high school degree including higher degrees or not. The married dummy represents whether the respondent has a spouse currently (yes=1 and otherwise=0). The working dummy indicates whether the elderly member works currently (yes=1 and otherwise=0). Regarding economic conditions, we control the logarithm form of personal income from all sources in the last year (Lnincome). The chronic disease dummy represents whether the respondents have at least one kind of chronic disease (yes=1 and otherwise=0). Table 2 represents descriptive statistics of the full sample based on two situations of child migration.

4. Econometric Strategy

Our primary goal is to examine whether children migration can affect the health status of parents left behind. If child migration is randomly assigned among respondents, it is easy to obtain the causal effect by comparing the means of the migrant group and non-migrant group (Khandker, Koolwal, & Samad, 2010). However, as discussed in previous studies, child migration is an endogenous variable. The self-selection problem may introduce some biases into my estimated results. Moreover, I do not know the direction of potential bias. If child migrants are positively selected based on health, I should expect a bias toward finding that parents of migrants have better health outcomes than those of non-migrants. However, it is also possible that bad health outcomes force adult children to migrate. If so, I should expect bias toward finding that parents of migrants have worse health outcomes than those of non-migrants. Dealing with this self-selection problem is very important in evaluating the impact of child migration. A number of previous studies use IVs to correct the endogeneity bias of child migration. The most common IV approach uses macroeconomic variables, such as network-growth-interaction (Marcus et al., 2015; Stohr, 2015), unemployment rate (Lian et al., 2014), and U.S. city-level employment statistics in two industries popular with Mexican immigrants (Antman, 2013). However, such IVs, if they are available, typically identify only between-community variation in migration activity, not variation between households within the same community (Kuhn et al., 2011). Additionally, some scholars use the characteristics of children as IVs (Antman, 2016; Tse, 2013). However, these IVs seem to have direct effects on health and fail to satisfy the exclusion restriction. Table 1 represents several IVs used in empirical studies.

In this paper, I use a counterfactual framework to detect the causal effect of child migration on health outcomes of elderly parents left behind. The problem is that child migration's impact can truly be assessed only by comparing actual and counterfactual health outcomes. However, the counterfactual is not observed. Accordingly, the challenge is how to create a convincing and reasonable control group (Khandker et al., 2010). I employ the propensity score matching method to obtain a propensity score and match the child migrant group and a non-migrant group from multi-dimensions to one dimension.

By applying a logit model, I predict the probability of child migration as follows:

$$\Pr\ (\text{Child Migration}_i=1) = \Lambda\ (X_i) \qquad (1),$$

where X is the multi-dimensional vector of characteristics including Age, Age squares/1000, Male dummy, Rural dummy, Hukou dummy, Education dummy, Married dummy, Work dummy, Logarithm form of income (Lnincome), Chronic disease dummy, Age of first child, Gender of first child, Marital status of first child, Educational attainments of first child, Age of second child, Gender of second child, Marital status of second child, Educational attainments of second child, Support to child1 dummy, Support from child1 dummy, Grandchild care to child1 dummy, Support to child2 dummy, Support from child2 dummy, and Grandchild care to child2 dummy. Λ is the logistic cumulative distribution function. The propensity score is the predicted probability of logit model. Because the estimated propensity score is continuous, it is impossible to find two respondents with the same propensity score. Several matching methods are used in previous studies to deal with this problem. Nearest neighbor matching, radius matching, and kernel matching are widely used (Becker & Ichino, 2002). Based on the propensity score, I can create pseudo-randomized experimental data and make sure the treatment case is matched by one or several comparable counterfactual cases. Here, there is an important assumption called the "area of common support," which is necessary to be valid. In addition, the treatment group and control group are necessary to be statistically similar from propensity score to covariates. This is called the balancing assumption. I will check these two important assumptions in section 5.

When completing matching, I will calculate the average effect of treatment on the treated (ATT) by the differences in the potential outcomes of the treatment group and the control group as follows:

$$ATT=E(y_{1i}-y_{0i} \mid \text{child migration}_i=1)=E(y_{1i}|\text{child migration}_i=1)-E(y_{0i}|\text{child migration}_i=1) \quad (2),$$

where y_{1i} and y_{0i} represent the potential outcomes of the treatment group and control group, respectively. Child migration is a binary variable indicating the status of child migration.

5. Empirical results

5.1 Propensity score (50+ with two children)

To employ a propensity score matching approach, I first estimate propensity score by using several pre-treatment characteristics of respondents. To get a good specification of the model, I follow previous studies to control the covariates, including individual characteristics and the characteristics of children. In addition, remittance and grandchild care are potential channels influencing the health outcome of the elderly parents left behind. Therefore, I incorporate the Support to child1 dummy, Support from child1 dummy, Grandchild care to child1 dummy, Support to child2 dummy, Support from child2 dummy, and Grandchild care to child2 dummy. In this paper, I estimate the propensity score using a logit model.

Table 3 shows the estimation results with logit models, including first child migrating case, and second child migrating case. Because the purpose of estimating the propensity score is to match the treatment group and the control group, it is very important to improve the goodness of fit in a logit model. Although there is no straightforward criterion to follow, the pseudo-R^2 seems to be used widely in empirical studies. To get a good pseudo-R^2, I try to incorporate many associated factors mentioned in the literature. Based on the estimation results of Table 3, I find that Age, the Rural dummy, Hukou dummy, Child1 age, Child1 male dummy, Child1 education dummy, Child1 married dummy, Support from child1 dummy, Child2 male dummy, Child2 married dummy, and Grandchild care to child 2 dummy are good predictors for child migration. With the development of economy, the economic inequality between eastern coastal areas and western inland areas in China is increasing. More and more young cohorts living in rural area choose to work outside.

5.1.1 Sample matching results (50+ with two children)

In this part, I discuss the matching results based on the nearest neighbor matching method. Figure 1 shows the kernel density of the migration and non-migration groups before and after matching for the two cases. I find that before matching there are significant differences between migration and non-migration groups, indicating that migration and non-migration groups are totally different in the pre-treatment variables. After matching, the kernel density functions of migration and non-migration groups become closer. Based on Figure 1, I find that treatment observations have enough controlling observations nearby in the propensity score distribution. The important assumption of common support is satisfied.

5.1.2 Comparison of ATTS (50+ with two children)

Table 4 shows the estimation results of average treatment effect on the treated (ATT). To ensure the robustness of estimated results, I calculate the ATTS using three kinds of matching methods, including nearest neighbor matching, radius matching, and kernel matching. Becker and Ichino (2002) show the details of these matching methods. In addition, I use a bootstrap with 500 replications to obtain the standard errors of ATTs.

Regarding the results of one child migrating for work, the estimated coefficients are not statistically significant, consistent with my hypothesis. In the case of one child migrating, because the sibling staying at home can provide more support for the parents instead of the migrant child, the incentive of free riding is very strong for migrant children and they would only give few remittances to their parents. Because substitutable relationship exists among siblings, the health status of the elderly parents may not be influenced by one child migrating for work.

5.1.3 Balancing test results (50+ with two children)

Employing a propensity score matching analysis is necessary to test the balance between the treatment group and the control group. The balancing test results using the nearest-neighbor matching method are shown in Table 5. I find that there are significant differences between the treatment group and the control group. However, after matching, I find that the significant differences between the two groups disappear. None of the mean differences is statistically significant, indicating that the balancing assumption is satisfied in my paper.

5.2 The estimation results (60+with two children)

Although using 50+ with two children sample provide some convincing evidence to support my hypothesis, many respondents may not demand physical support from their migrant children. Next, I will use the respondents aged 60 years and older to further test my hypotheses, because the elderly parents are old enough to demand physical and emotional support from their children. I list the descriptive statistics of 60+ with two children sample in Table 6. To employ propensity score matching, I need to estimate the propensity score using a logit model. Regarding the pretreatment variables, I incorporate the same factors used in the previous analysis. The estimation results of the logit model are shown in Table 7. In the case of first child migrating, I exclude child1 male dummy due to collinearity.

Regarding the matching results, I mainly use the matching results of a nearest neighbor matching method. Figure 2 shows the kernel density of the migration and non-migration groups before and after matching for the three migrant cases. Before matching, there are significant differences in the two groups, indicating that migration and non-migration groups have large variance among the pre-treatment variables. By comparing the descriptive statistics shown in Table 6, I further confirm this fact. However, after matching, the kernel density functions of migration and non-migration groups become closer than before, especially in the lower propensity score. From Figure 2, I also confirm that the common support assumption is satisfied.

Table 8 shows the estimation results of ATTs based on nearest neighbor matching, radius matching, and kernel matching. None of estimation results is statistically significant providing convincing evidence for my hypothesis. In addition, I also confirm that the sequence of the child sibling migrating for work does not influence the health status of the elderly parents.

Regarding the results of the balancing test, I find that before matching there are huge differences between the treatment and control groups among the pre-treatment variables listed in Table 9. After matching, the results of the mean difference test show that the mean differences between the treatment and control groups are not statistically significant, indicating that the two groups match very well.

6. Robustness check

There is one disadvantage of propensity score matching method that I need to control associated variables as many as possible. However, there are some unobservable variables influencing child migration and health status of the elderly. This may introduce some bias into my estimation results. By using DID-PSM, I try to control some time-invariant unobservable variables and relieve the potential problem of propensity score matching method. To implement this robustness check, I use two-period panel data from 2010 and 2012 waves of CFPS. Regarding propensity score matching, I include the same pretreatment variables as above. The estimation results for first child migrating and second child migrating are shown in Table 10 and Table 11, respectively. Neither of estimation results is statistically significant providing convincing evidence for my hypothesis.

7. Discussion and conclusions

Out-migration for work prevails in developing countries such as China. The impact of child migration on the health status of elderly parents has become an important issue. However, regarding the impact of child migration, previous studies do not provide a definitive conclusion due to the problem of self-selection of child migration.

This study employs the propensity score matching method to estimate the impact of child migration on the health status of the elderly left behind, using data from the 2010 wave of the CFPS. Because the social security system of China is weakly developed, supporting the elderly in China mainly depends on adult children. Consequently, child migration influences the provision of economic support, physical support, and emotional support for the elderly and further influences the health status of elderly parents. Because a substitutive relationship among child siblings exists in most households, an increase in the number of child siblings complicates the issue of supporting the elderly. To simplify my analysis, I chose respondents aged 50 years and above with only two children as research objects. In this paper, one hypothesis is tested. Hypothesis: in the case of one child migrating for work, child migration would not influence the health status of the elderly left behind. According to my estimation results, I find enough convincing evidence to support my hypothesis. Although the existing of free riding behavior for migrant children reduces the transfers for their parents, the siblings staying in the hometown provide more informal care for their parents. Thus, one child migration has no impact on the health status of the elderly left behind.

Because the social security system is weakly developed, supporting the elderly depends mainly on adult children in China. With the implementation of the one child policy, the optimal number of children is limited. Traditional forms of support of the elderly have begun to collapse. However, with the enlarging of the economic gap between coastal areas and inland areas, an increasing number of young people are choosing to migrate for work. Therefore, we want to know how child migration influences the health status of the elderly left behind in China. These findings can provide evidence for policy making targeting the elderly who are left behind. Because Chinese government abolished one-child policy and allowed young couples to have two children, in the future more and more elderly Chinese people will have two children. Since the channel of remittance may positively influence the health outcome of the elderly, it is necessary to maintain access to the formal care market and the health care market for the elderly. If the elderly can easily purchase some services from the formal care market or the health care market, the benefit of remittances will be extended. However, the behavior of free riding may hinder the benefit of remittances. Therefore, how to deal with free riding is strongly associated with the health status of the elderly left behind.

Although this study provides some convincing evidence for the impact of child migration on the health status of the elderly left behind, there are some limitations. First, because I chose respondents having only two children as research objects to simplify the situation of child migration, the estimated results may not be applied to other situations. Second, the propensity score matching method uses observable pretreatment variables to estimate the propensity score. Although I incorporate many factors into the logit model, I cannot deal with the problem of omitted variables. In the future, other associated analysis methods should be used to deal with this issue.

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Table

Table 1 Endogeneity variables and Instrumental variables

Authors	Endogeneity Variable	Instrumental Variables	Region
Lian et al. (2014)	child migration	1. the urban unemployment rate 2. the change rate of employment structure (1985–2009)	China
Tse (2013)	child migration	1. the proportion of migration population in the village 2. the female proportion of the adult children	China
Antman (2016)	child migration	1. the fraction of female children 2. the fraction of married children	Mexico
Antman (2011)	paternal migration	1. U.S. city-level employment statistics in two industries popular with Mexican immigrants	Mexico
Hildebrandt and David (2005)	paternal migration	1. Historic state-level migration rate	Mexico
Marcus et al.	child migration	1. Network-growth interaction	Moldova

(2015)		2. Military base	
Stohr (2015)	child migration	1. Network-growth interaction 2. Network-growth interaction × number of children	Moldova

Table 2 Descriptive Statistics (50+ with two children)

	First child migrating		Second child migrating	
	Treatment	Control	Treatment	Control
Dependent variable				
Health dummy	0.372	0.364	0.341	0.366
	(0.484)	(0.481)	(0.475)	(0.482)
Individual characteristics				
Age	57.265	59.346	56.810	59.343
	(5.534)	(6.391)	(4.745)	(6.417)
Age squares/1,000	3.310	3.563	3.250	3.563
	(0.681)	(0.809)	(0.578)	(0.812)
Male dummy	0.609	0.509	0.527	0.516
	(0.489)	(0.500)	(0.501)	(0.500)
Rural dummy	0.719	0.526	0.732	0.528
	(0.450)	(0.499)	(0.444)	(0.499)
Hukou dummy	0.854	0.701	0.893	0.701
	(0.354)	(0.458)	(0.310)	(0.458)

Education dummy	0.154	0.129	0.117	0.132
	(0.362)	(0.335)	(0.322)	(0.339)
Married dummy	0.945	0.910	0.927	0.912
	(0.229)	(0.286)	(0.261)	(0.284)
Working dummy	0.561	0.413	0.556	0.416
	(0.497)	(0.493)	(0.498)	(0.493)
Lnincome	6.578	5.815	5.800	5.886
	(3.468)	(4.076)	(3.793)	(4.050)
Chronic disease dummy	0.202	0.203	0.210	0.202
	(0.402)	(0.402)	(0.408)	(0.402)
Child characteristics				
Child1 age	30.178	33.690	30.732	33.588
	(6.154)	(6.826)	(5.534)	(6.888)
Child1male dummy	0.850	0.636	0.546	0.662
	(0.358)	(0.481)	(0.499)	(0.473)
Child1education dummy	0.158	0.164	0.083	0.170
	(0.366)	(0.371)	(0.276)	(0.376)

Continued

Child1married dummy	0.581	0.834	0.839	0.811
	(0.494)	(0.372)	(0.368)	(0.392)
Support to child1 dummy	0.016	0.047	0.015	0.046
	(0.125)	(0.211)	(0.120)	(0.210)
Support from child1 dummy	0.087	0.077	0.020	0.082
	(0.282)	(0.267)	(0.139)	(0.275)
Grandchild care to child1 dummy	0.075	0.090	0.044	0.092
	(0.264)	(0.286)	(0.205)	(0.289)
Child2 age	28.589	30.727	27.020	30.806
	(6.805)	(7.237)	(5.361)	(7.277)
Child2 male dummy	0.395	0.543	0.810	0.510
	(0.490)	(0.498)	(0.393)	(0.500)
Child2 education dummy	0.107	0.192	0.171	0.186
	(0.309)	(0.394)	(0.377)	(0.389)
Child2 married dummy	0.696	0.707	0.454	0.725
	(0.461)	(0.455)	(0.499)	(0.447)
Support to child2 dummy	0.012	0.040	0.020	0.039
	(0.108)	(0.197)	(0.139)	(0.195)

Support from child2 dummy	0.059	0.077	0.024	0.080
	(0.237)	(0.267)	(0.155)	(0.271)
Grandchild care to child2 dummy	0.024	0.069	0.102	0.063
	(0.152)	(0.254)	(0.304)	(0.242)
Observations	253	2,719	205	2,676

Note: 1. Standard deviations are in the parentheses. 2. Data source: 2010 wave of China Family Panel Studies.

Table 3 The Estimation Results of Logit Models (50+ with two children)

	First child migrating	Second child migrating
Dependent variable	Childmigration1	Childmigration2
Individual characteristics		
Age	-0.302*	0.128
	(0.183)	(0.259)
Age squares/1000	2.392	-1.058
	(1.480)	(2.141)
Male dummy	0.121	-0.035
	(0.156)	(0.170)
Rural dummy	0.666***	0.421**
	(0.168)	(0.185)
Hukou dummy	0.354	0.970***
	(0.221)	(0.272)
Education dummy	0.230	0.127
	(0.212)	(0.254)
Married dummy	0.338	-0.125
	(0.305)	(0.301)

Working dummy	0.038	0.107
	(0.156)	(0.168)
Lnincome	0.037*	-0.018
	(0.021)	(0.021)
Chronic disease dummy	0.062	0.184
	(0.175)	(0.189)
Child Characteristics		
Child1 age	-0.076***	-0.041
	(0.022)	(0.029)
Child1male dummy	1.074***	-0.251
	(0.191)	(0.160)
Child1education dummy	0.229	-0.534*
	(0.212)	(0.288)
Child1married dummy	-1.012***	0.707***
	(0.171)	(0.228)
Support to child1 dummy	-0.727	0.079
	(0.632)	(0.760)

Continued

Support from child1 dummy	0.958***	-0.849
	(0.361)	(0.677)
Grandchild care to child1 dummy	0.409	-0.359
	(0.291)	(0.414)
Child2 age	0.020	-0.020
	(0.021)	(0.025)
Child2 male dummy	-0.448***	1.286***
	(0.146)	(0.189)
Child2 education dummy	-0.342	0.221
	(0.236)	(0.216)
Child2 married dummy	0.443**	-0.942***
	(0.194)	(0.197)
Support to child2 dummy	-0.030	-0.185
	(0.724)	(0.680)
Support from child2 dummy	-0.395	-0.638
	(0.403)	(0.629)
Grandchild care to child2 dummy	-0.556	1.632***
	(0.454)	(0.326)

Pseudo R2	0.142	0.157

Note: 1. Standard errors are in the parentheses. 2. ***, ** and * represent significance at 1%, 5%, and 10% levels, respectively.

Table 4 Estimation Results of ATT (50+ with two children)

	Matching method	ATT	Bootstrap S.E.	Z
First child migrated	Nearest neighbor matching	-0.017	0.047	-0.37
	Radius matching	-0.007	0.043	-0.17
	Kernel matching	-0.015	0.033	-0.46
Second child migrated	Nearest neighbor matching	0.016	0.054	0.30
	Radius matching	-0.017	0.052	-0.33
	Kernel matching	-0.018	0.039	-0.47

Note: 1. ***, ** and * represent significance at 1%, 5%, and 10% levels, respectively. 2. Standard errors are calculated using a Bootstrap with 500 replications.

Table 5 The Results of Balancing Test (50+ with two children)

		First child migrating			Second child migrating		
		Treatment	Control	t	Treatment	Control	t
Individual characteristics							
Age	U	57.265	59.346	-5.010***	56.810	59.343	-5.540***
	M	57.265	56.939	0.660	56.810	56.665	0.320
Age squares/1000	U	3.310	3.563	-4.820***	3.250	3.563	-5.420***
	M	3.310	3.273	0.610	3.250	3.232	0.330
Male dummy	U	0.609	0.509	3.050***	0.527	0.516	0.290
	M	0.609	0.572	0.840	0.527	0.520	0.130
Rural dummy	U	0.719	0.526	5.940***	0.732	0.528	5.670***
	M	0.719	0.719	0.000	0.732	0.738	-0.150
Hukou dummy	U	0.854	0.701	5.160***	0.893	0.701	5.900***
	M	0.854	0.868	-0.470	0.893	0.899	-0.220
Education dummy	U	0.154	0.129	1.130	0.117	0.132	-0.620
	M	0.154	0.129	0.810	0.117	0.112	0.150
Married dummy	U	0.945	0.910	1.880*	0.927	0.912	0.740
	M	0.945	0.949	-0.200	0.927	0.914	0.490
Working dummy	U	0.561	0.413	4.560***	0.556	0.416	3.910***

	M	0.561	0.568	-0.150	0.556	0.533	0.460
Lnincome	U	6.578	5.815	2.880***	5.801	5.886	-0.290
	M	6.578	6.646	-0.210	5.801	5.771	0.080
Chronic disease dummy	U	0.202	0.203	-0.050	0.210	0.202	0.250
	M	0.202	0.178	0.680	0.210	0.207	0.080
Child characteristics							
Child1 age	U	30.178	33.690	-7.890***	30.732	33.588	-5.800***
	M	30.178	30.231	-0.100	30.732	30.688	0.080
Child1 male dummy	U	0.850	0.636	6.880***	0.546	0.662	-3.380***
	M	0.850	0.850	0.000	0.546	0.515	0.630
Child1education dummy	U	0.158	0.164	-0.260	0.083	0.170	-3.250***
	M	0.158	0.136	0.710	0.083	0.098	-0.520
Child1married dummy	U	0.581	0.835	-10.050***	0.839	0.811	0.990
	M	0.581	0.560	0.480	0.839	0.837	0.040
Support to child1 dummy	U	0.016	0.047	-2.290**	0.015	0.046	-2.130**
	M	0.016	0.014	0.120	0.015	0.010	0.450
			Continued				
Support from child1 dummy	U	0.087	0.077	0.550	0.020	0.082	-3.240***
	M	0.087	0.080	0.270	0.020	0.021	-0.120
Grandchild care to	U	0.075	0.090	-0.800	0.044	0.092	-2.340**
child1 dummy	M	0.075	0.076	-0.060	0.044	0.042	0.080
Child2 age	U	28.589	30.727	-4.520***	27.020	30.806	-7.300***
	M	28.589	28.494	0.160	27.020	26.909	0.200
Child2 male dummy	U	0.395	0.543	-4.510***	0.810	0.510	8.400***
	M	0.395	0.406	-0.240	0.810	0.828	-0.470
Child2 education dummy	U	0.107	0.192	-3.350***	0.171	0.186	-0.530
	M	0.107	0.109	-0.100	0.171	0.164	0.180
Child2 married dummy	U	0.696	0.707	-0.390	0.454	0.725	-8.320***
	M	0.696	0.668	0.670	0.454	0.488	-0.690
Support to child2 dummy	U	0.012	0.040	-2.280**	0.020	0.039	-1.440
	M	0.012	0.013	-0.130	0.020	0.021	-0.120
Support from child2 dummy	U	0.059	0.077	-1.030	0.024	0.080	-2.880***
	M	0.059	0.053	0.320	0.024	0.020	0.340
Grandchild care to	U	0.024	0.069	-2.800***	0.102	0.063	2.230**
child2 dummy	M	0.024	0.020	0.300	0.102	0.101	0.050

Note: 1. ***, ** and * represent significance at 1%, 5%, and 10% levels, respectively.

Table 6 Descriptive Statistics (60+ with two children)

	First child migrating		Second child migrating	
	Treatment	Control	Treatment	Control
Dependent variable				
Health dummy	0.373	0.343	0.314	0.345
	(0.488)	(0.475)	(0.471)	(0.476)
Individual characteristics				
Age	66.176	66.299	65.114	66.335
	(4.934)	(5.310)	(4.490)	(5.313)
Age squares/1,000	4.403	4.424	4.259	4.429
	(0.676)	(0.743)	(0.614)	(0.743)
Male dummy	0.686	0.560	0.600	0.565
	(0.469)	(0.497)	(0.497)	(0.496)
Rural dummy	0.765	0.403	0.657	0.413
	(0.428)	(0.491)	(0.482)	(0.493)
Hukou dummy	0.902	0.531	0.829	0.540
	(0.300)	(0.499)	(0.382)	(0.499)
Education dummy	0.039	0.142	0.086	0.139

	(0.196)	(0.349)	(0.284)	(0.346)
Married dummy	0.882	0.847	0.829	0.850
	(0.325)	(0.360)	(0.382)	(0.357)
Working dummy	0.392	0.220	0.457	0.221
	(0.493)	(0.415)	(0.505)	(0.415)
Lnincome	6.571	5.540	5.029	5.613
	(3.109)	(4.178)	(3.454)	(4.158)
Chronic disease dummy	0.216	0.235	0.286	0.232
	(0.415)	(0.424)	(0.458)	(0.422)
Child characteristics				
Child1 age	37.078	39.801	37.971	39.725
	(6.925)	(6.457)	(6.041)	(6.517)
Child1male dummy	1.000	0.705	0.743	0.719
	(0.000)	(0.456)	(0.443)	(0.450)
Child1education dummy	0.098	0.173	0.029	0.175
	(0.300)	(0.379)	(0.169)	(0.380)
	Continued			
Child1married dummy	0.784	0.893	0.914	0.887
	(0.415)	(0.309)	(0.284)	(0.317)
Support to child1 dummy	0.078	0.133	0.086	0.132
	(0.272)	(0.339)	(0.284)	(0.338)
Support from child1 dummy	0.431	0.219	0.114	0.234
	(0.500)	(0.414)	(0.323)	(0.424)
Grandchild care to child1 dummy	0.373	0.256	0.257	0.262
	(0.488)	(0.437)	(0.443)	(0.440)
Child2 age	35.941	37.020	33.314	37.097
	(8.310)	(6.692)	(6.493)	(6.759)
Child2 male dummy	0.529	0.550	0.943	0.534
	(0.504)	(0.498)	(0.236)	(0.499)
Child2 education dummy	0.078	0.208	0.057	0.207
	(0.272)	(0.406)	(0.236)	(0.405)
Child2 married dummy	0.824	0.887	0.800	0.887
	(0.385)	(0.317)	(0.406)	(0.317)
Support to child2 dummy	0.059	0.115	0.114	0.112
	(0.238)	(0.319)	(0.323)	(0.316)
Support from child2 dummy	0.294	0.219	0.143	0.226

	(0.460)	(0.414)	(0.355)	(0.419)
Grandchild care to child2 dummy	0.118	0.196	0.600	0.178
	(0.325)	(0.398)	(0.497)	(0.383)
Observations	51	957	35	973

Note: 1. Standard deviations are in the parentheses.2. Data source: 2010 wave of China Family Panel Studies.

Table 7 Estimation Results of Logit Model (60+ with two children)

	First child migrating	Second child migrating
Dependent variable	Childmigration1	Childmigration2
Individual characteristics		
Age	0.512	0.212
	(0.639)	(0.906)
Age squares/1000	-3.224	-1.422
	(4.639)	(6.638)
Male dummy	0.185	0.006
	(0.362)	(0.436)
Rural dummy	0.918**	0.216
	(0.384)	(0.438)
Hukou dummy	1.530***	1.491***
	(0.578)	(0.641)
Education dummy	-0.891	0.907
	(0.841)	(0.775)
Married dummy	0.392	-0.380
	(0.518)	(0.545)
Working dummy	0.015	0.234

	(0.347)	(0.454)
Lnincome	0.099**	-0.056
	(0.049)	(0.052)
Chronic disease dummy	0.047	0.827*
	(0.387)	(0.450)
Child Characteristics		
Child1 age	-0.100**	0.050
	(0.041)	(0.062)
Child1male dummy	-	0.297
		(0.471)
Child1education dummy	0.419	-0.945
	(0.602)	(1.147)
Child1married dummy	-0.846*	0.883
	(0.435)	(0.710)
Support to child1 dummy	-0.209	0.311
	(0.705)	(0.859)
	Continued	
Support from child1 dummy	1.039***	-0.623
	(0.392)	(0.786)
Grandchild care to child1 dummy	0.935***	-0.270
	(0.350)	(0.472)
Child2 age	0.074*	-0.103*
	(0.038)	(0.055)
Child2 male dummy	-0.093	2.225***
	(0.331)	(0.759)
Child2 education dummy	-0.372	-0.613
	(0.605)	(0.835)
Child2 married dummy	-0.488	-1.006*
	(0.479)	(0.552)
Support to child2 dummy	0.043	0.078
	(0.806)	(0.760)
Support from child2 dummy	-0.271	-0.532
	(0.423)	(0.734)
Grandchild care to child2 dummy	-0.490	2.160***
	(0.494)	(0.465)

Pseudo R2	0.197	0.293

Note: 1. Childmigration1, which is also a discrete variable, equals one if the first child migrated for work and the second child stays at home, and zero otherwise; The definition of Childmigration2 is similar to Childmigration1, equals one if the second child migrated for work and the first child stays at home, and otherwise 0. 2. ***, ** and * represent significance at 1%, 5% and 10% level, respectively. 3. Standard errors are in the parentheses. 4. Child1male dummy is excluded due to collinearity.

Table 8 Estimation Results of ATT (60+ with two children)

	Matching method	ATT	Bootstrap S.E.	Z
First child migrating	Nearest neighbor matching	0.065	0.106	0.62
	Radius matching	0.076	0.138	0.55
	Kernel matching	-0.010	0.093	-0.11
Second child migrating	Nearest neighbor matching	-0.029	0.125	-0.23
	Radius matching	0.070	0.203	0.34
	Kernel matching	0.027	0.108	0.25

Note: 1. ***, ** and * represent significance at 1%, 5%, and 10% levels, respectively. 2. Standard errors are calculated using a Bootstrap with 500 replications.

Table 9 Balancing Test (60+ with two children)

		First child migrating			Second child migrating		
		Treatment	Control	t	Treatment	Control	t
Individual characteristics							
Age	U	66.176	66.299	-0.160	65.114	66.335	-1.340
	M	66.176	66.869	-0.680	65.114	64.476	0.650
Age squares/1000	U	4.403	4.424	-0.190	4.260	4.429	-1.330
	M	4.403	4.500	-0.680	4.260	4.171	0.660
Male dummy	U	0.686	0.560	1.770*	0.600	0.565	0.410
	M	0.686	0.595	0.960	0.600	0.590	0.080
Rural dummy	U	0.765	0.403	5.150***	0.657	0.413	2.880***
	M	0.765	0.752	0.150	0.657	0.695	-0.340
Hukou dummy	U	0.902	0.531	5.260***	0.829	0.540	3.390***
	M	0.902	0.902	0.000	0.829	0.819	0.100
Education dummy	U	0.039	0.142	-2.090**	0.086	0.139	-0.900
	M	0.039	0.020	0.580	0.086	0.048	0.630
Married dummy	U	0.882	0.847	0.680	0.829	0.850	-0.350
	M	0.882	0.810	1.000	0.829	0.800	0.300
Working dummy	U	0.392	0.220	2.850***	0.457	0.221	3.280***

	M	0.392	0.399	-0.070	0.457	0.419	0.320
Lnincome	U	6.571	5.540	1.740*	5.029	5.613	-0.820
	M	6.571	5.901	1.020	5.029	5.848	-0.920
Chronic disease dummy	U	0.216	0.235	-0.320	0.286	0.232	0.730
	M	0.216	0.183	0.410	0.286	0.229	0.540
Child characteristics							
Child1 age	U	37.078	39.801	-2.920***	37.971	39.725	-1.570
	M	37.078	37.510	-0.290	37.971	37.629	0.250
Child1 male dummy	U	-	-	-	0.743	0.719	0.300
	M	-	-	-	0.743	0.657	0.770
Child1 education dummy	U	0.098	0.173	-1.400	0.029	0.175	-2.270**
	M	0.098	0.059	0.730	0.029	0.029	0.000
Child1married dummy	U	0.784	0.893	-2.410**	0.914	0.887	0.500
	M	0.784	0.758	0.310	0.914	0.933	-0.300
Support to child1 dummy	U	0.078	0.133	-1.120	0.086	0.132	-0.790
	M	0.078	0.072	0.120	0.086	0.076	0.140
			Continued				
Support from child1 dummy	U	0.431	0.219	3.520***	0.114	0.234	-1.660*
	M	0.431	0.438	-0.070	0.114	0.133	-0.240
Grandchild care to	U	0.373	0.256	1.850*	0.257	0.262	-0.070
child1 dummy	M	0.373	0.399	-0.270	0.257	0.200	0.560
Child2 age	U	35.941	37.020	-1.110	33.314	37.097	-3.260***
	M	35.941	37.105	-0.750	33.314	32.714	0.400
Child2 male dummy	U	0.529	0.550	-0.280	0.943	0.534	4.820***
	M	0.529	0.484	0.460	0.943	0.943	0.000
Child2 education dummy	U	0.078	0.208	-2.250**	0.057	0.207	-2.170**
	M	0.078	0.078	0.000	0.057	0.038	0.370
Child2 married dummy	U	0.824	0.887	-1.380	0.800	0.887	-1.580
	M	0.824	0.869	-0.640	0.800	0.771	0.290
Support to child2 dummy	U	0.059	0.115	-1.240	0.114	0.112	0.040
	M	0.059	0.059	0.000	0.114	0.124	-0.120
Support from child2 dummy	U	0.294	0.219	1.250	0.143	0.226	-1.160
	M	0.294	0.294	0.000	0.143	0.171	-0.320
Grandchild care to	U	0.118	0.196	-1.390	0.600	0.178	6.340***
child2 dummy	M	0.118	0.118	0.000	0.600	0.629	-0.240

Note: 1. ***, ** and * represent significance at 1%, 5%, and 10% levels, respectively.

Table 10 DID-PSM estimation results for first child migrating (50 years old with two children)

	Control	Treated	Diff (T-C)	Standard Errors	t
Baseline	0.387	0.372	-0.015	0.017	-0.88
Follow-up	0.064	0.045	-0.019	0.032	-0.6
Diff-in-Diff			-0.004	0.037	-0.12

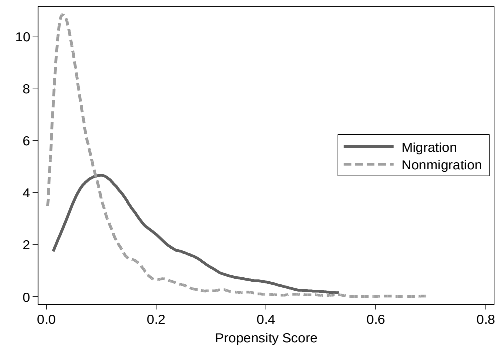
Table 11 DID-PSM estimation results for second child migrating (50 years old with two children)

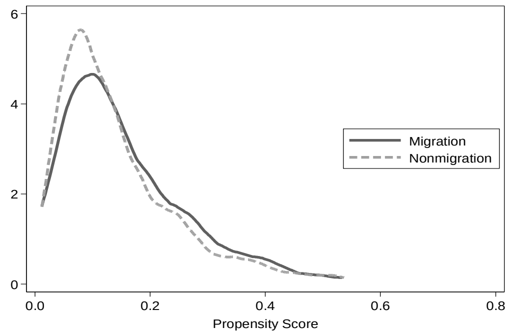
	Control	Treated	Diff(T-C)	Standard Errors	t
Baseline	0.352	0.341	-0.011	0.017	-0.63
Follow-up	0.062	0.049	-0.013	0.029	-0.46
Diff-in-Diff			-0.003	0.034	-0.08

Figures

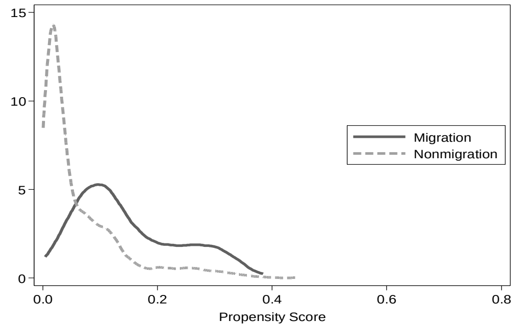
Figures 1 Kernel Density of the Migration and Non-migration Groups (50+ with two children)

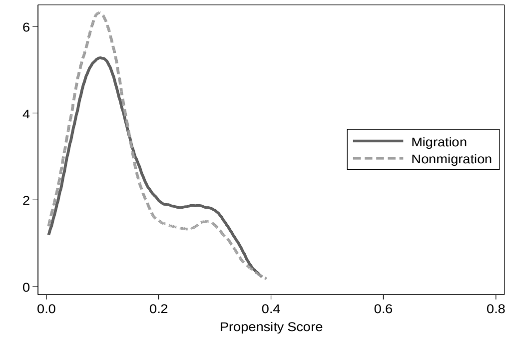
(1) Before Matching first child migrating (2) After Matching





(3) Before Matching second child migrating (4) After Matching

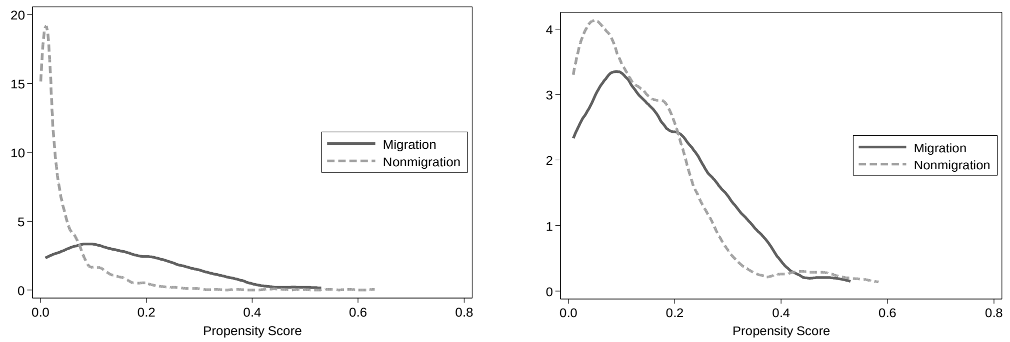




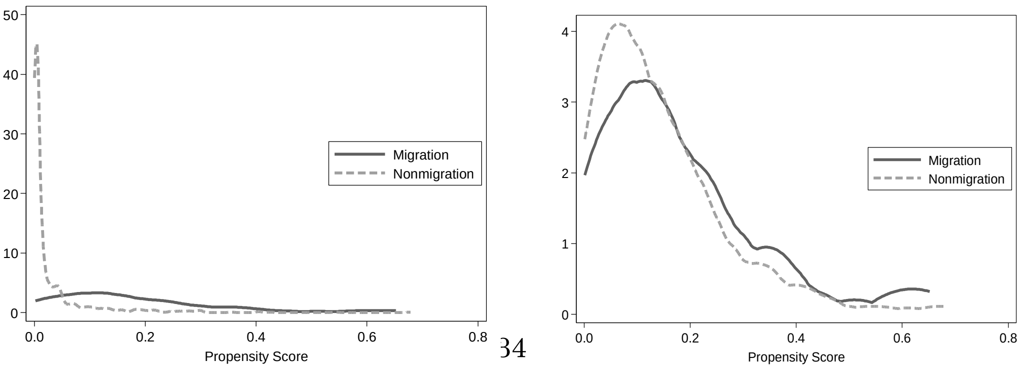
Note: 1) Matching method is nearest neighbor matching.

Figures 2 Kernel Density of the Migration and Non-migration Groups (60+ with two children)

(1) Before Matching first child migrating (2) After Matching



(3) Before Matching second child migrating (4) After Matching



Note: 1) Matching method is nearest neighbor matching.