Vol. 11(4), pp. 82-91, April 2019
DOI: 10.5897/JDAE2018.1011
Article Number: 200D9BF60677
ISSN 2006-9774
Copyright ©2019
Author(s) retain the copyright of this article
http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

The mobility of intergenerational income for rural residents: The case of China

Jie Chen[1,2] and Tingting Li[1]*

[1]Institute of Population and Labor Economics, Chinese Academy of Social Science, Beijing, China
[2]School of Economics, Nanjing University of Finance and Economics, Nanjing, China.

Received 30 October, 2018; Accepted 12 February, 2019

Based on the data of China Health and Nutrition Survey (CHNS) from 1989 to 2015, this paper analyzes the mobility and transmission mechanism of rural residents' intergenerational income. The OLS estimation of father and son yields a value of 0.549. The results of quantile regressions show that in rural China, the intergenerational income elasticity (IGE) is higher at the high end but lower at the low end. The human capital investment represented by the schooling years of the children is indeed an important factor explaining the intergenerational income mobility in the rural, and its contribution rate is 26.6%, much higher than the contribution of occupation. Further, the decomposition results indicate that education plays a more important role both at the low end and the high end, while occupation plays a more important role at the media quantile.

Key words: Rural resident, intergenerational income mobility, transmission mechanism.

INTRODUCTION

China’s economy has been growing at a rapid speed for around forty years since the reform and opening up. These rapid economic developments have also been accompanied by dramatic social transformations; the mobility of intergenerational income has been debated more and more recently. This paper estimates the intergenerational income mobility based on a micro-income dataset which spans 26-years from 1989 to 2015, and further analyses the mobility mechanism of the intergenerational income for Chinese rural residents.

Intergenerational income mobility is the extent to which parents’ income affects the income of their children. Becker and Tomes (1979) first put forward the theoretical framework of the intergenerational income mobility from the economic perspective. In this framework, intergenerational income mobility is generally expressed in terms of generational income elasticity. The higher the elasticity is, the greater the impact of parents’ income on the income of children is, indicating lower intergenerational income mobility. The intergenerational income elasticity (hereinafter IGE) in the United States is around 0.2 (estimated by Behrman and Taubman (1985) and Becker and Tomes (1979), indicating that intergenerational income liquidity is high in United States. However, these results were biased because the estimates of the intergenerational elasticity in previous studies tended to use earnings in one year for both fathers and children. Toward this, subsequent studies

*Corresponding author. E-mail: litingting@mail.sysu.edu.cn

Author(s) agree that this article remain permanently open access under the terms of the Creative Commons Attribution License 4.0 International License

continue to improve the relevant theories (Solon, 1992; Haider and Solon, 2006; Bohlmark and Lindquist, 2006). There are many literatures that examine the degree of intergenerational income mobility in developed countries (Lee and Solon, 2009; Lefgren et al., 2012; Lefranc et al., 2014; Palomino et al., 2018).

However, the existing literature seldom focuses on developing countries, more discussions are necessary for the case of developing countries. As the world's most populous nation, Chinese living standards have risen since 1979. These rapid economic changes have also been accompanied by dramatic social transformations. All this makes China a unique case study through which to better understand the relationship between societal change and income mobility.

For the case of China, Zhang and Eriksson (2010) estimated the relationship between the parents' income and the children's individual income in the same household using the CHNS data (1989 - 2006), and concluded that the generational income elasticity is about 0.45. Deng et al. (2013) have found that the intergenerational income elasticity of sons to fathers in 2002 is 0.53 and in 1995 is 0.47 when an accounting period of three years is applied. In a more recent work by Li et al. (2014) adopted the data from CHNS spanning from 1989 to 2009 to do the Instrument Variable (IV) estimation, and the finding revealed that the intergenerational correlation in terms of the long-run income is 0.83 in China. Based on the 1995 and 2002 waves of CHIP, Fan (2016) found that the estimated intergenerational income elasticity is 0.43 and 0.51 for cohorts educated prior to and after the market reform, respectively. Moreover, the intergenerational income elasticity for the urban households whose income is above average in the post-reform China reaches 0.71. All of the papers earlier mentioned have shown that intergenerational income mobility is low when intergenerational income elasticity is higher than 0.4.

Estimating intergenerational income elasticity is the most basic step in the study of intergenerational income mobility. What is even more remarkable is the mechanism by which the parents' income is passed to the children. In some empirical studies, the data of communities, siblings, twins, and adopters are used to study the roles of the congenital endowment and acquired environment in the mobility of intergenerational income (Mazumder and Fortunate, 2005). Almost all of these studies show that the genetic endowment has a great impact on the intergenerational income mobility, accounting for about 50% of the total contribution. For the impact of human capital, scholars mainly studied the role of education in intergenerational income flow. Gong et al. (2012) found that education, especially tertiary education, is an important channel through which earning ability is transmitted from parents to their children in urban China. With a simultaneous equations model, Qin et al. (2016) found that both education and health, especially education, play an important role in intergenerational transmission. In addition, due to the lack of sound labor market in China, the parents with high income will not only invest in human capital but beyond that, they will try their best to seek a good job for their children through their own social networks and personal connections. In general, the social capital of the parents influences the children's occupation mainly through three aspects: career transmission, social network and power rent-seeking; and indeed affect the income level of the children. Fan (2016) explored three channels of intergenerational income transmission: education, social capital and own ship of work unit, and declared that in the post-reform era, parents from various income groups invest in children's intermediating variables which generate statistically significant and high return: schooling for the lower 50% families and social capital for the upper 50% households.

Because of the household registration system, China has formed the urban-rural dual economic structure; most existing studies are confined to the study of the intergenerational income mobility of urban residents. But in fact the rural economy is a critical component of Chinese economy, as the reform in the countryside is the starting point of China's reform and opening up. Because of the importance and distinctiveness of rural development, it is meaningful and necessary to study the intergenerational income mobility of rural residents.

Generally, this paper will mainly estimate the intergenerational income mobility of rural residents, and discuss the micro-mechanism of intergenerational income transmission from the perspectives of education and occupation. In contrast to the previous researches, the main contributions of this paper are as follows: First, most of the previous studies about intergenerational income in China focused on the urban area, few of them concerned about the rural area. On the contrary, this study uses the latest data with a long time span at the micro-level, thus we can examine the intergenerational income elasticity for the rural residents in a clearer manner. Second, more and more studies begin to focus on the nonlinear characteristics of the intergenerational income mobility (Chen et al., 2017; Palomino et al., 2018); this latest research trend was followed to adopt the method of Quantile Regression (hereinafter QR) to examine the intergenerational income mobility of rural residents at different quantiles. Beyond that, the mobility mechanism of the intergenerational income was also compared at different quantiles.

METHODOLOGY

The model

Based on previous studies (Becker and Tomes, 1979; Solon, 1992), the basic equation of intergenerational income elasticity in this paper is specified as follow:

$$Lny_i^s = \alpha_0 + \rho Lny_i^p + \varepsilon_i \quad (1)$$

where y_i^s is children's permanent income, and y_i^p is the permanent income of the parents. ρ represents the degree to which parents' permanent income influences their children's permanent income.

As it is difficult to obtain the reliable data of parents' permanent income, we generally use the parents' annual income as a proxy of the permanent income. However, due to the large deviation between their annual income and permanent income, using the parents' annual income to estimate the intergenerational income elasticity is likely to result in downward bias. As the entire data of all available pairwise observations of adult sons and parents' income are allowed to be used to estimate the intergenerational income elasticity and the influence of the life cycle on income of both parents and children can be controlled in the approach in Lee and Solon (2009); this methodology was used in order to solve the problem of the life cycle bias, thus the basic equation can be adjusted as follow:

$$\ln y_{it}^s = \alpha + \beta \ln y_i^p + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_i^p] C_{it}^n + \varepsilon_{it} \quad (2)$$

The dependent variable y_{it}^s in the intergenerational regression equations estimated is the son's log annual income in years ranging from 2000 to 2015 and at ages ranging from 20 to 49. The independent variable y_i^p is the averaged parental household income of family *i* when the son was a child between 10 and 17 years old. This paper mainly estimates the elasticity of intergenerational income from fathers to sons for two reasons. First, a potentially important issue is that in the baseline estimates, only members of the two generations who co-reside were observed. If the co-residing parent/child pairs are systematically different from the residing separately parent/child pairs, the estimates based on the former sample could be biased due to sample selection (Deng et al., 2013).[1] Second, generally speaking, the father holds most resources in the family and may have a greater impact on the children in rural China. Compared to men, women's market participation rate is lower and more volatile, resulting in the selection bias when women enter the labor market and large estimation bias for the intergenerational income elasticity (Gong et al., 2012).

The influence of the life cycle on parental and son's income is well controlled in Equation (2). Variable A_i^n represents the age of the parent in family when the children were 10 and 17 years old. Variable C_{it}^n is included to control the son's age. It is calculated as the difference between the son's age and the age of 40 years old at each year when income is computed, thus centering the estimates at the age of 40. If c is the birth year of the individual, t-c is the age when the income is reported, therefore C=t-c-40. Variable $[\ln y_i^p]C_{it}^n$ is the interactive term of parental income and the age of the son, which interprets the possible divergences in life-income patterns depending on parental income.[2] γ_1 to γ_4, δ_1 to δ_4, and θ_1 to θ_4, are corresponding parameters, respectively.

Quantile regression

As discussed earlier in the model, it was confirmed that the parents' income has impact on the income of the children through OLS estimation and this impact is still valid even for the average income. However, some previous studies suggest that the intergenerational income elasticity may not be linear (Bhattacharya and Mazumder, 2011; Corak et al., 2014), that is, the intergenerational income elasticity under different income distributions may not be the same. Therefore, the method of Quantile Regression was adopted to examine the intergenerational income elasticity under different income distributions. Initially, the QR estimates are obtained for the pooled 2000-2015 sample. As Palomino et al. (2018) said, the large size of the sample allows us to obtain highly accurate QR estimates at the tails.

The OLS method assumes that the mean of the conditional distributions is a linear function of $\boldsymbol{x}$ and fits a linear equation of the desired condition. As with the OLS regression, the QR examines the conditional distribution of the dependent variable *y* on the basis of the given independent variable $\boldsymbol{x}$, but the overall q quantile $(y_q(\boldsymbol{x}))$ of the conditional distribution $(y|\boldsymbol{x})$ in the QR is a linear function of $\boldsymbol{x}$, that is:

$$y_q(\boldsymbol{x}_i) = \boldsymbol{x}_i' \beta_q \quad (3)$$

where y is the dependent variable, which is the income of children; $\boldsymbol{x}_i$ is the independent variable vector, which is the income of parents, the age of the parents and children, and β_q is the coefficient of q quantile, and the estimator can be constructed in the following minimization issue:

$$\min \sum_{i: y_i \geq \boldsymbol{x}_i' \beta_q}^{n} q \left| y_i - \boldsymbol{x}_i' \boldsymbol{\beta}_q \right| + \sum_{i: y_i < \boldsymbol{x}_i' \beta_q}^{n} (1-q) | y_i - \boldsymbol{x}_i' \boldsymbol{\beta}_q |.$$

OLS minimizes squared errors and yields the estimates at the mean of the distribution. In contrast, QR minimizes absolute errors at any particular quantile of the mean of the conditional Y|X distribution (Koenker and Bassett, 1978; Koenker, 2005). In addition, Mitnik et al. (2015) suggest that the OLS estimates of elasticity using log transformed income are centered at the geometric mean instead of the arithmetic mean; but different from OLS with the mean, the median and the quantiles estimated by QR are unaffected by a log transformation.

Decomposition of intergenerational income persistence

Following the literature (Blanden et al., 2007; Fan, 2016), the Blanden decomposition method was also used, which decomposes the intergenerational income persistence through several equations. First, the Blanden decomposition method uses the

[1] Constrained by the CHNS dataset, it is unable to launch more in-depth discussions. However, Deng et al. (2013) found that the impact of co-reside on the intergenerational income elasticity for the father-son pair is relatively less remarkable than that for the father-daughter pair, indicating the estimation bias induced by co-reside would be smaller by only using the father-son matching sample.

[2] As Lee and Solon (2009) declares, the measurement error in log current income as a proxy for log lifetime income is mean-reverting at the early stage of the life cycle, whereas mean-departing at the late stage of life cycle, as the systematic heterogeneity across individuals in their rates of income growth in their lifetime. Generally speaking, the individuals with high lifetime income tend to have steeper income growth trajectories. To account for this pattern, both the child's age and the interaction of child's age and parental income should necessary to be controlled in our study.

following equation to derive the intergenerational income elasticity γ.

$$\ln y_{it}^{s} = \beta_0 + \gamma \ln y_i^{p} + \mu \quad (4)$$

where y_{it}^{s} is the income of the children in year t and y_i^{p} is the parents' income when the son was a child between 10 and 17 years old. Similar to Equation 2, the age of father, the age of son, as well as the interactive term of the father's income and the age of son are controlled when Equation 4 is estimated. In the first step, the intermediate factor on the parents' income was regressed, and then in the next step we use the regress intermediate factors on the children's income as follows:

$$IN_k = \varphi_k + \lambda_k \ln y_i^{p} + \mu_k \quad (5)$$

$$\ln y_{it}^{s} = \omega + \sum_{k=1}^{2} \theta_k IN_k + \nu \quad (6)$$

where IN_k represents the intermediate factor, k=1, 2, represents the education and occupation factors, respectively. In general, the more educated a person is, the more likely he/she is to have a career with a higher score. Therefore, Fan (2016) was followed to control the education variable in order to acquire the pure effect (λ_2) of the father's income on son's occupation when Equation 5 is estimated. Moreover, the same control variables are introduced into the regressions when Equations 5 and 6 are estimated

Equations 5 and 6 can be regarded as the process that the parents obtain the return from the income of children through the investment on different factors, which can be referred to as the parents' investment equation and the children's return equation. λ_k and θ_k represent the investment coefficient of the parents and the rate of return of the children, respectively. The estimated value of intergenerational income elasticity is given by:

$$\gamma = \sum_{k=1}^{2} \lambda_k \theta_k + \frac{Cov(\nu, y_{ot})}{Var(y_{ot})}.$$

Thus, the parents' investment coefficient and the rate of return of the children determine the degree of interpretation of the intermediate factors to the intergenerational income mobility. The contribution of the intermediate variable to intergenerational income transmission is:

$$\tau_k = \frac{\lambda_k \theta_k}{\gamma}.$$

DATA

In this paper, the data is derived from China Health and Nutrition Survey (CHNS). CHNS is conducted collaboratively by the University of North Carolina (UNC) and the Institute of Nutrition and Food Safety of Chinese Center for Disease Control and Prevention (CDC). This paper adopts ten waves of CHNS, that is waves 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011 and 2015. Nine representative provinces in the eastern, central and western China are mainly covered, which are Liaoning, Jiangsu, Shandong, Heilongjiang, Henan, Hubei, Hunan, Guangxi and Guizhou.

Above all, the information of the parents (father) and the children (son) are separated in the sample of rural household, then the data of the parents and children in the same family are combined together to construct a comprehensive dataset t of one-to-one correspondence between the parents and their children. The father's income from 1989, 1991 and 1993 waves are averaged to obtain the father's income when the sons are 10 to 17 years old. In view of the basic characteristics of the general labor force in rural China and in order to avoid the bias of life cycle, this paper sets the upper limit of the age of the parent labor force to be 60 years old. The observations of income in the labor market from 2000, 2004, 2006, 2009, 2011 and 2015 waves are used to calculate the son's income. In the rural area, the laborers enter the labor market at relatively young age even many of them are still underage. However, including the children too young will lead to larger measurement error of income. As a result, this paper only regards the adult (20 to 49) children as the work force. Finally, income is adjusted by the consumer price index (CPI) in 2015 derived from CHNS.[3] After further deletion of the outliers, the sample in this paper consists of 795 valid observations (pairs).

Table 1 shows the descriptive statistics of the key variables such as annual income, age, education and occupation of the children. The variable, *income*, is total net income, which mainly includes wage income, business income and agriculture-related operational income (farming income, gardening income, animal livestock income and fishing income). As the net income data are deflated by the 2015 CPI, it can be compared directly in our sample. The observations of sons' income are available since 2000, with the mean of 20113 Yuan; while the observations of fathers' income are available in 1989, 1991 and 1993, with the mean of 4654 Yuan. For *Age*, the mean for the sample of sons is 28 years and the mean for the sample of fathers is 43 years. For *Education*, the average schooling year for the sample of sons is 9 years, which indicates the rural labor at the age of 28 have received junior high school education on average. Since the reform and opening up, the rural residents can access the non-farm employment because of the rapid development of China's non-agricultural economy, thus "farmer" no longer means a profession but a status instead. *Occupation* is calculated according to Erikson and Goldthorpe's (2002) occupational classification table and the average score is 3.6.

INTERGENERATIONAL INCOME MOBILITY OF RURAL RESIDENTS

Estimation of intergenerational income elasticity

Here, the results of pooled data regression were discussed. The estimated intergenerational income elasticity (β) from the pooled (1989 - 2015) sample is displayed in Table 2. Model 1 lists the estimation result of Equations 1 and Model 2 lists the estimation result of Equation 2. As discussed earlier in the data, the fathers' income average over three years is applied as the proxy of permanent income. Without any control variables, the estimate of intergenerational income elasticity is 0.432, but it increases to 0.549 as bias is reduced since the age of father, the age of sons and the interactive term of the age of son and father's income. This result is in accordance with the theoretical prediction (Lee and Solon, 2009) and reveals that a 10% increases in fathers'

[3] The consumer price index in 2015 has been adjusted according to local conditions, the calculation process can be found in "Individual Income Variable Construction" and "Household Income Variable Construction" in the database of CHNS.

Table 1. Descriptive statistics of the key variables.

Variable	Definition	Unit	Mean	SD
Sons				
Income	Annual net income of the son	Yuan	20113.2	54266.78
Age	The age of the son	Years	28.3	5.91
Education	Individual schooling years	Years	9.2	2.74
Occupation	Be calculated according to Erikson and Goldthorpe's (2002) occupational classification table	Points	3.6	2.06
Fathers				
Income	Average net income of three years of the father when the son was a child between 10 and 17 years old	Yuan	4654.1	2908.55
Age	The age of the father when the son was a child between 10 and 17 years old	Years	43.3	5.01

Occupational classification table: *occupation*=10 if the occupation of the children is administrator, executive, manager, army officer or police officer; *occupation*=9 if the occupation of the children is senior professional or technician; *occupation*=8 if the occupation of the children is junior professional or technician; *occupation*=7 if the occupation of the children is office staff; *occupation*=6 if the occupation of the children is skilled worker; *occupation*=6 if the occupation of the children is ordinary soldier or the policeman; *occupation*=5 if the occupation of the children is service worker; *occupation*=4 if the occupation of the children is driver; *occupation*=3 if the occupation of the children is non-skilled worker; *occupation*=2 if the occupation of the children is farmer, fisherman, or hunter; *occupation*=1 if the occupation of the children is something else. In this way, discrete variables can be transformed into continuous variables.

Table 2. The intergenerational income elasticity of rural residents.

Variable	Model (1)	Model (2)
Fathers' or Parents' income (logarithm)	0.432*** (0.083)	0.549** (0.267)
Observations	765	765
R-squared	0.033	0.166

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Robust standard errors is in parentheses.

Table 3. The review of the estimates of Chinese IGE in latest literature.

Variable	Elasticity			Data and Year	Source
	Total	Urban	Rural		
Father-son	-	0.468	-	UHEES (2004); UHIES (1987-2004)	Gong et al. (2012)
Father-son	-	0.491, 0.561	-	CHIP (1995, 2002)	Deng et al. (2013)
Father-son	0.442-0.615	-	-	CHNS (1989-2009)	Li et al. (2014)
Father-child	-	0.421	0.409	CHNS (1989-2009)	Qin et al. (2016)
Father-child	-	0.433, 0.512	-	CHIP (1995, 2002)	Fan (2016)

income will on average lead to a 5.49% increase in their son's income.

Table 3 reviews the estimate of the Chinese intergenerational income elasticity in the recent literature.

It can be easily found that, the estimate of the intergenerational income elasticity from fathers to sons and intergenerational income elasticity from fathers to both sons and daughters dominate the existing research, indicating the intergenerational income elasticity from fathers to sons is higher and the elasticity will slightly decrease if the sample of daughters is also used, which is consistent with the findings in Chadwick and Solon (2002) and Raaum et al. (2007). Besides, most research aimed at the urban area so far, few of them focus on the rural area. The estimated intergenerational income elasticity in rural China is 0.409 (Qin et al., 2016), but this result may be underestimated as its sample is fathers and children (both sons and daughters), with education and health variables controlled. Finally, it is obvious that the intergenerational income elasticity in China is higher, that is, the mobility of intergenerational income is lower compared with the estimation results in other countries,[4] no matter in the urban area or the rural area.

Intergenerational income elasticity based on quantile regression

More importantly, if we extend our studies to the conditional quantile regression estimations, the intergenerational elasticity is lower at lower quantile, even negative at the bottom end of income distribution. The intergenerational income elasticity shows an upward trend as the quantile of income moves to the upper tail. The intergenerational income elasticity grows at an increasing space since the 10th percentile. Although it fluctuates at the 80th percentile, the steadily increasing trend is maintained. At the quantile higher than the 80th percentile, the intergenerational income elasticity skyrockets, even higher than 1. These results indicate that the “inheritance” of family income in rural China varies when we move along the conditional income distribution of adult sons. Children at the upper low part of the conditional distribution show the smallest degree of intergenerational persistence, while top incomes are very much conditional by their childhood economic circumstances, represented here by parental income.

Previous studies estimating the IGE at different quantiles have not yet reach a consensus. Tejada et al. (2015) estimated the intergenerational income elasticity for the 1982 born cohort in the city of Pelotas (Brasil) and found higher values of the IGE at both ends of the income distribution. In line with this study, Palomino et al. (2018) also found a U-shaped relationship in the United States. On the other hand, if we measure intergenerational elasticity for child and parents labor earnings, there will be another result. For example, Bratberg et al. (2007) apply QR for earnings data from Norway cohorts born in 1950 to 1960, and find the decreasing relationship between the IGE and the position at the income distribution with higher IGE at the bottom tail, but more mobility (lower IGE) at the upper tail of the income distribution. Using a sample of 1424 observations, Cooper (2011) found a continuous decrease in the IGE as we go up the income distribution. As Palomino et al. (2018) declared, valuing the intergenerational elasticity of sons’ income would lead to underestimation of the actual IGE at the top quantiles, a possible cause is a great deal of the correlation between parental and children incomes at the upper part of the distribution could occur through capital income, which is counted in the total household income variable.

In the present paper, the father’s total income and the son’s total income are applied. No matter in Tejada et al. (2005) and Palomino et al. (2008) or in the present study, the similarity lies in the fact that the intergenerational income elasticity increases as the quantile moves to the top quantiles. The remarkable finding in the present paper is that the intergenerational income elasticity verified is lower at bottom quantiles, especially in rural China. The implications of this funding are as follows: (1) At bottom quantiles, if a father belongs to the low-income groups when his sons are 10 to 17 years old, it is possible for his sons to set themselves apart from the low-income groups via some kind of mechanisms. That is why the intergenerational income elasticity is lower at bottom quantiles in the rural area. (2) The intergenerational income elasticity approaches the peak at the top tail demonstrates that there are some mechanisms by which the fathers are much more likely to enable their offspring to remain in the high-income group. The transmission mechanism of the intergenerational income will be discussed in details subsequently.

The decomposition of the transmission mechanism of the intergenerational income

Education and occupation are two important transmission channels of intergenerational income. Here, these two channels were compared and analyzed the difference between the two mechanisms at different quantiles of income distribution.

In theory, education is one of the important transmission mechanisms of intergenerational income (Becker and Tomes, 1979; Solon, 2004). Offspring are better educated because of the human capital investment from their parents; meanwhile, the parents obtain higher return on investment. In addition, occupation is probably another important transmission mechanism. As mentioned earlier in the present study, the non-agricultural economy has been developing rapidly since the reform and opening up in China, “farmer” no longer means a

[4] For example, Lee and Solon (2009) found the intergenerational income elasticity in USA is 0.44 on average, and the estimated intergenerational income elasticity is 0.47 in Palomino et al. (2018), both are based on the PSID dataset; And Lefranc et al. (2014) based on Japanese Social Stratification and Mobility Surveys to obtain the intergenerational income elasticity in Japan is 0.35.

Table 4. The decomposition result based on the Blanden method.

Children's education		**Children's occupation**	
Investment coefficient λ_1	1.376	Investment coefficient λ_2	0.241
Rate of return θ_1	0.106	Rate of return θ_2	0.158
Contribution rate τ_1	0.266	Contribution rate τ_2	0.069

profession but a status instead, and then farming is no longer the only employment option for rural residents. In this context, parents can affect their children's income through their effect on their children's occupation. More specifically, the occupation channel may include two aspects: (1) Occupation inheritance. During the period of planned economy and the initial stage of reform and opening up, the phenomenon of "position replacement" and "generational succession" are normal and prevalent: Many positions are handed from parents to children unconditionally when the parents retired. After China's economic reform, although the *direct* phenomenon of "position replacement" and "generational succession" has been alleviated, the *indirect* phenomenon of "position replacement" and "generational succession", such as internal recruitment, still exist. Moreover, the influence of the parents on their children's career is more about the subtle influence of the family growth environment. The children's life habits are formed unconsciously by growing up in a particular family, thereby they tend to enter the labor market which their parents are familiar with. For example, a child whose father is a carpenter is more likely to do similar kind of work when he/she grows up. (2) Social connections (Chinese "Guanxi"). Nowadays, a large number of employment information in China's labor market are still opaque and asymmetric. The larger the patents' social network is, the more information can be gathered to help their children to search out and select the "good" career opportunities. On the other side, the "favor" still plays a vital role in China's present labor market because the open recruitment in competitive market coexists with the planned recruitment based on personal connections.

Table 4 shows the decomposition result of the intergenerational income transmission mechanism based on the Blanden method. It can be seen that the proportion of education of children in the intergenerational income transmission is 26.6%, which has certain explanatory power, and is consistent with previous research (Fan, 2016; Qin, 2016; Palomino et al., 2018). It can be found from further observation that the influence of parents' income on children's education is much greater than the rate of return of the education of children. The proportion of occupation of children is 6.9% in the intergenerational income transmission. It can be found from further observation that the investment impact of the parents' income on children's occupation is also greater than the rate of return of the occupation of children. Compare the role of education to the role of occupation in intergenerational transmission; the contribution rate of education is approximately 3.8 times the contribution rate of occupation. The investment coefficient of education is much higher than the investment coefficient of occupation, while the return rate of education is slightly lower than that of occupation.

Combining the quantile regression estimations with the Blanden decomposition method, we further investigate the roles of education and occupation in intergenerational income transmission at different quantiles. As displayed in Figure 2, the contribution rate of education is higher at the bottom of quantiles income; it exceeds 40% at 10th percentile. As the quantile moves to the upper part of distribution, the contribution rate of education rapidly descends at the 30 to 60th percentile, and then steeply rises to around 15% at 90th percentile. The results are in accord with the results of Palomino et al. (2018), which also found a trend of decreasing first and then increasing and the contribution rate of education reaches a maximum at the bottom quantile, while the contribution rate of occupation shows an inverted U-shaped relationship, peaking at the 30 to 60th percentile.

The decomposition results of education and occupation at different quantiles demonstrate that the intergenerational income transmission is through the channel of education at the tails of income distribution. To be more specific, at bottom quantile of income distribution, children can be disengaged from the low-income group in adulthood by a much higher probability if the parents attach more importance to education more and give their children a better education (The intergenerational income elasticity at 10th percentile as shown in Figure 1). At upper quantiles of income distribution, the children's income will also increase if their parents are able to invest more on their education (The intergenerational income elasticity reach the maximum at medium and upper percentile as shown in Figure 1). At medium part of income distribution, occupation is the main transmission channel of intergenerational income. In other words, occupation inheritance and social connections derived from the parents have great influence on the children's occupation, then further affects the children's lifetime income.

Conclusion

Reasonable intergenerational income mobility is helpful to alleviate the social pressure caused by the income gap,

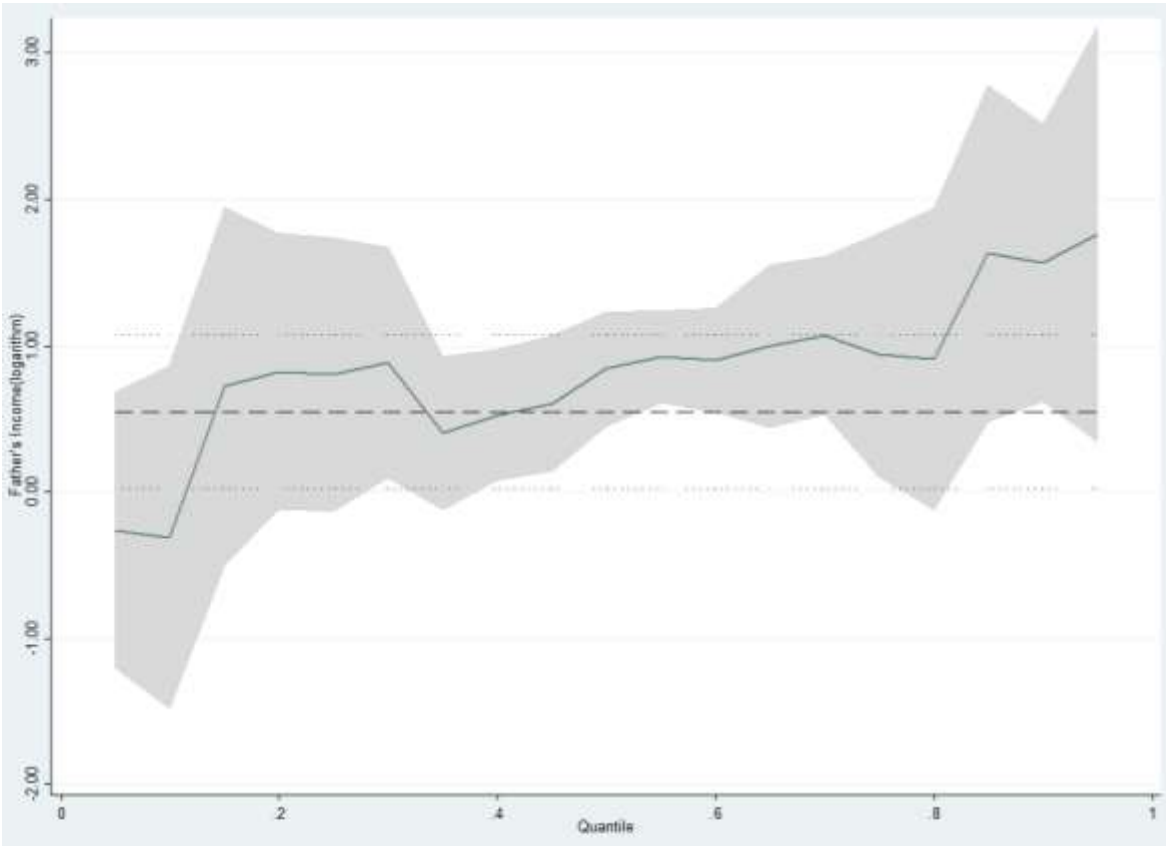

Figure 1. The coefficient of the father's income (Quantile regression).

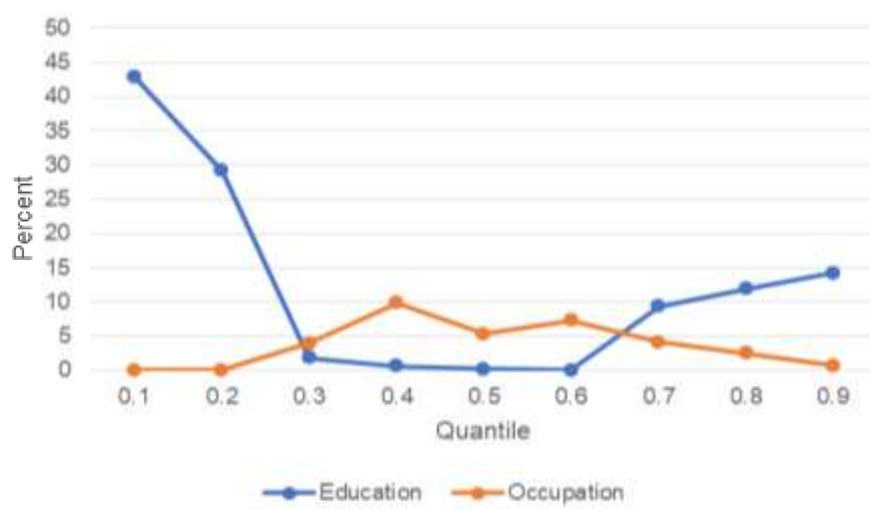

Figure 2. Impact of education and occupation in different income quantiles.

and stimulate people to work hard and make an investment in human capital, which is of great practical significance to current economic development of China. Based on the data of China Health and Nutrition Survey (CHNS) spanning from 1989 to 2015, the intergenerational income mobility and transmission mechanism of rural residents were analyzed. The estimation results indicate the following.

First, the OLS estimation of father and son yields a value of 0.549, which means a 10% increases in fathers' income will on average lead to a 5.49% increase in their sons' income. Compared with the research focused on China as well as other countries, the intergenerational income elasticity in rural China is higher, namely the mobility of intergenerational income in rural China is relatively lower. The quantile regression results show that, the intergenerational income elasticity for rural residents shows a steadily upward trend, which is consistent with the results of the existing research that the intergenerational income elasticity is higher at the upper quantiles. But different from the existing research, the present study found that the intergenerational income elasticity is lower at the bottom quantiles.

Second, the human capital investment represented by the schooling years of the children is indeed an important factor explaining the rural intergenerational income mobility, and its contribution rate is 26.6%. The social capital investment represented by the occupational type of children plays a less important role in the intergenerational income transmission mechanism for rural residents. Its contribution rate is probably 6.9%. At bottom quantile of income distribution, children can be disengaged from the low-income group in adulthood by a much higher probability if the parents attach more importance to education more and give their children a better education. At upper quantiles of income distribution, the children's income will also increase if their parents are able to invest more on their education. At medium part of income distribution, occupation is the main transmission channel of intergenerational income. The results of this study indicate that the promotion of education fairness in the rural areas will have positive effects on rural intergenerational income mobility through the further popularization of education, especially improving educational resources in low income groups.

Of course, because of the limitation of the data, the following shortcomings may exist in the present paper. The fact that the children settled in the city was not taken into account. Theoretically, the parents and their children have been decomposed into two families, of which the parents belong to the rural population and the children belong to the urban population, while CHNS data can only be traced to the former. In this case, the intergenerational income elasticity may be underestimated in this study.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

ACKNOWLEDGEMENTS

This work was funded by the Youth Fund of the Ministry of Education (No. 17YJC630008); Jiangsu Social Science Fund Project (No. 18EYC004).

REFERENCES

Becker GS, Tomes N (1979). An Equilibrium Theory of Distribution of Income and Intergenerational Mobility. Journal of Political Economy 87:1153-1189.

Behrman JR, Paul T (1985). Intergenerational earnings mobility in the United State: some estimates and a test of Becker's intergenerational endowments model. Review of Economics and Statistics 67:144-151.

Bhattacharya D, Mazumder B (2011). A nonparametric analysis of black-white differences in intergenerational income mobility in the United States. Quantitative Economics 2(3):335-379.

Blanden J, Gregg P, Macmillan L (2007). Accounting for Intergenerational Income Persistence: Non-cognitive Skills, Ability and Education. Economic Journal 117:C43-C60.

Bohlmark A, Lindquist MJ (2006). Life-cycle variations in the association between current and lifetime income: replication and extension for Sweden. Journal of Labor Economics 24:879-896.

Bratberg E, Øivind AN, Vaage K (2007). Trends in Intergenerational mobility across offspring's earnings distribution in Norway. Industrial Relations: A Journal of Economy and Society 1:112-129.

Chadwick L, Solon G (2002). Intergenerational income mobility among daughters. American Economic Review 92(1):335-344.

Chen WH, Ostrovsky Y, Piraino P (2017). Lifecycle variation, errors-in-variables bias and nonlinearities in intergenerational income transmission: new evidence from Canada. Labour Economics 44:1-12.

Corak M, Lindquist MJ, Mazumder B (2014). A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States. Labour Economics 30:185-200.

Cooper DP (2007). Unlocking the American dream: exploring intergenerational social mobility and the persistence of economic status in the United States. Georgetown University Library. Washington.

Deng Q, Bjorn G, Li S (2013). Intergenerational income persistence in urban China. The Review of Income and Wealth 59(3):416-436.

Erikson R, Goldthorpe JH (2002). Intergenerational Inequality: A Sociological Perspective. The Journal of Economic Perspectives 16(3):31-44.

Fan Y (2016). Intergenerational income persistence and transmission mechanism: Evidence from urban China. China Economic Review 41:299-314.

Gong H, Leigh A, Meng X (2012). Intergenerational income mobility in urban China. Review of Income and Wealth 58:481-503.

Haider SJ, Solon G (2006). Life-cycle variation in the association between current and lifetime earnings [J]. American Economic Review 96:1308-1320.

Koenker R, Bassett G (1978). Regression Quantiles. Journal of Econometrica 46(1):33-50.

Koenker R (2005). Quantile Regression. Number 38. Cambridge University Press, Cambridge.

Lee CI, Solon G (2009). Trends in intergenerational income mobility. The Review of Economics and Statistics 91(4):766-772.

Lefgren L, Sims D, Lindquist MJ (2012). Rich dad, smart dad: decomposing the intergenerational transmission of income. Journal of Political Economy 120(2):268-303.

Lefranc A, Ojima F, Yoshida T (2014). Intergenerational earnings mobility in Japan among sons and daughters: levels and trends. Journal of Population Economics 27(1):91-134.

Li Z, Liu L, Wang M (2014). Intergenerational income mobility and public education spending: Evidence from China. Children and Youth Services Review 40:89-97.

Mazumder B, Fortunate S (2005). New estimates of intergenerational mobility in the US using social security earnings data. Review of Economics and Statistics 87:235-255.

Mitnik P, Bryant V, Weber M, Grusky D (2015). New estimates of intergenerational mobility using administrative data. Technical report, SOI working paper, statistics of income division, internal revenue service.

Palomino JC, Marrero GA, Rodriguez JG (2018). One size doesn't fit all:

a quantile analysis of intergenerational income mobility in the U.S. (1980-2010). The Journal of Economic Inequality 16(3):347-367.
Qin X, Wang T, Zhuang CC (2016). Intergenerational transfer of human capital and its impact on income mobility: Evidence from China. China Economic Review 38:306-321.
Raaum O, Bratsberg B, Roed K, Osterbacka E, Erikson T, Jantti M, Naylor RA (2007). Marital sorting, household labor supply and intergenerational earnings mobility across countries. The B.E. Journal of Economic Analysis and Policy.
Solon G (1992). Intergenerational income mobility in the United States. American Economic Review 82:393-408.
Solon G (2004). A model of intergenerational mobility variation over time and place. In: Corak, Miles (Ed.), Generational income mobility in North America and Europe. Cambridge University Press, Cambridge.
Tejada CAO, Bertoldi AD, Carraro A, Ribeiro FG, Motta JVS, Barros FC, Horta BL, Barros AJ (2015). Poor dad, poor child? An investigation of intergenerational income mobility in the 1982 birth cohort in Pelotas, Rio Grande Do Sul State, Brazil. Cad. Saude Publication 31(6):1225-1233.
Zhang Y, Eriksson T (2010). Inequality of opportunity and income inequality in nine Chinese provinces, 1989-2006. China Economic Review 21:607-616.