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Intergenerational transfer of human capital and its impact on income mobility: Evidence from China

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ABSTRACT

This paper analyzes theoretically and empirically the impact of intergenerational transmission of human capital on the income mobility in China. We use a three-period overlapping-generations (OLG) model to show that the human capital transfer plays a remarkable role in determining the parent-to-offspring investment in human capital and the intergenerational elasticity of income. We then estimate a simultaneous equations model (SEM) using the 1989–2009 China Health and Nutrition Survey (CHNS) data to verify our theoretical predictions. The results show that (i) human capital, measured by health and education, is directly transmitted from one generation to the next, reflecting the parent-induced inequality of development opportunities among offspring in China; (ii) the estimated intergenerational income elasticity increases from 0.429 to 0.481 when the direct transfer of human capital is accounted for, suggesting that omitting this mechanism would overestimate China's income mobility. Our findings provide policy implications on strengthening human capital investments among the disadvantaged groups, reinforcing reforms that promote equality of opportunity, and improving the efficiency of labor markets in China.

1. Introduction

Social mobility, or the changeability of one's socio-economic status, is an important measure of the equality of a society and an essential determinant of a country's sustainability in economic growth. Since the 1980s, China's unprecedentedly rapid economic growth has been accompanied by emerging social problems such as rising income inequality and lack of social mobility. These problems challenge the continuous development of China's economy and threaten to drag the country into the middle income trap. In recent years, several studies that look at the intergenerational correlation of income have consistently found (i) internationally low income mobility (an important dimension of social mobility) in China, and (ii) the sustaining income inequality is to a high extent explained by the inequality of opportunity (Deng, Bjorn, & Li, 2012; Gong, Leigh, & Meng, 2012; Zhang & Eriksson, 2010). Table 1 summarizes the estimated intergenerational elasticity of income in major countries, among which China ranks higher than most of the developed and some of the developing countries, indicating a low level of intergenerational income mobility. This phenomenon is not only against the moral principal of social equity by giving poor people too few opportunities to improve their economic status, but also leads to decreased incentives among individuals to invest in human capital and thus negatively affects the long run economic efficiency (Moaz & Moav, 1999).

Based on the theory of human capital (Becker, 1993), one of the root causes of low intergenerational mobility is that human capital (including health and education) remains invariant through intergenerational transmission. In particular, some studies point out that

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Table 1
International comparison of intergenerational income elasticity.

Country	Elasticity	Data	Source
U.S.	0.45–0.48	PSID	Lee and Solon (2009)
Canada	0.23	Income Tax Information	Corak and Heisz (1999)
U.K.	0.37	Combined Dataset	Nicoletti and Ermish (2007)
Italy	0.33	SHIW	Piraino (2007)
France	0.41	FQP	Lefranc and Trannoy (2005)
Germany	0.24	G-SOEP	Vogel (2008)
Australia	0.25	Combined Dataset	Leigh (2007)
Finland	0.20	Administrative Register Information	Pekkarinen et al. (2009)
Norway	0.25	Administrative Register Information	Nilsen et al. (2008)
Denmark	0.14	Administrative Register Information	Hussain et al. (2008)
Peru	0.50	LSMS	Grawe (2004)
Malaysia	0.40	MFLS	Grawe (2004)
Pakistan	0.18	LSMS	Grawe (2004)
Brazil	0.52	PNAD	Dunn (2007)
China	0.45	CHNS	Zhang and Eriksson (2010)

Notes: (i) Some information in the table is quoted from Deng et al. (2012) and Björklund and Jäntti (2009); (ii) all coefficients represent father–son income elasticity; (iii) PSID stands for Panel Study of Income Dynamics; (iv) SHIW (Survey on Household Income and Wealth) is sponsored by Bank of Italy; (v) FQP (Formation, Qualification, Profession) is conducted by INSEE (Institut National de la Statistique et des Études Économiques); (vi) G-SOEP stands for German Socio-Economic Panel; (vii) LSMS (Living Standard Measurement Survey) is conducted by the Word Bank; (viii) MFLS stands for Malaysian Family Life Survey; (ix) PNAD stands for Pesquisa Nacional por Amostra de Domicilios; (x) CHNS stands for China Health and Nutrition Survey.

the low human capital accumulation of the disadvantaged population is consistently inherited from the previous generations, thus limiting the ability of the poor to improve their income (Yao & Zhao, 2007). To a large extent, China's recent experience has mirrored the above findings. In the health care sector, the traditional rural Cooperative Medical Scheme (CMS) and urban Labor Insurance Scheme (LIS) gradually collapsed during the marketization and privatization reforms in the 1980s and 1990s, leading to persistent deterioration in the access to basic health care (Blumenthal & Hsiao, 2005); consequently, inequality in health capital expands through intergenerational transmission, and people in poor-health groups see little chance to substantially improve their health status. From the perspective of education, the inequality in educational opportunities is also aggravated during China's education reforms in the 1990s that are characterized by industrialization and enrollment expansion in the higher education sector (Liu, 2006); specifically, well-educated parents who are generally in high socio-economic status manage to obtain better access to high-quality educational resources for their children (Li, 2006). Given the above stylized facts, an important theoretical and practical question is: whether and to what extent does the intergenerational persistence of human capital contribute to the decreasing income mobility in China? A valid answer to the above question is not only meaningful to economic theorists, but can also provide policy guidance to China's current reforms in education, health care and income redistribution.

This paper is among the first to study the impact of human capital transmission across generations on the intergenerational income mobility in China from both theoretical and empirical perspectives. In the theoretical analysis, we incorporate the mechanisms of direct and indirect transmission of human capital into a classical three-period overlapping-generations (OLG) framework based on Becker and Tomes (1979), the results of which provide a new way to solve for parents' optimal investment in their children's human capital and to calculate the implied elasticity of income across generations. In the empirical analysis, we use the 1989–2009 China Health and Nutrition Survey (CHNS) data to investigate the intergenerational transmission of income, health and education based on a simultaneous equations model, the results of which show remarkable transmission of human capital (health and education) across generations and that the parent–offspring income elasticity tends to be underestimated (i.e., income mobility tends to be overestimated) if the direct transfer of human capital is not accounted for. Our findings provide a new approach to estimate the intergenerational income elasticity, which facilitates deeper understanding on the root causes of the lack of social mobility in China.

The paper proceeds as follows: Section 2 briefly reviews the relevant literature; Section 3 lays out the theoretical model and its extension; Section 4 describes our empirical strategy and data; Section 5 presents the estimation results and robustness tests; Section 6 concludes the paper.

2. Literature review

The intergenerational income elasticity, estimated by the regression coefficient of parents' logarithmic permanent income on their children's, is commonly used as a measure of social mobility in the economic literature. Limited by data availability and measurement accuracy, the traditional estimates of intergenerational income elasticity tend to be biased downwards; an example is Solon (1999), which estimates that the elasticity in the U.S. is only 0.2. Facilitated by large databases such as the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth (NLSY) and the National Child Development Study (NCDS), recent studies are able to obtain more accurate estimates for different countries. For example, based on NLSY, NCDS and Nordic register data, Jäntti et al. (2006) conduct a cross-country study on the intergenerational elasticity of income, and find that the estimated elasticity is 0.517 in the U.S., 0.306 in the U.K., and less than 0.2 in three Nordic countries (Norway, Finland and Denmark). Vogel (2008) studies the intergenerational mobility in Germany by calculating permanent incomes based on the German Socio-Economic Panel (G-SOEP) data, and concludes that the elasticity is about 0.24.

In developing countries, empirical literature on this topic is relatively scant due to the often and abrupt social structural changes and the lack of reliable datasets. For example, China as the largest developing country has experienced dramatic social and economic transformation. Before the 1980s, measuring the intergenerational income mobility in China seemed barely meaningful. This is because the demand and supply of labor were strictly controlled by the government under the centrally planned economy, and thus the labor market does not exist and the marginal value of labor cannot be reflected by wages. However, after the economic reforms in the 1980s, the labor market in China has gradually developed and taken its role in determining the market wages, the income elasticity therefore becomes an important indicator to measure the social mobility and the equity of income distribution across generations. Several studies have discussed this issue: Zhang and Eriksson (2010) estimate the correlation of parental household income and children's individual income using the 1989–2006 CHNS data, and conclude that the elasticity is about 0.45; based on the 2004 Chinese Urban Household Education and Employment Survey (UHEES), Gong et al. (2012) explicitly take the impacts of life cycle and measurement errors into account in their estimation, and report that in urban China the father–son elasticity of income is about 0.6 and the father–daughter elasticity is up to 0.97, which is extremely high compared with the other related studies (e.g., Guo & Min, 2007 use the same data but get an estimate of 0.32 for father–son elasticity); based on the data from China Household Income Projects (CHIP) and Chinese General Social Survey (CGSS), Chen and Yuan (2012) find that the income elasticity in China fell dramatically at first and remained stable afterwards during 1988–2005, and that the estimated elasticity in urban areas (about 0.4) is higher than that in rural areas (about 0.3); Sun, Huang, and Hong (2012) also use the 2006 CGSS data and find that the labor migration plays an important role in reducing the intergenerational persistence of income in China.

Compared with the estimation of intergenerational elasticity, more attention is deserved on the mechanisms giving rise to the resemblance in income between parents and children. The commonly identified channels include, e.g., inheritance of wealth or family businesses, allocation of political rents, institutional perseverance and the environmental and behavioral influences by social cohorts (Borjas, 1992). Among all the contributing factors, the intergenerational transmission of human capital undoubtedly plays an important role: on the one hand, since one's income is largely determined by his human capital accumulation, parents' human capital can influence their financial capability to invest in children's human capital and thus influence their children's future income (we call this the indirect transmission mechanism); on the other hand, parents' human capital can be directly transferred to their children through genetic or non-genetic channels, which also influences the future income of their children (we call this the direct transmission mechanism).

Intergenerational investment in human capital within families (the indirect mechanism) is first studied by Becker and Tomes (1979). They discuss parents' trade-offs among consumption, financial investment and human capital investment in their children under the altruistic utility assumption. Their model contributes to the better understanding of the determination of income mobility across generations and sparks many follow-up studies. For example, Loury (1981) introduces the credit constraints to Becker's model and concludes that under the constraints, parents in low-income families can hardly borrow enough money to invest in children's human capital, contributing to the decreases in the intergenerational mobility. Moaz and Moav (1999) and Nakamura and Murayama (2011) also discuss this mechanism but under the assumption that human capital stock is discrete (uneducated vs. educated). Based on the above theoretical findings, some empirical studies also try to assess the possibility of improving the intergenerational income mobility through public policy tools, including public education policies (Restuccia & Urrutia, 2004) and income taxation policies (Zhu & Vural, 2012).

The second mechanism, in comparison, mainly refers to the direct transfer of human capital (such as education and health) across generations through the genetic channels (e.g. natural inheritance of cognitive abilities and health conditions) or behavioral channels (e.g. children learn from their parents by observing their activities). This direct transmission mechanism has drawn increasing attention in the recent literature. For example, using the NLSY data, Akbulut and Kugler (2007) show that height, weight (or BMI) and other health indicators of parents are highly correlated with those of their children. Eriksson, Bratsberg, and Raaum (2005) also demonstrate the strong similarity of health conditions between parents and offspring using the data from Denmark. However, the above studies did not address the endogeneity issue in their estimation, thus are mainly concerned with the intergenerational correlation (rather than causality) of human capital. In an effort to identify the causality, some studies use special samples to explicitly eliminate the influences of unobserved factors on the health capital of both generations. For example, Currie and Moretti (2007) control the influences of family background and genetic endowment using a sample of sibling mothers obtained from the Californian individual birth record data (assuming that sisters share similar family background and genes), and find that the low-birth-weight mothers also tend to have low-birth-weight children, suggesting a causal impact of health status across generations. Similarly, Royear (2009) identifies the causality using a confidential dataset of twins based on the 1960–2002 Californian birth records. Other studies also discover the intergenerational link of the health-related habits such as smoking, drinking and physical inactivity. For example, Loureiro, Sanz-de-Galdeano, and Vuri (2010) use data from the Birth Household Panel Survey (BHPS) to find that children's smoking behaviors are significantly influenced by their parents'.

Compared with the intergenerational transmission of health, the estimation on the direct transfer of educational attainment is more complicated, as the indirect transmission mechanism (parents' investment in children's education) can be a compounding factor. Nevertheless, several recent studies have demonstrated the genetic transmission of cognitive abilities: Black, Devereux, and Salvanes (2009) and Björklund, Eriksson, and Jäntti (2010) use data from the Swedish military enlistment tests to estimate the correlation in Intelligence Quotient (IQ) between fathers and sons, and find a high correlation coefficient around 0.32; based on the G-SOEP data, Anger and Heineck (2010) show that cognitive skills that are based on past learning are more strongly transferred from parents to children than those related to innate abilities. On the other hand, some recent studies also aim to identify the non-genetic transmission of education using special data samples or exogenous instruments. For example, Plug (2004) uses a sample of adoptees from the Wisconsin Longitudinal Survey (WLS) and finds that the adoptive father–child correlation of schooling is strong but the adoptive mother–child correlation is not significant; Chevalier (2004) and Black, Devereux, and Salvanes (2005) identify the non-genetic effects by using the education reforms in Britain and Norway as natural experiments, and they both find that only the mother–son transmission of schooling is significant while the other three pairs (i.e., mother–daughter, father–son, and father–daughter) are not.

3. Theoretical model

3.1. The benchmark model

We start by formulating an OLG model in which all individuals go through three life stages: dependent children, working young adults and retired old adults. We assume an individual accumulates human capital in childhood; he works and earns income in young adulthood while at the same time make decisions on consumption, savings for old age and investment in their children; in old adulthood, the individual retires and consumes on his savings. For simplicity, the benchmark model only accounts for parents' investment in their children's human capital (the indirect transmission) without considering the direct human capital transfer across generations.

In the above context, the expected utility of a representative working young adult can be expressed as follows:

$$EU_t^p = u(c_t^p) + \beta u(c_{t+1}^p) + \beta\alpha E_t u(y_{t+1}^c) \tag{1}$$

where superscript p denotes parent, and superscript c denotes child. $u(\cdot)$ is the instantaneous utility function, with $u'(\cdot) > 0$ and $u''(\cdot) < 0$. Working young adults earn an income of y_t^p in period t and make decisions on current consumption c_t^p, old-age savings s_t^p, and offspring human capital investment e_t^p. Following the altruistic assumption in the literature (Becker & Tomes, 1979; Solon, 2004), the adults also derive utility from their children's expected income in period $t+1$, y_{t+1}^c, when the children themselves become young adults, with α being the altruistic parameter and β being the discount factor. In period $t+1$, the working young adults retire and spend their deposits $(1+R_t)s_t^p$ on consumption c_{t+1}^p.

We assume human capital is the engine of economic growth, and one's income y_t is determined by his human capital accumulation h_t:

$$y_t^p = (h_t^p)^{\gamma}, \quad 0 < \gamma < 1 \tag{2}$$

where $0 < \gamma < 1$ ensures a diminishing marginal return of human capital on income. Furthermore, one's human capital stock depends on his innate ability A_t^c and the investment e_t^p from their parents, thus

$$h_{t+1}^c = A_t^c (e_t^p)^{1-\sigma}, \quad 0 < \sigma < 1 \tag{3}$$

where $0 < \sigma < 1$ ensures that the human capital investment is also subject to diminishing marginal returns. For simplicity, we assume that one's innate ability is randomly determined as follows:

$$\ln A_t^c = \ln \bar{A} + \varepsilon_t \tag{4}$$

where $\ln \bar{A}$ is the mean (constant) value of $\ln A_t^c$, and $\varepsilon_t \sim N(0, v^2)$ is the random shock following a normal distribution. Since the parents may not know their children's innate abilities, we assume they form expectations on $\ln A_t^c$ based on their own innate abilities A_t^p and make investment decisions accordingly.

Following the literature convention (e.g., Solon, 2004), we simplify the instantaneous utility function using the logarithmic form, thus the optimization problem becomes:

$$\underset{c_t^p, s_t^p, e_t^p, c_{t+1}^p}{Max} \; EU_t^p = \ln c_t^p + \beta \ln c_{t+1}^p + \beta\alpha E_t \ln y_{t+1}^c \tag{5}$$

$$s.t. \quad c_t^p + s_t^p + e_t^p \le y_t^p \tag{6}$$

$$c_{t+1}^p \le (1+R_t)s_t^p \tag{7}$$

$$y_{t+1}^c = (h_{t+1}^c)^{\gamma} \tag{8}$$

where Eqs. (6) and (7) are parents' budget constrains in period t and $t+1$ respectively (both are binding constraints), and Eq. (8) is the income determination equation. The associated first-order conditions (F. O. C.) are:

$$\frac{c_t^p}{c_{t+1}^p}\beta(1+R_t)=1 \tag{9}$$

$$\frac{1}{c_t^p}=\alpha\beta\gamma(1-\sigma)\frac{1}{e_t^p} \tag{10}$$

where Eqs. (9) and (10) respectively indicate that in the optimal equilibrium, parents' marginal utility of consumption in period t equals that in period $t+1$, and that parents' marginal utility of consumption equals the marginal utility return of human capital investment in their children. The resulting closed-form solution of e_t^p, derived by Eqs. (6), (7), (9) and (10), is:

$$e_t^p=y_t^p\frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)}. \tag{11}$$

Through standard comparative static analyses, we have the following proposition:

Proposition 1. In a stable growth-equilibrium regime, parents' optimal human capital investment e is positively influenced by parents' income y, the altruistic parameter α, the discount factor β, and the parameter γ in the income deterministic function, but is negatively influenced by the parameter σ in the human capital accumulation function.

Proof. Take the derivatives of e with respect to y, α, β, γ, and σ, respectively, we have:

$$\begin{aligned}
&\frac{\partial e_t^p}{\partial y_t^p}=\frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)}>0,\ \frac{\partial e_t^p}{\partial\alpha}=y_t^p\frac{(1+\beta)\beta\gamma(1-\sigma)}{[1+\beta+\alpha\beta\gamma(1-\sigma)]^2}>0\\
&\frac{\partial e_t^p}{\partial\beta}=y_t^p\frac{\alpha\gamma(1-\sigma)}{[1+\beta+\alpha\beta\gamma(1-\sigma)]^2}>0,\ \frac{\partial e_t^p}{\partial\gamma}=y_t^p\frac{(1+\beta)\alpha\beta(1-\sigma)}{[1+\beta+\alpha\beta\gamma(1-\sigma)]^2}>0\\
&\frac{\partial e_t^p}{\partial\sigma}=-y_t^p\frac{(1+\beta)\alpha\beta\gamma}{[1+\beta+\alpha\beta\gamma(1-\sigma)]^2}<0.
\end{aligned}$$

The proposition is intuitive and reasonable. Parents in high-income families are more financially capable, thus are more likely to invest in their children's human capital; if the altruistic parameter α increases, the marginal utility return on human capital investments will also increase and thus motivates parents to invest more in their children; the increase of the discount factor β indicates that children's future income becomes more important to parents and thus their incentive to invest grows (although parents' future consumption also becomes more important and will partially decrease the incentive); the increase of the parameter γ will lead to a higher marginal return of human capital on income, thus also contributes to parents' higher incentive to invest; however, the increase of the parameter σ will decrease the marginal return of human capital investment, therefore depressing the incentives to invest.

Since our main focus is on the intergenerational income mobility rather than parents' optimal investment decisions, we substitute Eqs. (3), (4) and (8) into Eq. (11) to form the intergenerational income transmission function as follows:

$$\ln y_{t+1}^c=\gamma\ln\overline{A}+\gamma(1-\sigma)\ln y_t^p+\gamma(1-\sigma)\ln\frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)}+\gamma\varepsilon_t. \tag{12}$$

Following the conventional functional form in the intergenerational income regressions (e.g. Jäntti et al., 2006), Eq. (12) can be simplified to:

$$\ln y_{t+1}^c=\eta_0+\eta_1\ln y_t^p+u_t \tag{13}$$

where the intercept η_0, the income elasticity η_1 and the residual u_t are given as follows:

$$\eta_0=\gamma\ln\overline{A}+\gamma(1-\sigma)\ln\frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)} \tag{14}$$

$$\eta_1=\gamma(1-\sigma) \tag{15}$$

$$u_t=\gamma\varepsilon_t. \tag{16}$$

In Eq. (13), the intergenerational income elasticity η_1 is the key parameter of interest, and its functional form in Eq. (15) suggests that the elasticity is effectively determined by the marginal return of human capital on income and the rate of return on parent-to-offspring human capital investment. When these two returns increase, parents' incentive to invest in their children's human capital grows, which in turn leads to a higher intergenerational income elasticity and lower income mobility.

3.2. The extended model

The above benchmark model only accounts for the indirect transmission of human capital through the parent-to-offspring investment. In the extended model, we further introduce the direct transmission mechanism and discuss its impact on income mobility. The model extension is motivated by several recent studies that characterize the direct transfer of human capital across generations independent of the investment channel, i.e. human capital can be directly transmitted through genetic inheritance and non-genetic influences. For example, Hertz et al. (2007) estimate the intergenerational persistence of educational attainment in 42 countries and report that the intergenerational correlations between parents' and children's schooling remain surprisingly high and stable around 0.4 to 0.6 for the past fifty years. Chevalier, Denny, and McMahon (2009) report similar results through a multi-country study of intergenerational educational mobility and find a positive relationship between intergenerational income mobility and return to education. Based on these findings, the human capital accumulation function can be modified to:

$$h_{t+1}^c = A_t^c \left(h_t^p\right)^{\sigma} \left(e_t^p\right)^{1-\sigma}, \quad 0 < \sigma < 1 \tag{17}$$

where $(h_t^p)^{\sigma}$ represents the direct transfer of human capital from parents to their offspring, which operates in conjunction with the indirect transmission channel e_t^p in determining h_{t+1}^c through the Cobb–Douglas function, with the parameters σ and $(1-\sigma)$ reflecting their relative contribution.

Replacing Eq. (3) with Eq. (17) in the optimization, the above modification does not change the optimal solution for e_t^p. However, the intergenerational income transmission function will be changed into the following form:

$$\ln y_{t+1}^c = \gamma \ln \bar{A} + \gamma\sigma \ln h_t^p + \gamma(1-\sigma) \ln y_t^p + \gamma(1-\sigma) \ln \frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)} + \gamma\varepsilon_t \tag{18}$$

which can be further simplified to:

$$\ln y_{t+1}^c = \theta_0 + \theta_1 \ln y_t^p + v_t \tag{19}$$

where the intercept θ_0, the income elasticity θ_1 and the residual v_t are given as follows:

$$\theta_0 = \gamma \ln \bar{A} + \gamma(1-\sigma) \ln \frac{\alpha\beta\gamma(1-\sigma)}{1+\beta+\alpha\beta\gamma(1-\sigma)} \tag{20}$$

$$\theta_1 = \sigma + \gamma(1-\sigma) \tag{21}$$

$$v_t = \gamma\varepsilon_t. \tag{22}$$

Eq. (21) suggests that the intergenerational income elasticity is determined by not only the two marginal returns but also the relative contribution of the two mechanisms (i.e., the direct transfer and indirect investment of human capital). Furthermore, a comparison of Eq. (15) in the benchmark model and Eq. (21) in the extended model leads to the following proposition:

Proposition 2. Ignoring the direct parent-to-offspring transfer of human capital will result in an underestimation of the intergenerational income elasticity and an overestimation of the intergenerational income mobility.

As the main prediction of our theoretical model, Proposition 2 will be verified empirically using China's nationally representative data in the following sections.

4. Estimation methods and data

4.1. Regression models

In the empirical analysis, we aim to verify the above theoretical propositions by estimating and comparing the intergenerational income elasticities based on a basic Ordinary Least Squares (OLS) model and a simultaneous equations (SE) model, which in turn correspond to the benchmark model and the extended model in Section 3 respectively.

Following the previous literature on intergenerational income elasticity (Jäntti et al., 2006; Solon, 2002)[3], the basic OLS model is specified as follows:

$$\ln y^c = \eta_0 + \eta_1 \ln y^p + \eta_2 edu^c + \eta_3 health^c + \eta_4 X + u_t \tag{23}$$

where y^c is the children's yearly income, and y^p represents parents' permanent income as measured by their average income in all sample years; edu^c indicates children's educational attainment (measured by years of schooling) and $health^c$ represents their health status (measured by height, BMI, presence of chronic diseases or self-rated health), which jointly reflect children's human capital stock. Eq. (23) can be considered as an empirical approximation of Eq. (13), with the parameter η_1 (i.e. the intergenerational income elasticity) being specified by Eq. (15) and the parameters η_2 and η_3 (i.e. the influence of human capital on income) being specified by Eq. (2). Vector X includes a set of control variables such as parents' age and occupation and children's age, gender and regional characteristics (urban/rural, coastal/inland). Consistent with the benchmark theoretical model, the above OLS model does not account for the direct transfer of human capital across generations.

In the SE model, we explicitly introduce the direct human capital transfer and study its impact on the intergenerational income elasticity. Specifically, the parent-to-offspring transmission of income, education and health can be specified as follows:

$$\ln y^c = \theta_0 + \theta_1 \ln y^p + \theta_2 edu^c + \theta_3 health^c + \theta_4 X + v_t \tag{24}$$

$$edu^c = \alpha_0 + \alpha_1 edu^p + \alpha_2 \ln y^p + \alpha_3 health^c + \alpha_4 X + \varepsilon_t \tag{25}$$

$$health^c = \gamma_0 + \gamma_1 health^p + \gamma_2 \ln y^p + \gamma_3 edu^c + \gamma_4 X + \mu_t \tag{26}$$

where Eqs. (24)–(26) are theoretically motivated by Eqs. (19) and (17), and they jointly form a system of simultaneous estimation equations characterizing the determination of children's income, education and health respectively. In Eqs. (25) and (26), we also consider the interaction of socio-economic factors to account for the income–education–health gradient as verified by the previous literature (Smith, 2004). Specifically, in Eq. (25), children's years of schooling (edu^c) are influenced by not only their parents' years of schooling edu^p (the direct transfer of education), but also their parents' income and their own health status; this is because parents' income may influence their financial capability of investing in children's education (the indirect transmission mechanism; see Taubman (1989) and Plug and Vijverberg (2005) for empirical support), and children's education may also be closely related to their own health status (education–health gradient; see Behrman (1996) and Glewwe, Jacoby, and King (2001) for empirical references). Similarly, in Eq. (26), children's health status ($health^c$) is influenced by their parents' health ($health^p$), their parents' income and their own educational attainment (empirical support can be found in Eriksson, Pan, & Qin, 2014; Goode, Mavromaras, & Zhu, 2014). Additionally, we also control the demographic and regional factors (as denoted by vector X) in all the three transmission equations.

In the above system, the interaction between children's education and health might cause endogeneity in Eqs. (25) and (26) due to reversed causality, i.e., $E[health^c \cdot \varepsilon_t] \neq 0$ in Eq. (25) and $E[edu^c \cdot \mu_t] \neq 0$ in Eq. (26).[4] To avoid the endogeneity bias, we use $health^p$ in Eq. (26) as the instrumental variable (IV) for $health^c$ in Eq. (25), and use edu^p in Eq. (25) as the IV for edu^c in Eq. (26). Consequently, we identify the SE model through Indirect Least Squares (ILS) by substituting the fitted values of edu^c and $health^c$ into Eq. (24) based on the IV estimation of Eqs. (25) and (26). The validity of this identification strategy depends on whether the IVs satisfy the "power condition" and "exclusion restriction". The former means that the IVs ($health^p$ and edu^p) should be highly correlated with their corresponding endogenous variables ($health^c$ and edu^c), and the latter means that the IVs should be uncorrelated with the corresponding residuals (ε_t and μ_t). As mentioned in Section 2, the "power condition" is widely supported by the empirical literature that shows strong correlation between parents' health (education) and their children's health (education). Moreover, this correlation will also be formally tested on our data using the F statistics for the significance of the IVs in the first stage regressions associated with Eqs. (25) and (26) (see Section 5.2). On the other hand, the "exclusion restriction" indicates that parents' health status should not directly influence their children's years of schooling, and parents' education should not have a direct impact on their children's health, i.e. there should not be a cross-transmission of human capital between the two dimensions (education and health). While there is continued debate regarding the validity of the above argument (see Currie, 2011 for a review on the "nature–nurture interaction" hypothesis), much recent literature has provided strong support for the "exclusion restriction". For example, based on the Demographic and Health Surveys in 22 developing countries, Desai and Alva (1998) find that parental education is not significantly correlated to infant mortality rates and children's height-for-age z scores; McCrary and Royer (2011) use the confidential natality data from Texas and California to find that mothers' years of schooling have no significant impact on infants' health status (birth weight); based on the NCDS data, Lindeboom, Liena-Nozal, and Klaauw (2009) also find no evidence of cross-transmission of human capital. For our

[3] In the previous studies, the OLS regression may exclude edu^c, $health^c$ or X; for comparison, we estimate the elasticity using different combinations of the explanatory variables in the basic OLS model (see Table 3).

[4] The endogeneity in Eqs. (25) and (26) may also be caused by the unobserved factors (such as genetic inheritance of cognitive ability and health condition) that influence both the human capital of children and of their parents. However, due to data limitation, we are not able to control such endogeneity using special samples or instrumental variables, which is an admitted limitation of our study.

data, the "exclusion restriction" condition is empirically verified through a direct test of the cross-transmission between education and health by re-specifying Eqs. (25) and (26) in the SE estimation (see Section 5.3).

4.2. Data and sample description

The data used in this paper are from the China Health and Nutrition Survey (CHNS), which is jointly sponsored by the Carolina Population Center at the University of North Carolina and the Chinese Center for Disease Control and Prevention. CHNS has so far included nine waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011). In each round of surveys, it uses a multistage random cluster process to draw a sample of about 4400 households with a total of 15,000 to 19,000 individuals in nine provinces (Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning and Shandong) that vary substantially in geographic and economic characteristics. In each province, four counties are randomly selected based on a weighted sampling scheme; within each county, "communities" are randomly selected as secondary sampling units (SSU) which represent urban neighborhoods or rural villages. The household survey collects detailed information on the respondent's socio-demographic characteristics, health status, nutrition intake, medical care utilization, etc. The community survey provides information on the local hygiene, public service infrastructure, health care resources, insurance coverage, etc.

We use the adult sample from the 1989–2009 CHNS household survey data and match each father–child pair using the family relationship information (considering the low female labor participation rate in rural China, we do not consider the mother–child pairs). The sample restriction criteria are then applied as follows. First, we exclude children under 25 years old as they may still be

Table 2
Sample summary statistics of select variables.

Variable	Definition	Overall	Rural	Urban	Son	Daughter
Children's variables						
cincome	Yearly income	8943.3	8397.4*	9706.1	9163.3	8087.8
	(*Yuan*)	(12224.3)	(12608.1)	(11634.9)	(12864.3)	(9297.2)
cedu	Education	9.949	9.347*	10.789	9.900	10.136
	(years)	(3.342)	(2.613)	(4.005)	(3.192)	(3.870)
cheight	Height	166.7	166.6	166.9	168.9*	158.1
	(cm)	(7.399)	(6.946)	(7.993)	(6.120)	(5.424)
csrh	Self-rated health	2.912	2.890	2.948	2.908	2.928
	(1–4)	(0.708)	(0.710)	(0.704)	(0.718)	(0.662)
coverweight	Overweight	0.279	0.264	0.299	0.306*	0.172
	(1 = yes)	(0.448)	(0.441)	(0.458)	(0.461)	(0.378)
cchronic	Chronic diseases	0.0213	0.0113*	0.0351	0.0230	0.0143
	(1 = have)	(0.144)	(0.106)	(0.184)	(0.150)	(0.119)
cage	Age	31.90	31.07*	33.06	32.10*	31.14
	(years)	(6.183)	(5.052)	(7.332)	(6.227)	(5.963)
cgender	Gender	0.205	0.141*	0.294	–	–
	(1 = female)	(0.404)	(0.348)	(0.456)	–	–
Fathers' variables						
fincome	Avg yearly income	9062.4	8214.6*	10246.8	8945.2	9518.1
	(*Yuan*)	(8287.0)	(7837.9)	(8746.9)	(7921.2)	(9580.3)
fedu	Education	8.354	7.587*	9.425	8.205*	8.935
	(years)	(3.486)	(2.730)	(4.095)	(3.334)	(3.975)
fheight	Height	165.1	164.7*	165.7	165.1	165.1
	(cm)	(6.039)	(6.095)	(5.923)	(6.147)	(5.609)
fsrh	Self-rated health	2.665	2.612*	2.753	2.649	2.738
	(1–4)	(0.752)	(0.735)	(0.772)	(0.754)	(0.738)
foverweight	Overweight	0.380	0.326*	0.455	0.388	0.348
	(1 = yes)	(0.486)	(0.469)	(0.498)	(0.488)	(0.477)
fchronic	Chronic diseases	0.212	0.156*	0.290	0.208	0.226
	(1 = have)	(0.409)	(0.363)	(0.454)	(0.406)	(0.419)
fage	Age	60.41	58.33*	63.30	60.39	60.46
	(years)	(7.586)	(6.616)	(7.907)	(7.662)	(7.300)
fstate	Job sector	0.424	0.403*	0.453	0.399*	0.520
	(1 = state-owned)	(0.494)	(0.491)	(0.498)	(0.490)	(0.501)
Environmental variables						
Urban	Urban/rural	0.417	–	–	0.371*	0.599
	(1 = urban)	(0.493)	–	–	(0.483)	(0.491)
Coast	Costal/inland	0.410	0.403	0.420	0.405	0.430
	(1 = costal)	(0.492)	(0.491)	(0.494)	(0.491)	(0.496)
Sample size		1364	795	569	1085	279

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) * denotes 10% significance level in t-test for urban–rural or son–daughter differences; (iii) BMI = weight (kg) / squared height (sq. m); one is overweight when BMI ≥25; (iv) self-rated health 1–4 are "poor, fair, good and excellent", respectively; (v) all income are measured in 2009 *Yuan*.

in school (especially for those who receive higher education) and thus may not have a stable income. Second, we exclude individuals with no income or those whose income values are missing, as they cannot be used for income elasticity estimation. Third, we exclude observations with missing information on education, health, father's education and health, as well as other control variables. Our final study sample thus contains 1364 father–child pairs, among which urban residents account for 41.7% and the father–son relationship accounts for 79.5%. Table 2 reports the sample descriptive statistics of the main variables, which are analyzed as follows.

(1) *Income*. CHNS collects household and individual income data on a yearly basis. The annual income is calculated from seven main sources: home gardening, collective and household farming, raising livestock or poultry, collective and household fishing, small handicraft and small commercial household business, pension gratuity and wages paid by formal sectors. An interpolation method is applied for observations with missing information in one or some (but not all) of the income sources. We accept this official interpolation method, but drop the individuals with negative or missing total income values. We then convert all income measures into 2009 *Yuan* and apply the natural logarithm transformation. To smooth the impact of unobserved shocks to one's permanent income, we follow the literature convention (Mazumder, 2005; Solon, 1992) and take the average values of fathers' annual income in all sample waves as a proxy measure of fathers' permanent income. Although we cannot apply the same treatment to children as most of them do not have multiple-wave data on income, their yearly income may still serve as a valid proxy for permanent income, because (i) the life cycle impact on income is partially controlled by children's age in the regressions; (ii) recent studies on intergenerational income elasticity show that the single-year income can be a reliable proxy for one's permanent income for individuals aged between 30 and 40 (Bohlmark & Lindquist, 2006; Haider & Solon, 2006), which is indeed the case for a significant portion of our sample children; (iii) since children's income is the dependent variable in the regression, the measurement errors in this variable will not cause the error-in-variable problem and the associated estimation bias. As shown in Table 2, fathers' average permanent income is 9062.4 *Yuan*, while children's average income is 8943.3 *Yuan* for the full sample. Meanwhile, the incomes of both generations are higher in the urban areas compared to the rural areas, but no significant difference is found between the son sample and the daughter sample.

(2) *Education*. CHNS collects individuals' educational information by directly asking their years of formal schooling and the highest level of education attainment. Based on this information, we construct the continuous variables *ceduyear* and *feduyear* to measure children's and fathers' educational human capital stock. Table 2 indicates that the children's average years of schooling is 9.9 for the full sample; the urban residents are significantly better educated than their rural counterparts (10.8 vs. 9.3), and the female children sample has higher average education levels than the son sample (10.1 vs. 9.9). Possibly because of the Great Cultural Revolution and other historical factors, the sample fathers' average years of schooling is only 8.4, which is substantially lower than their offspring; moreover, the urban–rural gap in education is larger for fathers (9.4 vs. 7.6) than for their offspring.

(3) *Health*. CHNS has rich and comprehensive information on individual health and nutrition. Following the literature convention, we use the following variables to measure an individual's health capital stock: (i) Height. Largely determined by childhood nutrition intake and medical conditions, height is commonly used in health economics as a measure of a person's long-term health, especially in developing countries (Strauss & Thomas, 1998). In our sample, the mean of children's height is 166.7 cm, which is about 2-cm taller than that of their fathers', reflecting an improvement of nutrition and health status in the past decades. (ii) Self-rated health (SRH). CHNS asks respondents to rate their health status since the 1997 wave,[5] with “Excellent, Good, Fair and Poor” as possible answers (valued sequentially as 4, 3, 2 and 1).[6] In our sample, children's average SRH is 2.9, which is greater than that of their fathers' (2.7); meanwhile, the proportion of children who choose “Excellent” and “Poor” is smaller than fathers, reflecting not only the improvement but also a more concentrated distribution of health in the younger generation. (iii) Overweight. This dummy variable is generated based on the Body Mass Index (BMI) calculated from respondents' self-reported height and weight (BMI $=$ weight (kg) / height $(\text{m})^2$). BMI is widely used as a measure of health status among adults; according to the WHO recommended thresholds, a person is defined as overweight when his BMI is greater than or equal to 25. As shown by Table 2, 27.9% of children and 38.0% of parents in our sample are overweight, and the prevalence of overweight in the son sample is higher than that in the daughter sample. (iv) Presence of chronic diseases. This dummy variable is generated based on Xie (2011), i.e., if one reports in the disease history that he suffers from hypertension, diabetes, stroke or transient ischemic attack, asthma (either told or diagnosed by a doctor) or other chronic conditions (e.g., heart disease or chest pain) during the past 4 weeks, then the respondent is considered to have chronic diseases. Table 2 shows that the prevalence of such diseases is 2.13% among children and 21.2% among fathers, with higher prevalence found in the urban sector. Among the above health indicators, we use height as the main measure, and use the others for robustness check in Section 5.3.

(4) *Other control variables*: From Table 2, the sample average age for children is 32 (rural children are younger), which is close to the optimal age for the permanent income approximation (Bohlmark & Lindquist, 2006; Haider & Solon, 2006). Fathers who work in the state-owned sector (including government and state-owned enterprises) account for 42.4% of the sample, and the ratio is higher in urban areas than rural areas (45.3% vs. 40.3%). Additionally, our regressions also control for fathers' age (averages 60.4 for the whole sample), urban status (averages 41.7%) and whether living in the coastal region (averages 41.0%).

[5] The question for SRH has been slightly changed since the 2009 wave, and becomes “How do you rate your life at present” (U420), with “Excellent, Good, Fair, Bad, Very bad” as possible answers. CHNS has officially confirmed the comparability of this question with the previous ones on self-rate health. For consistency, we combine “Bad” and “Very bad” into “Poor” as the lowest SRH value.

[6] Some studies prefer to use the ordered-probit or other sequential choice models on such variables. However, Ferrer-i-Carbonell and Frijters (2004) point out that traditional OLS regression on such discrete psychometric indicators may give more precise standard error estimation compared to the non-linear models. For robustness test purpose, we use both OLS and ordered-probit for the evaluation of self-reported health, and get consistent results.

Table 3
Estimation results of the OLS model.

Dependent variable: log(cincome)				
Variable	(1)	(2)	(3)	(4)
log(fincome)	0.536***	0.457***	0.487***	0.429***
	(0.034)	(0.035)	(0.035)	(0.035)
cedu	–	–	0.034***	0.029***
	–	–	(0.007)	(0.007)
cheight	–	–	0.013***	0.010**
	–	–	(0.004)	(0.004)
cage	–	0.069**	–	0.071**
	–	(0.033)	–	(0.033)
$cage^2$	–	−0.001*	–	−0.001*
	–	(0.000)	–	(0.000)
cgender	–	−0.058	–	0.058
	–	(0.062)	–	(0.077)
fage	–	−0.016	–	−0.015
	–	(0.040)	–	(0.038)
$fage^2$	–	0.000	–	0.000
	–	(0.000)	–	(0.000)
fstate	–	−0.463***	–	−0.438***
	–	(0.057)	–	(0.058)
Urban	–	0.061	–	0.006
	–	(0.055)	–	(0.055)
Coast	–	0.238***	–	0.202***
	–	(0.051)	–	(0.052)
Constant	4.116***	4.112***	1.998***	2.319*
	(0.304)	(1.144)	(0.624)	(1.374)
Sample size	1364	1364	1364	1364
R-square	0.185	0.251	0.205	0.261

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) ***, ** and * denote 1%, 5% and 10% significance levels, respectively; (iii) household-level clustered standard errors are in parentheses; (iv) please refer to Table 2 for definitions of variables.

5. Empirical results

5.1. Results of the OLS model

Table 3 presents the OLS regression results based on Eq. (23). Model (1) has a simple univariate specification that focuses on the intergenerational income elasticity without considering the impacts of other covariates. The estimated income elasticity is 0.536, which means a 10% increase in fathers' income will on average lead to a 5.36% increase in their children's income. The estimate is relatively high compared to other countries,[7] reflecting the low intergenerational income mobility and the persistently high income inequality in China. To check the robustness of the linear specification of the simple OLS model, we also perform a non-parametric estimation on the relationship between children's and fathers' log-income based on the (Epanechnikov) kernel regression (see Fig. 1). The results indicate that the parametric and non-parametric estimations basically coincide with each other in areas where the sample data are densely populated, but the two estimations somewhat diverge in the boundary areas where the data points are sparse.

To further control the impact of personal and environmental factors on children's income, Model (2) introduces the variables in vector *X* into the regression, and sees the estimated elasticity being reduced to 0.457, which is close to the estimation in the comparable studies (e.g., Zhang & Eriksson, 2010). Models (3) and (4) focus on the impact of children's human capital accumulation, and add children's education and health status to the estimation of Models (1) and (2) respectively. The results suggest that the estimated intergenerational income elasticity decreases from 0.536 to 0.487 in the simple OLS model after the human capital impact is accounted for. For the multivariate OLS model that controls the vector *X*, the estimated elasticity further decreases to 0.429, which means that a 10% increase in fathers' income will on average lead to a 4.29% increase in their children's income. These findings pinpoint the non-negligible role of children's human capital stock in the intergenerational income transmission process. In the following, we will use the estimated elasticity of the multivariate OLS model (0.429) as the benchmark to compare with the SE model estimates.

Table 3 also reveals the influence of other factors on children's income. For example, the coefficient estimate of education is 0.029 (significant at 1% level), which means the return to one-year increase in formal schooling is a 2.9% increase in the yearly income. This estimate is consistent with the prior studies (e.g., Sun, 2004 finds that the returns to schooling in China during the 1980s and 1990s are 3–5%), but somewhat lower than the more recent estimates (e.g., Deng & Ding, 2013 find that the returns are higher than 7% in both rural and urban China after 2000), possibly because a large portion of our sample comes from the pre-2000 period. As another human capital indicator, health (measured by height) also has a positive effect on income (the coefficient is 0.010 and significant at 5% level),

[7] According to Table 1, the estimated elasticity is between 0.45–0.48 in the U.S., 0.3–0.4 in the Western European countries, 0.2 in the Nordic countries, and 0.4–0.5 in the Latin American countries.

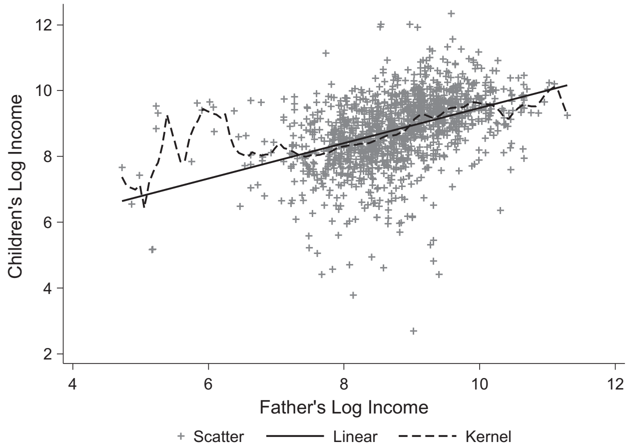

Fig. 1. Parametric and non-parametric estimations of intergenerational income elasticity. Notes: (i) The figure presents the predicted relationship between children's and fathers' logarithmic income based on parametric and non-parametric regressions using the same sample drawn from the 1989–2009 China Health and Nutrition Survey (CHNS); (ii) the solid (straight) line represents a linear regression; (iii) the dashed line represents a kernel regression using the Epanechnikov kernel function when the optimal bandwidth is derived by minimizing the mean integrated squared error (MISE).

which is in line with the findings in the relevant literature (e.g., Becker, 2007; Currie & Madrian, 1999). Moreover, the impact of children's age on their own income has an inverted U shape, reflecting the diminishing marginal return of age (which can also be considered as the potential working experience). With regard to regional differences, children's income in coastal areas is on average 20.2% higher than that in inland areas (significant at 1% level), but the difference between the urban and rural areas is not significant when other factors are considered.

5.2. Results of the SE model

The SE model illustrated by Eqs. (24)–(26) characterizes the more complicated mechanisms of intergenerational transmission. To identify the model, we first use the IV techniques to estimate Eqs. (25) and (26), and then substitute the fitted values of education and health into Eq. (24) to apply the ILS estimation. The standard errors and the associated statistical inference of the ILS estimates are based on the bootstrap procedure. Table 4 reports the main results of the SE model.

We first focus on the equations of human capital transmission. Models (2) and (4) report the second-stage estimation of the IV regressions for the transmissions of education and health, respectively. Model (2) suggests a significant direct transfer of education across generations: after controlling the endogeneity of parental education, a 1-year increase in fathers' formal schooling will averagely lead to a 0.310-year increase in children's years of schooling (when other factors are controlled, similarly hereinafter). As predicted by the human capital theory, well-educated parents tend to pay more attention to their children's cultivation, thus the high educational attainment can be transferred from parents to offspring through genetic and non-genetic channels. This finding is also confirmed by other empirical studies, e.g., Hertz et al. (2007) estimate the intergenerational correlations of schooling in 42 countries and find a strong persistence of educational attainment: the coefficient is around 0.6 in African countries, 0.46 in the U.S., about 0.4 in the Western European countries, and lowest in the Nordic countries. Model (4) shows that the father–child transmission of health is also evident: a 1-cm increase in fathers' height will on average lead to a 0.485-cm increase in children's height. This intergenerational transmission in health indicators is also empirically supported by other studies (e.g., Currie & Moretti, 2007; Eriksson et al., 2005; Eriksson et al., 2014).

In addition, Models (2) and (4) also demonstrate the impact of fathers' income on children's education and health: a 10% increase in fathers' income will lead to a 0.039-year increase in children's formal schooling (significant at 1% level) and 0.03-cm increase in children's height (not statistically significant). This to some extent reflects the indirect human capital transmission mechanism, i.e., parents' education can influence their financial capability (measured by income) of investing in their children and thus indirectly impact their children's human capital. Apart from the above factors, children's schooling is also significantly correlated with their living locations and fathers' employment sectors, while their height is significantly correlated with their age, gender, living locations, fathers' age and working sectors.

Furthermore, Models (3) and (5) report the corresponding first-stage estimations of the IV regressions. As expected, children's heights and schooling are significantly correlated with their corresponding IVs—fathers' heights and schooling—with F values of 426.88 and 139.98, which far exceed the recommended threshold ($F \geq 10$) in the literature (Stock, Wright, & Yogo, 2002), suggesting that the IVs are not likely to be weak.

Next, we turn our attention to the estimation of intergenerational income transmission. Model (1) shows the ILS estimation results of Eq. (24), which indicates that the estimated income elasticity will increase from 0.429 (in the benchmark OLS model) to 0.481 (in the SE model) after accounting for the direct transfer of human capital. This in turn suggests that ignoring the direct human capital transmission tends to result in an overestimation of parent-to-offspring income mobility, a finding that is consistent with the

Table 4
Estimation results of the simultaneous equations model.

	(1)	(2)	(3)	(4)	(5)
	Income	Education	1st Stg Edu	Health	1st Stg Hlth
Variable	log(cincome)	cedu	cheight	cheight	cedu
log(fincome)	0.481***	0.394***	0.320*	0.305	0.393***
	(0.043)	(0.106)	(0.172)	(0.194)	(0.106)
fedu	–	0.310***	0.012	–	0.310***
	–	(0.026)	(0.043)	–	(0.026)
fheight	–	–	0.485***	0.485***	−0.001
	–	–	(0.023)	(0.023)	(0.014)
cedu	−0.043	–	–	0.038	–
	(0.026)	–	–	(0.137)	–
cheight	0.017*	−0.002	–	–	–
	(0.010)	(0.030)	–	–	–
cage	0.077**	0.138	−0.525**	−0.531**	0.139
	(0.034)	(0.119)	(0.194)	(0.192)	(0.119)
cagesq	−0.001**	−0.002	0.006**	0.006**	−0.002
	(0.000)	(0.002)	(0.003)	(0.003)	(0.002)
cgender	0.133	−0.140	−11.153***	−11.148***	−0.120
	(0.124)	(0.395)	(0.340)	(0.338)	(0.209)
fage	−0.023	−0.141	0.564**	0.570**	−0.142
	(0.042)	(0.150)	(0.246)	(0.244)	(0.151)
fagesq	0.000	0.001	−0.004*	−0.004*	0.001
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)
fstate	−0.465***	−0.591***	−0.981***	−0.959***	−0.589***
	(0.061)	(0.185)	(0.299)	(0.304)	(0.183)
Urban	0.084	0.901***	1.140***	1.106***	0.899***
	(0.064)	(0.195)	(0.309)	(0.347)	(0.190)
Coast	0.204***	0.119	1.464***	1.460***	0.117
	(0.056)	(0.189)	(0.287)	(0.286)	(0.176)
Constant	1.534	6.411	75.911***	75.674***	6.272
	(2.004)	(6.415)	(8.063)	(7.977)	(4.949)
Sample size	1364	1364	1364	1364	1364
R-square	0.254	0.186	0.559	0.560	0.186
IV 1st Stage F	–	–	426.88***	–	139.98***

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) ***, ** and * denote 1%, 5% and 10% significance levels, respectively; (iii) bootstrap standard errors (1000 replications) are reported for model (1), household-level clustered standard errors are for other models; (iv) IV 1st Stage F is the F statistics for the significance of the IVs in the first stage regressions; (v) please refer to Table 2 for definitions of variables.

theoretical Proposition 2. To formally test the statistical significance of the difference between the two models, we conduct a Hausman test by treating the main coefficients of the benchmark OLS model as efficient estimators and those of the SE model as consistent estimators, and find that the P value is about 0.008, suggesting the null hypothesis that these two sets of coefficients are identical can be rejected at 1% level. With regard to the other control variables, the SE model (Model (1) in Table 4) gives similar estimation compared to the OLS model (Model (4) in Table 3). Overall, the above results indicate that the intergenerational income elasticity is underestimated by the traditional model (OLS) that leaves out the direct transmission of human capital, thus China's income mobility can be even poorer than what the recent studies have shown (e.g. Chen & Yuan, 2012; Zhang & Eriksson, 2010).

5.3. Robustness tests

In addition to the above main results, we will also check the robustness of the empirical specifications by running regressions on various sub-samples, using alternative health indicators, and testing the cross-transmission of human capital.

Table 5
Sub-sample estimates of intergenerational income elasticity.

	(1)	(2)	(3)	(4)	(5)
	Overall	Son	Daughter	Rural	Urban
OLS model	0.429***	0.415***	0.464***	0.409***	0.421***
	(0.035)	(0.041)	(0.067)	(0.047)	(0.050)
SE model	0.481***	0.468***	0.520***	0.501***	0.463***
	(0.043)	(0.051)	(0.075)	(0.069)	(0.059)
Sample size	1364	1085	279	795	569

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) ***, ** and * denote 1%, 5% and 10% significance levels, respectively; (iii) for the OLS model, household-level clustered standard errors are in parentheses; (iv) for the SE model, bootstrap standard errors are in parentheses; (v) all regressions control for the individual- and region-level characteristics.

Table 6
Estimated intergenerational income elasticity using alternative health indicators.

	(1)	(2)	(3)	(4)
	Height	SRH	Overweight	Chronic Diseases
OLS model	0.429***	0.369***	0.428***	0.433***
	(0.035)	(0.036)	(0.035)	(0.035)
SE model	0.481***	0.426***	0.510***	0.488***
	(0.043)	(0.050)	(0.043)	(0.044)
Sample size	1364	1364	1364	1364

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) ***, ** and * denote 1%, 5% and 10% significance levels, respectively; (iii) for the OLS model, household-level clustered standard errors are in parentheses; (iv) for the SE model, bootstrap standard errors are in parentheses; (v) all regressions control for the individual- and region-level characteristics.

First, we estimate both the OLS and the SE models in different sub-samples based on gender and regional stratifications. Table 5 summarizes the estimated elasticities for the samples of father–son, father–daughter, father–child in rural areas and father–child in urban areas. The results suggest that the father–daughter elasticity is higher than the father–son elasticity in both the OLS and SE models, which is consistent with the prior findings (e.g., Gong et al., 2012; Raaum et al., 2007). This result in turn indicates that women are at disadvantage in the intergenerational transmission in China as they lack the socio-economic resources to break the intergenerational persistence of income. More interestingly, we also find that the urban–rural differences of the father–child elasticity are reversed in the OLS and SE models: the elasticity in urban areas is slightly larger than that in rural areas (0.421 vs. 0.409) in the OLS model, while the difference is "0.463 vs. 0.501" in the SE model, suggesting that the income mobility in urban areas is actually higher than that in rural areas after considering the direct transmission of human capital. One possible reason is that the allocation of labor resources is more market-oriented and thus one's socio-economic status is more changeable in urban China. This result also corresponds to the fact that the Gini coefficient in rural China has been persistently higher than the urban one (Sutherland & Yao, 2011), reflecting that income is more unequally distributed in China's rural sector. Lastly, we find that the estimated elasticity of the SE model is robustly larger than that of the OLS model in each sub-sample, which validates the main conclusion drawn from our empirical analysis.

Next, we test the sensitivity of health measures by using alternative indicators of individual health status in the SE regressions. Table 6 reports the estimated father–child income elasticity using height, SRH, overweight status and presence of chronic diseases. In summary, we find that the elasticity estimates are quantitatively consistent across different health indicators, and that the SE model gives robustly larger estimates than the OLS model in all regressions.

Lastly, we discuss the cross-transmission of human capital. In the labor economics literature, the continued debate on the "nature–nurture interaction" focuses on whether there is a reciprocal effect between the inborn factors (e.g. genes) and the acquired traits (e.g. family environment) in the process of intergenerational transmission (Currie, 2011). In the current context, the existence of nature–nurture interaction would suggest a cross-transmission of human capital, i.e. fathers' health (nature) would impact children's education (nurture), and vice versa (see Fig. 2 for the illustrated mechanisms). In the above SE model, we simply omit the cross-transmission of human capital in both the education and health regressions. Here we estimate the cross-transmission for robustness check purpose by adding fathers' health into Eq. (25) and fathers' education into Eq. (26).[8] Table 7 reports the results of the new model, which provides no supporting evidence on the "nature–nurture interaction": the correlation is not statistically significant between fathers' height and children's schooling and between fathers' schooling and children's height, respectively. This finding on the non-existence of cross-transmission is also confirmed by other empirical studies (e.g., Lindeboom et al., 2009; McCrary & Royer, 2011), and in turn provides validating support for the "exclusion restriction" condition for our original IV strategy. Furthermore, the estimated income elasticity remains statistically significant and quantitatively similar with the main model, which further verifies the robustness of our previous findings.

6. Conclusions

Social mobility is an important measure of the degree to which a society gives equal opportunities to its members, and it largely determines the sustainability of a country's economic development. However, looking back upon history, the lack of social mobility has been a malady in China for millennia. Since the Wei dynasty (220–265), social mobility had been deficient for a long time due to the nine-rank system, where only the rich and powerful could be selected as candidates for the privileged administrative officials. After the Sui dynasty (581–619), the imperial examination system started to give the poor a chance to join the upper classes, but it was not sufficient to fundamentally remedy the lack of social mobility for various reasons.[9] In modern times before the 1980s, a free labor market was still absent in China under the centrally planned regime where the demand and supply of labor were strictly controlled by the government. Since the 1980s, the labor market has gradually developed and taken its role in determining the market wages,

[8] With the addition of variables, Eqs. (25) and (26) cannot be identified using the original IV strategy and thus will be estimated using OLS with their fitted values employed in the ILS estimation of Eq. (24).

[9] For example, some people in the lower class were banned from taking the imperial examination.

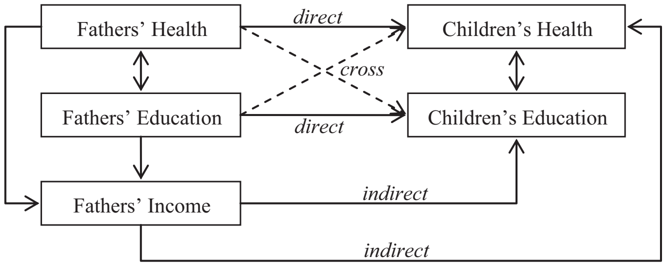

Fig. 2. Mechanisms of intergenerational transmission of human capital. Notes: The solid lines represent the direct and indirect transmission paths of human capital, and the dashed lines represent the (hypothesized) paths of cross-transmission of human capital.

enabling the measurement of social mobility by estimating the intergenerational elasticity of income. However, under the influences of the one-child policy, the household registration (*Hukou*) system, the reforms of social security and the enrollment expansion of higher education, the mechanisms of income transmission in China become more and more complicated. Nevertheless, it has been commonly recognized that the continuous development of China's economy is increasingly challenged by the lack of social mobility despite its impressive growth record during the past decades. In recent years, several empirical studies have shown that the intergenerational elasticity of income in China is internationally high, implying that the society does not give equal economic opportunities to all its members. In this paper, we aim to address the root causes of the problem by studying the impact of parent-to-offspring transmission of human capital on the intergenerational income mobility.

In the theoretical analysis, we incorporate the direct and indirect transmission of human capital into a classical three-period overlapping-generations (OLG) framework, which enables us to analyze the determination mechanism of parents' optimal investment in their children's human capital and the implied income mobility across generations. In this framework, parents' investment behavior is not only motivated altruistically by the return on human capital investments in terms of children's future income (the indirect human capital transmission), but also influenced by the efficiency of the direct transfer of human capital across generations. The most important conclusion derived from the theoretical model is that the intergenerational elasticity of income will be underestimated if we omit the direct transfer of human capital. In the empirical analysis, we verify the theoretical prediction using the nationally representative CHNS data and a simultaneous equations model accounting for the intergenerational transmission of income, health and education, comprehensively. The results show that the direct transfer of education and health is significant with coefficients of 0.310 and 0.485 respectively, reflecting that the opportunities in education and health are not equally/randomly distributed, i.e., children's development opportunities depend greatly on their parents' human capital. Meanwhile, after controlling the direct transfer of human capital across generations, the estimated income elasticity increases to 0.481, which is higher than that given by the benchmark OLS model (0.429). This finding is consistent with the theoretical prediction, suggesting that the traditional estimations in the literature, without considering the direct transmission mechanism of human capital, may have painted an over-optimistic picture on China's income mobility. Our sub-sample analyses further indicate that the intergenerational income elasticity is higher for the father–daughter pairs than the father–son pairs and for the urban areas than the rural areas, suggesting that the vulnerable groups (such as women and rural residents) are put into further disadvantage in development by the intergenerational persistence of socio-economic status.

Table 7
Robustness test results assuming cross-transmission of human capital.

	(1)	(2)	(3)
	Income	Education	Health
Variables	log(cincome)	cedu	cheight
log(fincome)	0.471***	0.380***	0.279
	(0.041)	(0.106)	(0.173)
fedu	–	0.310***	−0.021
	–	(0.026)	(0.045)
fheight	–	−0.020	0.485***
	–	(0.017)	(0.023)
cedu	−0.032	–	0.104**
	(0.024)	–	(0.044)
cheight	0.019**	0.039**	–
	(0.009)	(0.017)	–
Sample size	1364	1364	1364

Notes: (i) Data source: 1989–2009 China Health and Nutrition Survey (CHNS). (ii) ***, ** and * denote 1%, 5% and 10% significance levels, respectively; (iii) model (1) is estimated by Indirect Least Squares, and models (2) & (3) are estimated by Ordinary Least Squares; (iv) bootstrap standard errors are in parentheses; (v) all regressions control for the individual- and region-level characteristics; (vi) please refer to Table 2 for definitions of variables.

Our findings provide several policy implications for remedying the lack of social mobility and promoting the equity in opportunities in China: (i) given the important role of human capital transmission in determining the offspring socio-economic status, emphasis should be put on promoting the accumulation of human capital in the impoverished areas and disadvantaged groups through "equal opportunity" reforms (e.g., encouraging the enrollment of high schools and colleges in rural areas, facilitating access to basic health care among migrant workers, etc.); the interaction between income mobility and human capital transmission suggests that such reforms are conducive to alleviating the negative impact of income inequality and may help China avoid the middle-income trap. (ii) Since the intergenerational transmission of education and health is remarkable, the above "equal opportunity" reforms promise to not only facilitate the human capital accumulation for the current generation but also improve it by the "multiplying effect" for future generations, which is beneficial to the long-run economic growth of China; likewise, the current education and health system reforms by the Chinese government (such as quality improvement in the rural primary and secondary schools and the establishment of a universal health insurance system) are also likely to play a crucial role in maintaining the sustainable and harmonious social development in China in the long run. (iii) Our theoretical analysis also suggests that the intergenerational elasticity of income depends to a large extent on the marginal return of human capital investment on income; thus, in order to improve social mobility, it is important to further enhance the efficiency of labor market institutions towards better allocation of human resources. To achieve this goal, the following policy reforms are recommended: gradually alleviating the restrictions on labor migration under the household registration (*Hukou*) system, which gives the poor a chance for better labor market returns through migration; phasing out the attachment of social welfares (e.g. health insurance and housing funds) with one's working location so as to prevent the "job lock" and facilitate the regional mobility of labor force; finally, reforming the wage determination mechanisms to allow wage rates to reflect the marginal productivity of human capital, which in turn gives more incentives for human capital investment in both the private and public sectors.

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