Return of Migrant Workers, Educational Investment in Children and Intergenerational Mobility in China

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Abstract

The slowdown in China's economic growth in the past decade has forced many migrant workers to return or plan to return to their rural hometowns temporarily. Extant studies on intergenerational mobility pay less attention to temporary migrant households. This paper investigates how migrant father's return intention influences children's educational outcomes and permanent incomes using a high-quality nationwide dataset of China (CLDS2012-2018). It finds that though there is no significant correlation between fathers' and children's educational attainments, the higher the return probability of the father, the less educational investment he would make in his child. This paper contributes to the literature in two ways: theoretically, it provides a new perspective to observe the intergenerational mobility of migrant workers; and methodologically, it corrects life cycle bias by controlling for the ages of fathers and children and using multi-year mean incomes.

Keywords: intergenerational mobility, migrant workers, return migration, educational investment, intergenerational income elasticity, China

JEL Classification: E24, J61, O15

1. Introduction

Internal migration from countryside to cities is one of the most important characteristics of labour mobility in China since 1990s. In the past three decades, millions of rural labour force have emigrated resulting from continuing economic expansion in cities and the enormous disparities in infrastructure between urban and rural China. According to the World Migration Report (IOM 2018), Chinese internal migrants (mainly referring to migrant workers) reach 277 million in 2015, 33 million more than the total international migrants in the world. However, as China's economic growth is slowing down in past 10 years, the National Development and Reform Commission of China reports that in 2016 alone, 7.4 million migrant workers returned to their hometowns to set up their businesses.[1] Revealing by the statistics of Chinese Household Income Project (CHIP 2013), more than half of the migrant families currently living in cities plan to return in the next five years.[2] This kind of migration is regarded as temporary migration because these migrant workers do not intend to live permanently in host cities (Dustmann 1997, 1999; Dustmann and Weiss 2007; Dustmann and Görlach 2016).

The behavior of temporary migration not only has an immediate effect on their own earnings, wealth accumulation and skill composition, but also on their offspring's human capital accumulation and earnings. Assessing intergenerational mobility of migrant households is one of the important approaches to understand the influence of migration, as such, it has attracted the attention of many scholars. The extant research on intergenerational mobility in China mainly presents two characteristics:

On the one hand, most studies on the intergenerational mobility separately either focus on urban (e.g. Gong et al. 2010; Deng et al. 2012; Qin et al. 2016) or rural households (e.g. Chyi et al. 2014; Chen et al. 2015; Wu et al. 2019), only few focus on the "dual marginal people" in China (e.g. Démurger and Xu 2011; Xu 2015; Jiang 2017).[3] In other words, we know little with regards to intergenerational mobility of migration families as "dual marginal people" in China. Intergenerational income elasticity (IIE) is commonly used to measure intergenerational income mobility, which is equal to $1 - IIE$.[4] In China, relevant studies report that China's IIE ranges between 0.40 and 0.60 and discover the intergenerational mobility is comparatively higher in rural areas compared with that in urban areas (e.g. Chyi 2014; Xu 2015). So far, in the study of intergenerational

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[1] It is the National Development and Reform Commission's estimate based on the sample survey, available from http://www.xinhuanet.com/finance/2018-07/25/c_1123176883.htm .

[2] The data are from the samples of migrant workers in the Chinese Household Income Project (CHIP) conducted in July and August 2014.

[3] The "double marginal people" means migrant workers move back and forth like migratory birds between city and countryside because they cannot integrate into the mainstream society of city but also lose dependence on agriculture and the countryside.

[4] The smaller the IIE, the higher the intergenerational income mobility is.

mobility, migrant workers have been more or less ignored, and few literatures measure the intergenerational income elasticity of migrant workers, which is exactly what this paper is trying to make up.

On the other hand, most of the studies on investigating intergenerational income mobility and its transmission channels (see Gang and Zimmermann 2000; Mazumder 2005; Bjørklund et al. 2006; Aaronson and Mazumder 2008; Blanden 2013; Nicolas and Guyonne 2016) focus on intergenerational transmission through education and other human capital, with a growing attention paid to social capital. Up to now, most studies have found that education and occupation are the two dominant channels in the process of intergenerational income transmission(Yan and Deng 2022;Wang et al. 2022;Duan et al. 2022). In addition, it is worth noting that some recent literature has revealed that government expenditure plays a crucial role in the intergenerational income transmission process(Le et al. 2021;Huang et al. 2021). However, these studies still target urban households and rural households, and we still remain ignorant of the intergenerational income transmission channels for migrant families. It is necessary to explore the intergenerational mobility and its transmission mechanism of migrant families as they are different, compared to that for purely with urban or rural families, and therefore it is also urgent to have more studies on this topic because China is now at a turning point facing economic downturn with more and more migrant families intend to return to their hometowns in a foreseeable future.

Compared to relevant research conducted in other countries (e.g. Dustmann 2008; Yuksel 2009; Vogt and Kluge 2015; Bolotnyy 2018; Raj and Nathaniel 2018; Raj et al. 2020;Sandra et al. 2020), there are questions unanswered in China with respect to intergenerational mobility of migrant workers. For example, for migrant workers as the “dual marginal people”, how much is their income related to the offspring's income? Will the educational attainment of fathers directly affect their children? How to correct life-cycle income bias and endogeneity effectively in the process of measuring the IIE?[1] Will IIE be different from income groups? In response to these questions, we attempt to focus on one characteristic that may affect the process of intergenerational mobility: the return probability. In this paper, we investigate how fathers’ return probabilities, as opposed to a permanent migration intention, affect investment in their children’s education and intergenerational income mobility. Adopting migrant households survey data from the China labour-force

[1] Nybom and Stuhler (2011) state it will result in what is known as a life-cycle bias if a snapshot of income over a shorter period is not used in the estimates of intergenerational mobility to simulate the results of lifetime. The estimate of intergenerational earnings mobility always suffers from the measurement problem since researches do not observe permanent and lifetime earnings (Grawe 2006). Various refined methods to address such life-cycle bias have recently been presented. Particularly, Haider and Solon (2006) propose a tractable generalization of the classical errors-in-variables model.

Dynamics Survey (CLDS 2012-2018), this paper expands the relationship between return probability of the father and his investment in children's education, as well as the intergenerational economic correlation. In the empirical analysis, we will discuss possible endogenous and heterogeneous problems and use instrumental variables (IV) to reduce possible biases.

This paper contributes to the literature from two aspects. Theoretically, it provides a new perspective to analyze the intergenerational mobility of migrant workers. Instead of investigating the human capital correlation between fathers and children through educational channels which is well-documented in the existing literature, we focus on the influence of father's return intention on his child's human capital. Methodologically, it takes heterogeneity and endogeneity in IIE estimates into account and corrects life-cycle bias by controlling for the ages of fathers and children and using multi-year mean incomes. In order to distinguish the heterogeneity of intergenerational mobility, this paper estimates IIE by differentiating father's incomes, regions and different distances from the nearest county town and schools, while trying to solve the endogeneity by using the proportion of migrant workers in hometown as an instrumental variable.

The remainder of this paper is organized as follows. In the next section, we commence a two-stage theoretical model to demonstrate the relationship between the return probability and father's educational investment in children, then discuss its empirical implications. Section 3 describes the data and estimate methods. Section 4 presents the basic regression results, and Section 5 places the discussion of endogeneity, heterogeneity and robustness. The last section concludes the paper and highlights its limitations.

2. Theoretical model

Dustmann et al. (2016) hold the view that internal migration mechanisms are largely similar with that of international migration from developing to developed countries. Following early work of Solon (1992, 2002, 2014), Dustmann (2008) and Dustmann and Görlach (2016), this paper attempts to build a model of intergenerational income mobility in order to investigate the intergenerational transmission mechanism from father to children. The model includes father's return probability and educational investment in his children, which extends Solon (2002, 2014) model by considering that it is the father's return probability (rather than the return on human capital) may affect the father's decision on investing in his child's education.[1] The main differences between this model and Dustmann (2008) model are: (1) we do not pay attention to the father's decision to settle down permanently in city, but examine his decision to return whenever possible; (2) we focus on internal rather than cross-border migration, and consequently there is no purchasing power difference associated with exchange rates.

2.1 Objective function

Considering a representative family which only has one child and one father who has emigrated to a city. There are two periods for the family: in the first period (Period 1) both father and child live in the city; the return probability of father in the second period (Period 2) is p, and the corresponding probability of father remaining in the city is $1-p$.

The father's income in Period 1 is y_1 and has no income after retires in Period 2. His child receives full-time education in Period 1 and earns revenue in Period 2, either in the hometown or in the city.

Presuming that the father is altruistic and wants to maximize his intertemporal utility function by determining the saving S_1 in the first period and the educational investment in child I_1. Giving the following intertemporal utility function of the father as:

(1) $U = u(c_1) + p[u(u_2^H) + \gamma v(y_2^H)] + (1-p)[u(c_2^C, b) + \gamma v(y_2^C)]$

where $u(\cdot)$and $v(\cdot)$ are the utility functions of father and child, respectively. The meanings of each variable are defined as follows: c_1 is the consumption of father in Period 1, c_2^j and y_2^j are the consumption of father and the income of child in Period 2, and j is the working location, e.g. $j = H$ if they live in hometown or $j = C$ if they live in city. γ is the degree of altruism; for example, $\gamma = 0$ means father does not consider his child's welfare at all in Period 2. The parameter b is the preference degree of the father and child to consume in different location, indicating the consumption location preference in hometown or city. For example, if $b > 1$,

[1] To keep the results comparable, we follow Dustmann (2008) approach that educational investment is measured by educational attainment. Some Chinese scholars also support family educational investment is a strong predictor of children's educational attainment in rural China (Xu 2015; Qin 2016).

the utility obtained from consumption in hometown will be more than in city.

The father's investments I_1 in education translate into the child's human capital h_2 according to the following human capital accumulation equation:

(2) $h_2 = \theta log I_1 + e_1$

The parameter θ is a technology parameter measuring the conversion rate of educational investment. The term e_1 is human capital of child without father's direct investment. In the similar human capital accumulation equation given by Solon (2002), it is related to the family environment and depicts the human capital brought by the father's personality, the child's talent, upbringing, genes, environment and even luck. Human capital converts into child's income through the following function:

(3) $\log y_2^j = \mu^j + r^j h_2$

where $j = H; C$, refers to his hometown or the city where he currently lives. This equation allows children to obtain different basic income μ^j, as well as different rates of returns to human capital r^j in different places. By substituting equation 2 into equation 3, we can associate the earnings of child in the second period y_2^j with the investment of family education in the first period I_1, and get:

(4) $\log y_2^j = \mu^j + r^j \theta \log I_1 + r^j e_1$

The father's consumption in period 1 is $c_1 = y_1 - I_1 - S_1$, where y_1 is the father's income in Period 1. When the father retires in Period 2, the consumption in Period 2 is his savings in Period 1. Choosing a relatively simple logarithmic utility function form, and let equation 4 be substituted into equation 1, the optimization problem of the father can be expressed as:

(5) $$\max U = \log(y_1 - I_1 - S_1) + p[\log S_1 + \gamma(\mu^H + r^H \theta \log I_1 + r^H e_1)]$$
$$+(1-p)[b\log S_1 + \gamma(\mu^C + r^C \theta \log I_1 + r^C e_1)]$$

2.2 Optimal educational investment

Referring to the constraint equation of savings and investment $c_1 = y_1 - I_1 - S_1$, maximizing equation 5 and solving the first-order condition for the optimal educational investment I_1^* can be expressed as:

$$(6) \quad I_1^* = \frac{\gamma\theta[pr^H+(1-p)r^C]}{\gamma\theta[pr^H+(1-p)r^C]+[2-p+bp]}y_1 = \Phi(p; r^H, r^C, b, \gamma, \theta)y_1$$

The first term in the denominator is equal to the numerator, which represents the expected utility obtained by father's investment in human capital with a logarithmic unit for his child. The second term in the denominator is the expected utility generated by an additional unit of consumption.

Observing equation 6, the relationship between the optimal educational investment I_1^* and the probability p of returning to hometown can be obtained through simple calculation:

$$(7) \quad \frac{\partial I_1^*}{\partial p} = \frac{\gamma\theta[2r^H-(1+b)r^C]}{[p(\gamma\theta\alpha+b-1)+\gamma\theta r^C+2]^2}y_1$$

China bears obvious urban-rural dual economy characteristics due to historical reasons, which results in two consequences. One is the rate of return to human capital in cities is significantly higher than that in rural areas,[1] which means $r^C > r^H$. The other is the prices and consumption level in urban areas are also significantly higher than that in rural areas. Consequently, the real purchasing power of isoquant money is higher in hometown. Additionally, consumption in hometown is likely to be more conspicuous than in cities because migrant workers may feel superiority among their peers given that prices are lower in hometowns.[2] Both reasons tend to increase the corresponding utility level in hometown, which implies $b > 1$. These two inequalities are clearly true based on some documents (Deng et al. 2012; Xu 2015; Qin et al. 2016; IOM 2018). Therefore, it can be found that $\frac{\partial I_1^*}{\partial p} < 0$ when: (1) the rate of return to human capital in city is higher than the rate in hometown ($r^C > r^H$) and (2) the father and his child prefer to consume in hometown ($b > 1$).

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1 According to the China National Bureau of Statistics, the average earning in urban areas is 2.8 times higher than that in rural areas in 2018 (http://www.stats.gov.cn/tjsj/zxfb/201901/t20190121_1645791.html).

2 Huang & Wang(2018) find that migrant workers in emerging markets have conspicuous consumption characteristic, their conspicuous consumption is mainly driven by the bandwagon effect to associate with aspiration group, differing from those more privileged consumers who may engage in conspicuous consumption to disassociate from the crowd.

The negative sign of the first partial derivative indicates that father's investment in child's education will decrease with the increase of the father's propensity to return. In other words, the higher return probability will lead to father's less investment in his child's education, thus obtaining a higher intertemporal total utility. At this point, the father tends to save more resources for his own future consumption and decreases educational investment in his children. It is noticed that this reduction is also associated with γ and θ.

2.3 Measurement equation

A more simplified formula can be obtained by taking the logarithm of equation 6 and adding an error term:

$$(8) \quad \log childedu_i = a_1 + a_2 P_i + a_3 X_1 + b \log Y_{ifather} + e_i$$

where $childedu_{ic}$ measures child's educational attainment and P_i is returning possibility of his migrant father, X_1 is the control variables vector, $Y_{ifather}$ is his father's permanent income. In Section 4, we will verify that educational investment in child decreases along with the increase of his (her) father's returning possibility in the case of $r^C > r^H$ and $b > 1$; if it is true, we should expect a_2 would be negative.

Considering the relationship between the permanent income of fathers and the permanent income of children in Period 2, we substitute equation 6 into equation 4 and rearrange terms obtains:

$$(9) \quad \log y_{child} = \mu + r\theta \log \Phi + r\theta \log y_{father} + re_2$$

Similar with the equation of Solon (2002), equation 9 shows the intergenerational income relationship between father and child except for the equation containsΦ, which decreases with the return probability as we show above. The simplified form of equation 9 is given by:

$$(10) \quad \log Y_{ichild} = \alpha_1 + \alpha_2 P_{\mathrm{i}} + \alpha_3 X_2 + \beta_1 \log Y_{\mathrm{i}father} + e_i$$

where P_i is a measure of return possibility of migrant fathers, Y_{ichild} and $Y_{ifather}$ are the permanent income of the child and father separately, X_2 is the vector of the control variable. Although these indicators may vary widely due to factors such as location, as long as $r^C > r^H$ and $b > 1$, the educational investment in child will decrease with the increase of return possibility P_i ($\frac{\partial I_1^*}{\partial p} < 0$), then the human capital of the offspring will decrease and the income of the offspring will decrease accordingly (i.e. α_2 is negative). This will be verified in the following sections.

3. Data and methods

3.1 Data and sample description

The data are collected from the questionnaires in the China labour-force Dynamics Survey (CLDS 2012-2018).[1] CLDS is a nationwide labour tracking survey sponsored by Sun Yat-sen University. It starts in 2012 and updates every two years. Investigators need to get training and go to the local community to conduct a survey. The survey is an in-home survey using a computer-aided survey system (CAPI). A face-to-face question and answer session will be held between the interviewer and the respondent. The survey covers a wide variety of information about interviewees' educational attainment, work, family, migration, health, social participation, economic activities and grass-roots organizations. CLDS adopts the multi-stage, multi-level and proportional probability sampling method, and takes the lead in the country to adopt the rotation sample tracking method, which can not only adapt to the drastic changing environment in China, but also take into account the characteristics of cross-sectional survey. Therefore, it is widely used to study income distribution and labour mobility in China. It is also the most suitable database for this article because all the variable information for this article is available from it. The survey is launched in June 2012, covers 29 provinces, municipalities and autonomous regions which are the most frequent regions of labour mobility in China and includes information from 10,612 households and 16,253 individuals (CLDS2012). We extract a sample of 3,161 migrant households which share two characteristics in the sample: (1) the householder has an agricultural *hukou* [2] and is away from his hometown; (2) he had lived in the host city (or town) for more than 6 months upon the point of CLDS2012

[1] The latest version available at http://css.sysu.edu.cn/

[2] *Hukou* is a system of household registration in China and the unit of the population management system which demonstrates the legality of a natural person to live in a place. The current system divides household registration into "agricultural" and "non-agricultural" *hukou* (or household registration) based on geographical location and family relationships. Regulating population mobility from rural to urban areas is an important function of the system. Hukou migration (changing the category and location) or permanent migration has traditionally been tightly controlled by the central government. Since the 21st century, some of the larger cities have phased out immigration quota restrictions, instead of the so-called "access points" hukou, based on a stable occupation and qualified dwellings, such as economic capacity (investment and purchase of commercial housing) and educational attainment (higher education or above) of migrants. However, for the majority of migrant workers, the threshold for obtaining a *hukou* in metropolises remains high.

survey conducted.

When researchers need to match individual data and household data, they can use FID2012/FID2014/ FID2016/FID2018 as the key variable. In the individual data of labour force, individual nationality, spouse information, parents information and so on are asked in the family questionnaire. For the convenience of researchers, the current version has matched these information from the family data, which can be directly used by researchers. For the comparability of the results, only match father-child pairs are eligible to be included. Finally, 964 pairs of observations are matched from 3,161 migrant households. Additional criteria are applied to select sample: (1) more than one reported income observations is available; (2) the youngest and oldest ages of the children are 20 and 40 respectively for capturing valuable income information, while the father is alive and aged 40-60 years old; (3) for the households reported multiple children, only the oldest one is chosen. Finally, we match 964 father-child pairs, including 756 father-son pairs and 208 father-daughter pairs. Different from Dustmann (2008), Yuksel (2009) and Gong et al. (2010) who only report on father-son pairs, we retain all 964 father-child pairs taking the sample size into account.[1] Table 1 below lists the information collected via defined variables and descriptive statistics.

Table 1: Variable definition and descriptive statistics

Variable	Definition	Obs	Mean	Std.Dev.	Min	Max
P	return probability of the father	964	0.268	0.449	0	1
lnyfather	log income of the father	964	9.805	0.838	5.704	12.861
fatheredu	educational attainment of the father	964	2.805	0.813	1	4
fatherage	age of the father	964	50.610	6.123	40	60
lnychild	log income of the child	964	10.140	0.719	4.7	12.283
childedu	educational attainment of the child	964	4.341	1.741	2	8
childage	age of the child	964	28.390	4.341	20	40
childhealth	subjective evaluation level of the child's health	964	1.585	0.631	1	3
sibling	number of siblings of the child	964	2.614	1.961	0	8
ysm	years since first migration	964	15.677	9.417	1	38
lf	less than 6 months away from home	568	0.3124	0.814	0	6
nlf	more than 6 months away from home	396	11.098	1.041	6.3	12
childgende	son=1	756	-	-	-	-

[1] In fact, recent literature has found that intergenerational elasticities for daughters show a similar trend of father-son elasticity in economic status (Olivetti 2013). This evidence provides rationale for merging father-son and father-daughter pairs in this paper.

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Source:CLDS(2012-2018)

The value of P comes from the question "How long would you like to live here?" in the questionnaire, assigning 0 to the answer "permanent" and 1 to the other answers. Table 1 indicates that most migrant workers in cities are reluctant to return to their hometowns. And it also reveals the levels of both income and educational attainment of the father are lower than their children. The average log income of fathers is 9.805 compared with 10.14 of their children, and their educational attainment is 1.5 level lower than their children. The table also provides some information about other variables, such as the average ages of fathers and children are 50.61 and 28.39 years old respectively, fathers are 1.5 levels less educated than their children.

3.2 Permanent income estimation

Researchers argue that the estimation of permanent incomes is rife with life cycle bias (see Haider and Solon 2006; Grawe 2006). Haider and Solon (2006) suggest that with this type of measurement error, the direction of the bias is determined by the age at which earnings are observed. They estimate the coefficients for all ages using American data and find that an individual's income in his early 30s and mid-40s is closest to the average lifetime income. To be on the safe side, we choose to use CLDS(2012-2018) tracking survey data to minimize the impact of life cycle bias. Similar to the present literature (Dustmann 2008), we estimate the fixed effect regression equation of earnings based on the above data. Our regression equation is as follows:

(11) $\log y_{ij} = \alpha_1 + \alpha_2 age_i + \alpha_3 age_i^2 + v_i + u_i$

Where $\ln y_{it}$ are log real earnings of individual i in period t, v_i are individual fixed effects and u_{it} are iid error terms, which include measurement error. The value of $\ln y_{it}$ comes from the question "What is your total earning?" in the questionnaire. The log real incomes of fathers and children are estimated respectively for the convenience of observation, the overall trends of real incomes of fathers and children are consistent with the life-cycle hypothesis and both show an inverted U-shape. Taking incomes at father's age of 40 as an indicator of lifetime incomes can minimize the attenuation bias, resulting in deviations that are statistically identical to zero. Conditioning on age fixes individuals at the same point in their life cycle. As for our measure of permanent earnings, we predict $\hat{\alpha}_1 + \hat{\alpha}_2 age_i + \hat{\alpha}_3 age_i^2 + \hat{v}_i$ at age 40 for migrant workers and 30 for their children respectively and we display the distribution of their predicted earnings in table 2.

Although $\hat{\alpha}_2$ and $\hat{\alpha}_3$ estimation is unbiased and consistent, and $\hat{v}_i$ is estimated to be unbiased but inconsistent for panels with a small number of time periods. And estimates of permanent incomes suffer from measurement errors if the sample contains individuals with a small number of incomes observations. For our estimates, we will control the ages of the children and parents to minimize this bias. In this approach, Hertz (2007), Aaronson and Mazumder (2008) both allow the age-earnings profile to change over time.

Table 2: Average log real earnings and predicted earnings

Percentile	10th	25th	50th	75th	90th	Mean	Std.Dev.
Son's average log real earning	8.621	9.255	10.142	10.864	11.245	10.140	0.719
Son's predicted log real earning age 30	8.658	9.271	10.182	10.886	11.268	10.181	0.752
Father's average log real earning	8.532	9.012	9.802	10.523	10.871	9.805	0.838
Father's predicted log real earning age 40	8.511	8.993	9.788	10.488	10.829	9.785	0.833

3.3 Return probability estimation

Same as estimating permanent income, the willingness to return reported in the survey might be subjective and inaccurate. As such, it is necessary to simulate/adjust the father's real return probability through his age or duration as a migrant worker. *Ysm* is the years since emigration which measures the period between the first year of migration to the year of the survey conducted. The value of *ysm* comes from the question "What was the first time of your migration since you were 14 years old?" in the questionnaire. It is worth noting that *ysm* does not mean that migrant workers never return home during this period, however, this measure can be regarded as a proxy of the migration experience of migrant workers.

To verify the association between father's willingness to return *pf* and migration duration *ysm* in the subsample, we also estimate individuals aged at 40 years and reported the return probability and time of their first migration in the migrant household survey[1], in order to compare it with the subsample. The equation for estimating P_i is similar with that for estimating permanent income, we use fixed effect regression equation to estimate P_i, where we condition years since the first migration and years since the first migration squared:

(12) $P_{it} = \beta_1 + \beta_2 ysm_i + \beta_3 ysm_i^2 + \varepsilon_i + e_{it}$

where $P_i = 1$ if individual i reports the intention of returning to hometown in period t, while ysm_i measures years since the initial migration of individual i. The ε_i refers to individual fixed effect, and e_{it} refers to iid error terms, including measurement error. We calculate $\hat{\beta}_1 + \hat{\beta}_2\overline{ysm}_i + \hat{\beta}_3\overline{ysm}_i^2 + \hat{\varepsilon}_i$ to measure return probability, where $\overline{ysm}_i$ and $\overline{ysm}_i^2$ is father's duration since his first emigration when his child is 12 years old. We will replace the original willingness reported with the predicted willingness at age 12 of their children in the following sections.[2] Because a kid will graduate from a primary school when he(or she) is nearly 12 in China[3], and the choice after primary school is the most critical step to determine future educational attainment for a Chinese student. Therefore, at this assumed age, the relationship between the father's return probability and the educational investment in children can be accurately captured. The distribution of return probability is listed in Table 3.

Table 3: Distribution of predicted return probability

Percentile	10th	25th	50th	75th	90th	Mean	Std.Dev.
Permanent return probability when child is 12 years old	0.008	0.138	0.265	0.402	0.525	0.268	0.449

4. Empirical results and discussion

4.1 Educational investment

The independent explanatory variables in equation 8 are father's willingness to return *P* and the logarithm of his permanent income *lnyfather*, while the control variables include three main categories, namely the father's educational attainment, the child's personal characteristics and hometown characteristics. Using the logarithm of

[1] Refer to the last paragraph of this section for the reasons.

[2] 40 years old is also the age at which we capture father's lifetime incomes.

[3] For most Chinese students, the age of 12 should be graduate from primary school.

the father's educational attainment *lnfatheredu* states the father's educational attainment. The third category of control variables reflects the characteristics of the hometown, composed of the amount of cultivated land in the hometown *area*, the distance from home to the downtown of the nearest county (*distance1)*, the distance from home to the primary school and to the junior high school (*distance2* and *distance3)*. In addition in order to identify whether there is a phenomenon of "son preference" in educational investment, we conducted two interactive variables, which are the gender of child multiplied by the logarithm of the age gap between father and child *childgender×lndage* and the gender of child multiplied by the number of siblings *childgender×sibling.*

The CLDS(2012-2018) provides one educational attainment dimensions which comes from the question "What is your highest educational level ?" . We list estimates in Table 4, it shows that the coefficients of independent variables pass the significance test, while the coefficients of *sibling* and *cgender×sibling* in the control variables are not significant.

Table 4: Educational investment in children by OLS estimate

dependent variable: **lnchildedu**		
	Coef.	**St.Err.**
independent variable		
P	-0.369***	0.061
lnyfather	0.056*	0.007
control variable		
lnfatheredu	0.107	0.087
childgender	-8.787***	1.213
childhealth	-0.065**	0.03
sibling	-0.031	0.032
lndage	-3.866***	0.549
childgender×lndage	2.669***	0.36
childgender×sibling	0.019	0.027
area	0.029***	0.005
distance1	-0.011***	0.001
distance2	-0.037***	0.006
distance3	-0.030***	0.005
Constant	14.053***	1.831
R-squared	0.815	
F-test	176.707	
Numbers of obs.	964	

**** p<0.01, ** p<0.05, * p<0.1*

The main finding in Table 4 is fathers' educational attainment has no direct impact on the children's educational attainment. The result suggests that the influence of fathers on children's intergenerational incomes is mainly attributed by the accumulation of children's human capital through educational investment, rather than directly passing on their own human capital to their children. One explanation for this weak correlation is that migrant fathers are poorly educated on average, then educational attainment is not a good predictor for their earnings.

4.2 Intergenerational income elasticity

The same principle as applied for the previous estimate of the child's educational investment, we add control variables to reflect the child's personal characteristics and the hometown's characteristics in equation 10. The results are reported in Table 5. It indicates that Model 1 without control variables may underestimate the intergenerational income elasticity (IIE) as we can see it increases from 0.141 to 0.171 after considering the control variables in Model 2. Moreover, if the father intends to return rather than permanently lives in cities, the drop range in his child's permanent income will rise from 0.212% to 0.392% when control variables are added. This result is consistent with previous estimates of the educational investment equation, where the father's return probability has a negative effect on the educational attainment of his offspring.

Table 5: Intergenerational Income Elasticity by OLS estimate

	Model 1		Model 2	
***dependent variable:* lnychild**	**Coef.**	**St.Err.**	**Coef.**	**St.Err.**
independent variable				
lnyfather	0.141^{**}	0.057	0.171^{**}	0.088
P	-0.212^{***}	0.073	-0.392^{***}	0.099
control variable				
childgender			8.52^{**}	2.483
childhealth			2.226^{***}	0.262
lndage			3.007^{***}	0.918
distance1			-0.004^{***}	0.002
distance2			-0.074^{***}	0.011
distance3			-0.022^{***}	0.008
sibling			-0.034	0.08
area			-0.009	0.012
Constant	8.918^{**}	0.589	-0.355^{**}	3.634
R-squared	0.174		0.755	
Numbers of obs.	964		887	

**** p<0.01, ** p<0.05, * p<0.1*

In addition, the regression results reveal two significant findings:

(1) The IIE of father-child in migrant households is significantly lower than that reported by other similar studies in China. For example, the estimates of the intergenerational income elasticities in Gong et al. (2010) are 0.74 for father-son, 0.84 for father-daughter in urban China using the Chinese Urban Household Education and Employment Survey 2004 (UHEES 2004); Deng et al. (2012) measure the intergenerational mobility for urban households in China using China Income Distribution Project (CHIP 1995 and 2002) and report the elasticity for the father-son pairs as 0.47 for 1995 and 0.53 for 2002; Qin et al. (2016) estimate IIE of father-child pair increasing from 0.429 in 1989 to 0.481 in 2009 based on China Health and Nutrition Survey (CHNS) data. Our finding is in line with the conclusion reported in other studies that rural area has lower IIE (or higher intergenerational income mobility) compared with urban areas (Hau et al. 2014; Wu et al. 2019). For instance, Xu (2015) and Jiang (2017) estimate that the IIE of migrant households in China is around 0.20. However, due to different measurement used in different studies, some researches draw an opposite conclusion that the IIE in rural China is higher than the urban (see Huang et al. 2016), which might be caused by the fact that they use the association of father-son's educational attainment as a proxy of intergenerational mobility.

Why is there a lower intergenerational correlation between fathers and children in migrant families? One reasonable explanation for this difference is that in our sample, many children of migrant workers work in cities. For instance, among the 964 families, 568 have children working in cities with their parents as shown in Table 1. In fact, there are three main paths for rural labour force to immigrate to urban China: the first is transferring agricultural labour force to urban through the process of urbanization; the second is to start a business and then settle down in cities, and the third is to become a “new urban residents” via higher educational level. As such, the children of rural migrants can, to a large extent, eliminate the impact of low income of their parents and reduce the intergenerational persistence by immigrating to cities. Another possible reason is that our IIE estimates might have a downward bias, which we will discuss it in more details in the next section. In addition, the results from different studies might not be necessarily comparable because they are conducted in different periods when the characteristics of people or generations may change over time. Evidence supported by recent research of Chen et al. (2015) for China’s long-run intergenerational mobility, they target people born between 1930 and 1985 and reveal that the persistence of socioeconomic across generations follows a robust U-shaped pattern.

(2) The higher fathers’ attention to return to hometown, the fewer children have permanent income, though the effect is modest. The sign of the coefficient for P accords with the theoretical inference in section 2, the mechanism is likely to be that the father is reluctant to invest more in his child’s education due to his increasing return possibility, which results in decreasing the child’s human capital and permanent income in future. However, it is worth noting that since some of the factors that determine a child’s permanent income (e.g. individual endowment and social environment) are difficult to observe, it is likely that this regression equation may have endogeneity problem although the coefficients of P and *lnyfather* are significant. We will discuss the endogeneity in the next section.

As noted by recent literature (e.g., Corak and Heisz 2001; Blanden 2013; Chyi et al. 2014; Nybom and Stuhler 2014), families with different income may have different intergenerational income mobility, and there is lower mobility for the top and bottom of the income range. Given this fact, we divide fathers’ income ranges into three groups in Table 6 which exhibits the intergenerational elasticity of the high-income group and the low-income group are greater than the middle-income group. It implies that children from middle-income families are the least correlated with their fathers in economic status within the migrant worker community. Analogously, Clark and Cummins (2015) and Wu et al. (2019) also argue parental incomes have a greater influence on the children in the highest and lowest income family groups in the US and Canada.

Table 6: Estimates of intergenerational income elasticity by father's income groups

dependent variable: **lnychild**						
	low-income group		**middle-income group**		**high-income group**	
	Coef.	**St.Err.**	**Coef.**	**St.Err.**	**Coef.**	**St.Err.**
independent variable						
P	-0.387**	0.142	-0.352***	0.128	-0.404**	0.129
lnyfather	0.175*	0.107	0.142***	0.403	0.208*	0.187
Constant	12.087***	1.715	14.260***	4.244	12.836**	2.357
R-squared	0.669		0.675		0.664	
Numbers of obs.	295		296		296	

**** p<0.01, ** p<0.05, * p<0.1*

5. Endogeneity, heterogeneity and robustness test

5.1 Endogeneity

As mentioned above, the OLS estimation might be biased potentially because the independent variable *lnyfather* might be related to the errors term. This can be caused by missing variables or measurement errors. An alternative solution to the classical measurement errors problem is to use instrumental variables (IV). As discussed by Mazumder (2005) and Grawe (2006), the extent of the bias will depend upon the degree to which the instruments are directly related to the child's income and the strength of their ability to predict father's income. The larger the R-squared in the first-stage regression, the smaller the bias will be.[1] The same approach of the measurement IIE is observed in the studies in other nations, for example, in Sweden (Bjørklund et al. 2006), in the USA (Hertz 2007) and in a multi-nation study (Blanden 2013).

In the search of instrumental variables, we have tried six variables sequentially to test which is valid or weak instrumental variable. They are the topography of hometown (*topo*), siblings of father (*fathersibling*), the emigration proportion of the hometown labour (*prop*), GDP per capita of the hometown (*yht*), self-evaluation of household consumption (*chs*), self-evaluation of household economic level (*yhs*). We find only the emigration proportion of the labour in hometown (*prop*) is an effective instrumental variable which meets the requirements of exogenous and correlation of IV. The reason might be related to children's high educational level and fathers'

1 Due to word limitation, we are unable to present the results from the first stage regression, however they are available upon request.

"fellow villagers" relationship. [1] The emigration proportion *prop* is used to show the strength of the villagers' network. Xu (2015) points out that the older generation of migrant workers rely more on the relationship with the fellow villagers to find jobs, in contrast, the new generation of migrant workers mainly rely on the Internet because of their high educational level. Therefore, we can infer that the *prop* is likely to be related to the income of the parents, but almost unrelated to the income of the children.The first stage regression results of 2SLS show the statistical value of F=58.36 is higher than the empirical standards of F=10, which can exclude the risk of weak instrumental variable. Meanwhile, the regression coefficient of *prop* in the first stage is significant, implying it is an effective IV.

The Wu-Hausman Test is used to test whether the previous OLS model has endogeneity. The test result shows that the *P* is almost zero which means the result of IV is significantly different from that of OLS, suggesting the OLS equation has the estimation errors caused by endogeneity. To eliminate this potential hazard of a small sample, we apply the limited information maximum likelihood method (LIML) to the regression and display the three regression results in Table 7. There is little difference between the estimated results of 2SLS and LIML, however, there are some changes in the coefficients of endogenous variables relative to OLS. It should be noted that the IIE under OLS is underestimated after considering IV.

Table 7: Estimates of Intergenerational Income Elasticity by OLS, 2SLS and LIML

***dependent variable:* lnychild**	**OLS**		**2SLS**		**LIML**	
independent variable	**Coef.**	**St.Err.**	**Coef.**	**St.Err.**	**Coef.**	**St.Err.**
lnyfather	0.171**	0.088	0.211**	0.184	0.225**	0.289
p	-0.392***	0.099	-0.365*	0.177	-0.373*	0.231
childgender	8.52**	2.483	5.264***	3.119	6.227**	3.136
childhealth	2.226***	0.262	2.016***	0.258	2.022***	0.269
lndage	3.007***	0.918	2.698***	1.433	2.923***	1.572
distance1	-0.004***	0.002	-0.002***	0.002	-0.002***	0.002
distance2	-0.074***	0.011	-0.042***	0.019	-0.043***	0.020
distance3	-0.022***	0.008	-0.016***	0.015	-0.018***	0.019
sibling	-0.034	0.08	-0.165	0.021	-0.175	0.026
area	-0.009	0.012	-0.009	0.014	-0.009	0.016
Constant	-0.355**	3.634	17.21**	3.112	20.05***	4.592
R-squared	0.753		0.502		0.511	
Number of obs.	887		812		812	

[1] China is a society with family relations as a network. The fellow villagers are an extension of this family relationship. Early immigrants, whether they migrate out of the province or abroad, usually start their first job through the introduction by fellow villagers (Xu 2015).

*** p<0.01, ** p<0.05, * p<0.1*

The estimates in 2SLS and LIML are closer to the IIE estimated by some relevant literature on migrant households in China (see Deng et al. 2012; Xu 2015; Jiang 2017). Specifically, the estimates of IIE in 2SLS and LIML are 123% and 132% of OLS estimate respectively. The reason for this difference might be caused by the original OLS regression equation is endogenous, i.e. the permanent income of fathers is related to the errors term, which leads to an underestimate of the IIE. In general, some coefficients are still statistically significant though they have been changed; therefore, the OLS estimate of IIE is valid.

5.2 Heterogeneity

Extant studies have shown that the IIE may be overestimated or underestimated due to various heterogeneous reasons, such as the income of father or family, race, country or region, geographical conditions, etc. For example, Xu (2015) and Wu et al. (2019) explore heterogeneity of intergenerational mobility in different income cohorts and confirm its existence.

In the analysis, we use a slightly different way to divide east, central and west of households in China for the provinces/municipalities included.[1] Meanwhile, three distance variables *distance*$_i$ used as control variables previously are divided into three categories: near, middle and far distances. To verify whether IIE exhibits significant differences among different groups, we add a region or distance dummy variable into equation 4, which is transformed into equation 5, and use LIML method for regression.

(13) $\log Y_{ichild} = \alpha_1 + \alpha_2 P_i + \alpha_3 X_2 + \sum_{k=1}^{K} \alpha_{4k} D_{ik} + \beta \log Y_{ifather} + e_i$

where D_{ik} is the dummy variable of region or distance, the subscript i represents the household code, and the subscript k states the categories of regions or distances, $k = 1{,}2{,}3$. X_i is a set of control variables, and *prop* is still used as IV. To be concise, only the coefficient of *lnyfather* (i.e., intergenerational income elasticity), robust standard error and the numbers of observations are presented. The results are reported in Table 8.

Table 8: Estimating Intergenerational Income Elasticity by region and distance

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[1] Different from the data description section, we classify Heilongjiang province into the central China because it is the only province in the northeast China in CLDS(2012-2018). Specifically, the three regions are divided into: East China includes Beijing and Shanghai, Jiangsu, Zhejiang, Guangdong and Fujian; Central China includes Hubei, Hunan, Henan, Anhui, Shanxi and Heilongjiang; and West China includes Shaanxi, Gansu, Sichuan, Guizhou and Yunnan.

		2SLS		LIML		
		Coef.	**St.Err.**	**Coef.**	**St.Err.**	**N**
region	east	0.206**	0.184	0.219**	0.177	318
	central	0.242*	0.191	0.238**	0.162	295
	west	0.237	0.155	0.240*	0.152	274
distance1	0-10	0.210**	0.178	0.221**	0.166	357
	10-50	0.214*	0.196	0.233*	0.190	278
	50-	0.191*	0.191	0.212**	0.171	252
distance2	0-2	0.215**	0.182	0.227*	0.172	453
	2-5	0.209	0.175	0.199*	0.164	417
	5-	-	-	-	-	17
distance3	0-2	0.216*	0.155	0.235***	0.145	415
	2-5	0.212*	0.155	0.217**	0.144	355
	5-	0.253	0.193	0.268**	0.180	117

**** p<0.01, ** p<0.05, * p<0.1*

Note: All units of the distance are *km*, and all the critical values are included in the former group. Regression results are not reported when *distance2 >5* because there are only 12 samples. The reason may be explained that the near-enrolment policy has led to the primary school distance is no longer more than 5 km away in the sample.

It is obvious that Table 8 does not take on substantial heterogeneity in regions and distances, as the overall IIE is 0.211 (2SLS) or 0.225 (LIML) in Table 7 respectively. Practically speaking, IIE appears slight heterogeneity among regions. The east region has the smallest IIE, while IIE of the west and the middle region are quite close, which is about 10% higher than that of the east. In terms of distance heterogeneity test, the distance from home to the downtown of the nearest county (*distance1*) has the lowest significance level and the distance from home to the nearest junior high school (*distance3*) has the highest significance level. In the 11 groups estimated, only 2 groups' IIE fluctuates by more than 10%. Overall, IIE does not bear substantial heterogeneity characteristics in different regions and distances.

5.3 Robust test

After dealing with endogenous problems based on IV, verifying the possible heterogeneity, and obtaining a plausible IIE, we need to confirm whether the estimates are robust because some potential measurement errors are still possible which may affect the results, such as the reliability of the father's income *yfather* as an endogenous variable to estimate IIE when the mother is the breadwinner of the household (Plug 2004; Bongoh 2011). In order to prevent these factors from affecting estimated results, we need to conduct robustness test by replacing father's income *yfather* with family's income *yhome*. To be consistent with the previous IIE estimates and its endogeneity test, equation 4 needs to be estimated using permanent income.

In order to obtain the permanent income of the family, we predict the incomes of father and mother at age

40.[1] In addition, even if we change the independent variable *lnyfather*, equation 4 may still have endogenous problem. This suggests that we need to consider IV using the same method. As mentioned earlier, we have tried six variables to test which is valid or weak IV. Here, we repeat the procedure and find only "self-evaluation of household economic level *yhs"* is the valid IV. [2] The Wu-Hausman Test verifies that the robust test equation exists endogeneity and IV method is feasible. Similar with endogeneity and heterogeneity tests and considering the small sample size, the LIML method may be more effective, we report both the regression results of the 2SLS and LIML in Table 10.

Table 10: Robust test using 2SLS and LIML

dependent variable: lnychild	**2SLS**		**LIML**	
independent variable	**Coef.**	**St.Err.**	**Coef.**	**St.Err.**
lnyfather	0.227^{*}	0.166	0.241^{*}	0.258
p	-0.201	0.225	-0.173^{*}	0.220
R-squared	0.302		0.331	
Number of obs.	764		764	

**** p<0.01, ** p<0.05, * p<0.1*

The results present a slight increase in intergenerational income elasticity, and the LIML estimates confirm the validity of previous OLS estimates of IIE, despite the significant level is declined. Importantly, the robustness test also confirms the negative correlation between the fathers' return probability and their children's permanent income. In case of the estimation bias caused by age setting, we change the average age of parents to 45, 50 years old and retest, and the estimated results of IIE are still close at the 10% significant level. Based on all test results, the IIE of migrant households is firmly stable within the range of 0.211 to 0.241.

6. Conclusion

This paper examines the intergenerational mobility of migrant families in China in general, and migrant father's return probability and its influence on children's educational outcomes and permanent incomes in specific. After controlling age and adopting multi-year mean incomes to simulate permanent income, the intergenerational income elasticity is estimated by OLS, we find that the middle-income group has the highest intergenerational

[1] It is important to note that we cannot use the total household disposable income data though the questionnaire reports the data in each year of 2012-2018, because the total household disposable income contains the income of children.

[2] The self-evaluation of family economic level is divided into four levels, which are assigned 4, 3, 2 and 1 successively, from the highest to the lowest.

mobility with no substantial heterogeneity in regions and distances. Furthermore, there is no direct relationship between fathers and children in terms of educational attainments. Additionally, we use IV to correct the possible endogenous biases in order to test the validity of OLS regression and confirm the IIE estimate via robust test replacing father's income with the family's income. Finally, we conclude that the return willingness of migrant fathers does have a negative impact on their investment in children's education, while the robust volatility range of IIE is 0.211-0.241.

The paper can conclude: (1) the migrant households in China show higher intergenerational mobility compared with other studies on urban or rural families in China; (2) the stronger the willingness of migrant workers in cities to return to their hometowns, the less their investments in education for their children are; (3) the intergenerational income mobility of migrant families does not appear substantial heterogeneity based on different regions and distances from the nearest county town and schools, while the middle-income group in terms of fathers' income cohorts shows the highest mobility.

These conclusions should have distinctive policy implications. First, the higher intergenerational mobility of migrant workers suggests that their intention to return might be attributed by the high threshold for permanent migration in cities based on *hukou* system and or less earning opportunities due to the economic downturn. Second, it is necessary for relevant government departments to further loosen institutional restrictions in order to encourage two-way mobility of migrant workers between urban and rural areas because fathers' return willingness possibly leads to a decrease in educational investment in their children and aggravate the income inequality of the next generation. Third, the measures of strengthening educational attainment of migrant workers' children should also include improving the quality of primary and secondary education in rural areas to offset the impact from the reduction of educational investment in children by the migrant fathers. Understandably it takes time for legislations and multiple policies in place and effective cooperation between central and local governments.

We recognize that this study has two limitations. The first is that we have a small sample size. This is due to our research nature for only including matched father-child pairs while limited pairs in the survey (i.e. CLDS2012-2018). The second limitation relates to that we are unable to consider family collective decision-making for return intention in the survey mentioned, though a growing literature suggests that family interests play an irreplaceable role in their migration decisions (Plug 2004; Olivetti 2013; Huang et al. 2016). These limitations can be addressed as future research directions, if possible. In addition, more researches with larger sample sizes, more variables and longer period should be better to provide a wider picture of this interesting topic.

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