Does social identity matter in individual alienation? Household-level evidence in post-reform India

Prashant Gupta [a], Sushanta Mallick [b,⇑], Tapas Mishra [c]

Abstract

Does consumption distance as a measure of individual alienation reveal the effect of social identity? Using the central idea of Akerlof's 'social distance' theory, individual distance is calculated from their own group mean consumption and then we examine whether individuals from different social groups – caste and religion – are alienated across the distance distribution. Using India's household-level micro- data on consumption expenditure covering three major survey rounds since the inception of the reform period, we find a non-unique pattern where the marginalised and minority group households tend to be alienated across the distance distribution. However, among them, the households with higher educational attainment become more integrated as reflected in the interaction effect of education. These results are robust even after controlling for the endogeneity of education. Given this significant group difference in consumption, we undertake a group-level comparison by creating a counterfactual group through exchanging the characteristics of the privileged group to the marginalised group (or Hindus to non- Hindus), and find that the privileged group still consumes more than the counterfactual marginalised group, explaining around 77% of the estimated average consumption gap at the median quantile in 2011–12 (or 59% for Hindus versus Non-Hindus). This suggests other inherent identity-specific social fac- tors as possible contributors to within-group alienation (relative to a better-off category) that can only be minimised through promoting education for the marginalised (or minority religion) group.

Does Father's Income Matter?
Causal Mechanisms in Intergenerational Transmission of Income in China

Yaping Yang[a] Jack W. Hou[b] Shengzheng Shi[c]

In this paper, we use current income data from 2010 China Family Panel Studies (CFPS), identifying the causal effect of father's income and human capital in the intergenerational transmission of income between fathers and children. We find that the majority of the intergenerational income elasticity can be plausibly attributed to the causal effect of father's financial resources, rather than human capital. Moreover, we provide a lower bound of the elasticity, which is 0.359, and the adjusted value is range from 0.620 to 0.748. The results suggest a relative low intergenerational mobility, but also imply that any policies attempting to equalize father's investment will be conducive to increasing intergenerational income mobility in China.

I. INTRODUCTION

The extent to which economic status is transmitted between generations is one of the fundamental issues of intergenerational mobility. The literature generally uses intergenerational income elasticity (IIE) to measure income mobility across generations; the larger the elasticity the less mobility in a given society.

Even though China's current economic state is somewhat stagnated, no one can dispute the remarkable growth it has managed after more than three decades of economic reform, but it did not come without cost (Hou, 2011), of which the widening income gap (Naughton, 2005) is the focus of this research. In a market-oriented economy, workers are paid according to their marginal productivity, and this productivity is largely determined by various forms of human capital accumulation based on a level playing field of equal opportunity. It is deemed unjust if economic success is inherited without merit. If the poor in a society loses hope for any upward social mobility, not only will this be inefficient, but will eventually lead to class conflict and social unrest.

a College of Economics, Jinan University
b Dept. of Economics, California State University, Long Beach. Corresponding author: jack.hou@csulb.edu
c School of economics, Xiamen university

The emergence and dominance of *Fuerdai* (rich second generation) in China has generated a sizable literature studying the transmission of income between generations. The majority (e.g. Gong *et al*., 2012; Hau, 2014; Fan, 2016; Yuan, 2017) find a relatively low social mobility in China. The empirical estimates of the IIE differ depending on the data sets from which they are based. However, estimating the elasticity is just the first step as the IIE is not, in and of itself, a measure of equality of opportunities. As Roemer (2004) emphasized, an intergenerational elasticity of zero is not an optimum. In order to make an inference about equality of opportunity from the degree of intergenerational income elasticity, we must draw a line between differences in circumstances, for which individuals should in some sense be compensated, and personal choices for which they should be responsible.

Furthermore, we need to identify the mechanisms that generate the intergenerational transmission of income, without which, it is impossible to understand how to make changes (Black and Devereux, 2011). This causal mechanism is the central issue in the research on intergenerational income mobility. The literature has focused on the father's income as a major transmission channel. However, as the father's income is correlated with many factors that affect the child's income, ordinary least squares (OLS) suffers from endogeneity bias, thus rendering the estimated IIE as merely a descriptive measurement of intergenerational association in income between father and child. It is simply a "catch all" measure of all channels of transmission, rather than the "true" causal effect of father's income on that of the child (Bowles and Gintis, 2002; Black and Devereux, 2011).

In the past decade, the literature has focused on identifying the underlying factors that determine the intergenerational correlation of income with a certain degree of success. However, due to data constraints, similar studies in China are somewhat lacking. Whatever exists is suggestive at best, as they are not really true causal measures, and hence cannot be relied upon for policy formulations. This study is aimed at filling this void.

Following the method of Lefgren *et al*. (2012), we utilize a newly constructed database, China Family Panel Studies (CFPS), to examine the role of father's income and human capital on the intergenerational transmission of income. Our main finding is that intergenerational income elasticity is mainly attributed to the causal effect of father's income, and the true value is at least 0.359; which, after reasonable adjustment, reaches 0.620, suggesting a relatively low intergenerational mobility in China.

The remainder of the paper is organized as follows. We start with a brief review of the development of the study on intergenerational income mobility, especially the causal mechanisms. In Section 3, we describe the measurement error with a one-year income data, and present the model and estimation strategies. This is followed by the data description and instrumental variables that will be used in our estimation. Empirical estimates are reported in Section 5, which will be followed with conclusions and policy implications.

II. LITERATURE REVIEW

The trailblazing work of Becker and Tomes (1979) set the foundation for the research on parent-child income linkages. Early estimates of the intergenerational elasticity have been based on single year income. Solon (1992) and Zimmerman (1992) demonstrated that sizeable biases arose from this method and use father's "average" income (over several years). This generated higher income elasticity for the U.S. compared to the old single-year income approach.

This paved the way for an increasing number of international studies, estimating intergenerational income elasticity for different countries. The consensus is that the IIE shows significant variations across countries. For Scandinavian countries and others with high social welfare, the elasticity is low (Björklund and Jäntti, 1997; Corak and Heisz, 1999; Bratberg *et al*., 2005), while many industrialized nations exhibit higher IIE (Mazumder, 2005; Mocetti, 2007; Chau, 2012). Lack of suitable data has limited similar studies for developing countries, those that do exist tend to show a high level of IIE estimates (Dunn, 2007; Torche, 2014). In addition to improving the estimates of intergenerational income elasticity, two additional branches of the literature included the comparison of mobility across countries (Solon, 2002; Bratsberg et al., 2007; Blanden, 2013) and across time (Nicoletti and Ermisch, 2007; Lee and Solon, 2009).

Several studies have attempted to understand the mechanisms that underlie the income correlations; these include Becker and Tomes (1979, 1986), and Solon (2004). However, testing these mechanisms in a rigorous manner has proven to be difficult (Mulligan, 1999; Grawe, 2004; and Lefgren *et al*., 2012) as certain factors are genetic and unobservable. To overcome this, some studies have relied on specialized data sets to isolate specific mechanisms and obtain credible causal effects. Case in point, Björklund *et al*. (2006) uses Swedish adoption data to decompose the IIE into pre-birth and post-birth factors. The former includes parents' genes and prenatal environment, everything else is grouped into the latter. They find that both factors play a significant role in producing the observed IIE. However, these specialized data are rare, and many countries even lack relevant "basic" surveys, which further constrains research on this subject.

As an alternative, some researchers have attempted to decompose the IIE and evaluate the effect via intermediate variables. Bowles and Gintis (2002) decomposed the IIE into direct and indirect effects. The direct effect is how the father's income *directly* affects the son's income, and indirect effect is how the father's income influences son's income through intermediate variables. Blanden *et al.* (2007) examine the role of non-cognitive skills and ability on intergenerational income persistence in Britain. In their work, they demonstrate that covariates can account for approximately half of the estimated intergenerational income elasticity, with a sizeable portion attributable to cognitive and non-cognitive skills that work through educational attainment. However, it is difficult to interpret these decompositions as the intermediate variables have both genetic and environmental underpinnings and the approach provides no way of getting at causal effects (Black and Devereux, 2011).

To solve these issues, some studies have relied on econometric techniques to shed light on the mechanisms and causes that underlie the parent-child correlations. Lefgren *et al.* (2012) construct a simple model, in which paternal human capital and financial investments are combined to produce sons' economic outcomes. They use a range of instrumental variables to provide bounds on the relative contributions of financial investments and human capital. Cardak *et al.* (2013) took a similar approach but based on the stochastic frontier model. Using maximum likelihood methods, they investigate the contribution of investments and endowments in generating intergenerational persistence in earnings[1]. Both studies find that approximately one-third of the intergenerational earnings elasticity can be attributed to parental financial investments, with the remaining two-thirds due to endowments or human capital. However, other studies (Corcoran *et al.,* 1992; and Mazumder, 2005) find that paternal education has no independent correlation with son's earnings once controlling for father's permanent income, which means that only the father's income plays a role in the intergenerational income transmission.

Research on the intergenerational income mobility in China began relatively recent and studies are far and few in between. Wang (2005) was perhaps the first to estimates the Chinese intergenerational income elasticity based on one-year urban residents' income data. The estimated IIE is 0.384 and 0.424 in 1988 and 1995, respectively, which suffer downward bias. To reduce the bias stemming from using single year income, Gong *et al.* (2012) used a two-sample instrumental variables approach to estimate the intergenerational income elasticity in urban China, and obtain a rather high value (0.63) of the IIE. Finally, Yuan (2017) find that China is less mobile than most developed countries and investigate the distributional pattern of China's intergenerational mobility across income levels.

In recent years, a small literature has accumulated attempting to investigate the transmission mechanisms of Chinese intergenerational income mobility. Yuan and Chen (2013) estimate the contributions from human capital, social capital and wealth to intergenerational income mobility, and show an increasing contribution from social capital. Fan (2016) estimates the contribution from social capital and ownership of work unit across cohorts and income groups. Yang and Qiu (2016) analyses the effects of innate ability, compulsory education and noncompulsory education on inequality and intergenerational mobility of income. They find that innate ability and family investment in early education play important roles in explaining income inequality and intergenerational income mobility. Qin *et al.* (2016) find that human capital transfer plays a remarkable role in determining the parent-to-offspring investment in human capital and the intergenerational elasticity of income. However, there is no reason to believe that the methodology in these papers provide consistent estimates, as there are likely to be many omitted variables. As such, these approaches are suggestive but not a compelling source of evidence on causal mechanisms, and thus can't be used for policy formation. To our knowledge, no attempts has been made to investigate the causal effect of father's financial resources and human capital on the intergenerational transmission of income in China, and this study is aimed at filling this important gap; not to mention adding to the literature on developing nations, which is decidedly weak in the c

urrent literature.

III. METHODOLOGY: MEASUREMENT ERRORS AND THE THEORETICAL MODEL

The equation used to estimate the intergenerational income elasticity is:

$$y_{1i} = \alpha + \beta y_{0i} + u_{1i} \qquad (1)$$

where y_{0i} represents the father's permanent log income of family i, and y_{1i} is the same for the child of family i[2]. u_{1i} is a stochastic term which is uncorrelated with y_{0i}. The slope coefficient, β is the intergenerational income elasticity which measures the degree of intergenerational income mobility. The problem is that β represents the combined effect of different mechanisms, which includes the effects that come from genetic inheritance, prenatal environment, and the environment in which the child was raised. It can only be interpreted as the "raw" correlation between income of fathers and children, and cannot be viewed as a causal effect of father's income (Björklund *et al*, 2006).

1 Cardak *et al's* method is sensitive to the specification of the distribution of the endowment, and using stochastic frontier analysis of macroeconomics on causal identification of microeconomics is debatable. In contrast, the method of Lefgren *et al's* (2012) is theoretically more suitable for causal identification and the few restrictions of the instrumental variable make it easy to deal with the estimation. Therefore, we employ Lefgren *et al's* (2012)'s method in our research.

2 The conventional research practice equates class background solely with a father's class position. This assumes that mothers' economic participation is not common or important to class background and that father-headed families are the norm. The low rate of married women's labor force participation in China greatly raises the frequency of nonobserved earnings in the estimation, and complicates any analysis of intergenerational relationships involving mothers and daughters. Even in the field of sociology, researchers have long had difficulty in assigning women to their appropriate social class (Hirvonen, 2008). Therefore, we only focus on the father's role in the intergenerational transmission of income in this paper.

3.1. Measurement error

It is well established in the literature that direct estimate of β needs to be based on permanent income for both fathers and children, otherwise the estimate will be biased. The potential sources of this bias can be categorized into the following three types.

Transitory Shocks

Early studies usually adopt the classical errors-in-variable (CEV) model, in which short-run income is a combination of the long-term income and a transitory fluctuation:

$$y_{0is} = y_{0i} + \omega_{0is} \tag{2}$$

$$y_{1it} = y_{1i} + \omega_{1it} \tag{3}$$

where y_{0is} and y_{1it} are the short-term income in period s and t for fathers and children, respectively. y_{0i} and y_{0i} are the corresponding permanent income. ω_{0is} and ω_{1it} are the transitory shocks, which is the difference between current income and permanent income. Let σ^2_{y0} and $\sigma^2_{\omega 0}$ denote the population variance of y_{0i} and ω_{0is} , then applying least square to equation (1) we can obtain the probability limit of the estimated slope coefficient $\hat{\beta}$

$$p\lim \hat{\beta} = \frac{\sigma^2_{y0}}{\sigma^2_{y0} + \sigma^2_{\omega 0}} \beta \tag{4}$$

Obviously, transitory shocks in one-year income of fathers result in attenuation bias of the estimate of the IIE whereas the transitory shocks of the one-year income of children do not cause any bias. To alleviate the impact of transitory shocks, some researchers use the average (over several years) of the father's income as a proxy for permanent income (Solon, 1992; Blanden *et al.,* 2007; Cardak et al., 2013). However, Mazumder (2005) showed that even estimates based on five-year average of the earnings variable for fathers are subject to substantial bias,of approximately 30% or more.

Age-Related Bias

Estimates of the IIE may also be sensitive to the age at which father's income is measured. Baker and Solon (2003) and Mazumder (2005) provide evidence that $\sigma_{\omega 0}$ varies over the life-cycle, following a U-shaped pattern, and is at its minimum at around age 40. This suggests that measures of fathers' income around age 40 can produce less attenuation bias than those taken at age 30, and substantially less than those taken at age 55.

Life-Cycle Bias

Of the three biases, the life-cycle bias is the most problematic. The life-cycle bias refers to the presence of individual heterogeneity in income growth over the life-cycle (Grawe 2006; Haider and Solon 2006). The error is not of the classical type and is correlated with age. To get a sense of how the age of fathers and children matter, consider the following generalized error-in-variables model.

$$y_{0is} = \lambda_s y_{0i} + \omega_{0is} \tag{5}$$

$$y_{1it} = \lambda_t y_{1i} + \omega_{1it} \tag{6}$$

where λ_s and λ_t denote the time-dependent bias arising when advancing the unobservable dependent variable y_{0i} and y_{1i} by an annual measure. If λ_s and λ_t are equal to 1 for all s and t, then the model (5) and (6) collapses back into the classical measurement error model as equation (2) and (3), and no life-cycle bias exists.

With the generalized error-in-variables model, the OLS estimator of the IIE, $\hat{\beta}$, converges to

$$p\lim \hat{\beta} = \frac{\operatorname{cov}(y_{0is}, y_{1it})}{\operatorname{var}(y_{0is})} = \lambda_t \phi_s \beta \tag{7}$$

where

$$\phi_s = \frac{\lambda_s \operatorname{var}(y_{0i})}{\lambda_s^{\,2} \operatorname{var}(y_{0i}) + \operatorname{var}(\omega_{0is})} \tag{8}$$

Notice that ϕ_s is affected by two types of measurement errors: the attenuation bias caused by the transitory income component and the life-cycle bias caused by a changing permanent income component. Life-cycle bias cancels when $\phi_s = 1$ for all s. The striking insight of this model is that a proxy of the dependent variable might create a bias, which is represented by λ_t. It attenuates the true value whenever $\lambda_t < 1$ and amplifies it whenever $\lambda_t > 1$.

3.2. Theoretical model

Following Lefgren *et al.* (2012), paternal permanent income are expressed as a function of the father's human capital and other idiosyncratic factors. This relationship is given by:

$$\mathrm{y}_{0i} = \gamma + HC_{0i} + \eta_{0i} \tag{9}$$

where human capital, HC_{0i}, consists of education, health, and genetic endowments that carry a return in the marketplace and is denominated in dollar equivalents, while η_{0i} captures variation in paternal income that is due to luck. This might include an unusually good job match, benefiting from a generous union contract and so on. η_{0i} is assumed to be orthogonal to paternal human capital.

It is naturally assume that child's income is generated in the same way as his father's income, which is given by the following equation.

$$y_{1i} = \gamma + HC_{1i} + \eta_{1i} \tag{10}$$

Fathers increase their children's human capital through financial investments and direct transmission of their human capital. Consequently,

$$HC_{1i} = \rho + \pi_1 y_{0i} + \pi_2 HC_{0i} + \varphi_{1i} \tag{11}$$

Substituting equation (11) into equation (10) yields the following expression:

$$y_{1i} = \pi_0 + \pi_1 y_{0i} + \pi_2 HC_{0i} + v_{1i} \tag{12}$$

Thus, the child's permanent income is determined by the father's investment and transmission of human capital. This model is similar to that derived from Becker and Tomes (1979) and Solon (2004).

Given the above model, if there is an instrument of father's permanent income, and is uncorrelated with transitory shocks (ω_{0is} and ω_{1is}), then the IV slope estimator of the IIE based on current income, $\hat{\beta}^{IV}_{\text{current}}$, converges to[3]:

$$\begin{aligned} p\lim\left(\hat{\beta}^{IV}_{\text{current}}\right) &= \frac{\operatorname{cov}(y_{1it}, Z_{0i})}{\operatorname{cov}(y_{0is}, Z_{0i})} \\ &= \kappa\left[\pi_1 + \pi_2 \frac{\operatorname{cov}(HC_{0i}, Z_{0i})}{\operatorname{cov}(HC_{0i}, Z_{0i}) + \operatorname{cov}(\eta_{0i}, Z_{0i})}\right] \end{aligned} \tag{13}$$

where $\kappa = \frac{E\lambda_t}{E\lambda_s} \in (0,1)$ represents an attenuation factor.

We can see that $\hat{\beta}^{IV}_{\text{current}}$ is composed of four parts, including a constant coefficient (κ), the impact of father's income operating through financial investments (π_1), the direct effect of father's human capital on child's income (π_2), and

[3]We use subscript 'current' and 'permanent' to indicate estimates that use current income and permanent income respectively. To obtain the limiting form, $\operatorname{cov}(y_{0i}, \lambda_s) = 0$, $\operatorname{cov}(y_{1i}, \lambda_t) = 0$, $\operatorname{cov}(Z_{0i}, \lambda_s) = 0$ and $\operatorname{cov}(Z_{0i}, \lambda_t) = 0$ need to hold. As λ is a function of age, plus y_{0i}, y_{1i} and Z_{0i} vary with individuals, it is reasonable to assume that these conditions are satisfied. It should be clearly noted that our research is based on the data only from a single year, so we consider the relationship between current income and permanent income is characterized as the generalized error-in-variables model in section 3.1 when using the methodology of Lefgren et al. (2012).

$\operatorname{cov}(HC_{0i}, Z_{0i}) / \left[\operatorname{cov}(HC_{0i}, Z_{0i}) + \operatorname{cov}(\eta_{0i}, Z_{0i})\right]$
which represents the proportion of the covariance between income and the instrument that is attributable to human capital.

Note that in the case of estimate with permanent income of fathers and children, $E\lambda_t = E\lambda_s = 1$, then κ equals to one, thus we can obtain the following equation:

$$p\lim\left(\hat{\beta}^{IV}_{\text{permanent}}\right) = \left[\pi_1 + \pi_2 \frac{\operatorname{cov}(HC_{0i}, Z_{0i})}{\operatorname{cov}(HC_{0i}, Z_{0i}) + \operatorname{cov}(\eta_{0i}, Z_{0i})}\right] \quad (14)$$

Given these, we can address the following question:

Is father's income the sole causal mechanism?

To test whether the IIE operates through ***<u>both</u>*** financial investment and human capital, or only via ONE channel, we construct two instruments for the father's permanent income, Z_0^a and Z_0^b, and according to Eq.(13), we can write

$$p\lim\left(\hat{\beta}^{IVa}_{\text{current}}\right) - p\lim\left(\hat{\beta}^{IVb}_{\text{current}}\right)$$
$$= \kappa\pi_2 \left[\frac{\operatorname{cov}(HC_{0i}, Z_{0i}^a)}{\operatorname{cov}(HC_{0i}, Z_{0i}^a) + \operatorname{cov}(\eta_{0i}, Z_{0i}^a)} - \frac{\operatorname{cov}(HC_{0i}, Z_{0i}^b)}{\operatorname{cov}(HC_{0i}, Z_{0i}^b) + \operatorname{cov}(\eta_{0i}, Z_{0i}^b)}\right] \quad (15)$$

Since $\kappa > 0$, $p\lim\left(\hat{\beta}^{IVa}_{\text{current}}\right) = p\lim\left(\hat{\beta}^{IVb}_{\text{current}}\right)$ *if and only if* $\pi_2 = 0$ or

$$\frac{\operatorname{cov}(HC_{0i}, Z_{0i}^a)}{\operatorname{cov}(HC_{0i}, Z_{0i}^a) + \operatorname{cov}(\eta_{0i}, Z_{0i}^a)} = \frac{\operatorname{cov}(HC_{0i}, Z_{0i}^b)}{\operatorname{cov}(HC_{0i}, Z_{0i}^b) + \operatorname{cov}(\eta_{0i}, Z_{0i}^b)} \quad (16)$$

As equation (16) is generally not true, any two instruments should yield a different estimate for the IIE as long as they differ in their relative covariance either via luck or human capital differentials. By rejecting over-identifying restrictions in an IV context, we can conclude that $\pi_2 \neq 0$.

On the other hand, if $\pi_2 = 0$, a by-product is that we can amend the underestimated IIEobtained from using current income of fathers and children. To clarify this, we first get the consistent estimate of the IIE by applying OLS estimation to Eq. (1) using father and child's permanent incomes, which can be expressed in a probability limit form as

$$\beta \equiv p\lim\left(\hat{\beta}^{OLS}_{\text{permanent}}\right) = \left[\pi_1 + \pi_2 \frac{\operatorname{var}(HC_{0i})}{\operatorname{var}(HC_{0i}) + \operatorname{var}(\eta_{0i})}\right] \quad (17)$$

The above equation is similar to Eq. (14), with the difference that π_2 is multiplied by the fraction of variance in father's income that is attributable to human capital variation in Eq. (17). This implies that if $\pi_2 \neq 0$, IV estimate of the IIE will be biased as what has been mentioned in Solon (1992), while if $\pi_2 = 0$, OLS and IV estimates of the IIE are identical, which allows us to derive the IIE from IV estimate using current income by dividing $p\lim\left(\hat{\beta}^{IV}_{\text{current}}\right)$ with κ according to Eq. (13).

Causal effect of father's income and human capital

$\pi_2 \neq 0$ implies that the father's investment is not the ***sole*** mechanism, and that the transmission of human capital also matters. The problem then becomes how to identify the causal effect of these ***two*** mechanisms. Suppose there is an instrument (I_1) that is *only* correlated to the idiosyncratic luck component of paternal income, then according to Eq. (13), $\hat{\beta}^{IV}_{\text{current}}$ will converge to $\kappa\pi_1$. Alternatively, if there is an instrument (I_1) that is only correlated to the paternal human capital, but *not* to luck, then the estimator converges to $\kappa(\pi_1 + \pi_2)$. Therefore if κ is known, we can estimate the causal effect of father's income and human capital. Even the value of κ is not available, we can also get a lower bound of the relative importance of father's income by dividing I_1 by I_2, which we will denote as μ

$$\mu = \frac{I_1}{I_2} = \frac{\pi_1}{\pi_1 + \pi_2} \tag{18}$$

And since $\pi_1 + \pi_2 \geq \beta$[4], then $\mu \leq \pi_1/\beta$, of which the right side (π_1/β) denotes the relative effect of the father's investment. In conclusion, if we have two feasible instruments, we can obtain a lower bound of the relative importance of father's financial investment in the intergenerational transmission of income.

3.3 Data and Instruments

The data used is the China Family Panel Studies (CFPS), which is a nationally representative, annual longitudinal survey of Chinese communities, families, and individuals launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University. The CFPS is designed to collect individual-, family-, and community-level longitudinal data in contemporary China, and is China's first large-scale academic-oriented panel survey project. The sample of CFPS is drawn from 25 provinces/municipalities/autonomous regions (excluding Hong Kong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia and Hainan), covering 95% of China's total population. The 2010 baseline survey interviewed a total of 14,960 household and 42,590 individuals, who will participate in a long-term follow-up survey. The CFPS is the most recent microeconomic database available in China, through which we can study intergenerational income mobility in China. Moreover, it collected detailed information on demographic characteristics, educational attainment, labor market status, and annual income in 2010 for all household members residing in the household as well as non-residing parents of the household head and his or her spouse.

To reduce life cycle bias as far as possible and avoid the complication if a family has more than one child, we select only the eldest child of a family who is closest to mid-career which is considered the stage that life cycle bias is minimal (Haider and Solon, 2006). The sample is also restricted to individuals aged 20-60 years old. The main reason for excluding individuals older than age 60 is that many people in this sample start retiring and living on pension from this age in China. The "income" variable is defined as the individual ***total*** income, including wage income, business income, property income, transfer income and other income (gifts from relatives and friends, and other income claimed by the respondent families). We further restrict our sample to those who are working, and have a positive income. With these restrictions, 735 father-child pairs remain in the sample, and descriptive statistics are shown in Table 1.[5]

Table 1. Descriptive Statistics

	Min	Mid	Mean	Max	SD	Observations
Father						
Age	38	52	51.75	60	4.91	735
Years of schooling	0	9	7.04	16	4.44	735
Log annual income	5.70	9.39	9.29	11.98	1.09	735
Child						
Age	20	25	25.65	39	3.89	735
Gender (Male = 1)			0.76			735
Years of schooling	0	9	10.16	19	3.98	735
Log annual income	6.68	9.55	9.43	11.51	0.91	735

4Since $0 < \mathrm{var}(HC_{0i}) / [\mathrm{var}(HC_{0i}) + \mathrm{var}(\eta_{0i})] < 1$ and $\pi_2 \geq 0$, this follows from Eq. (17).

5In case it is not clear to the reader why we respect our sample to father-child pairs that are in the same household, it is because we need the income level of both father and son. In the survey, even if they do not cohabitate, basic information of the father or son is available, but *not* their income. This restrictive election bias naturally raises the question of selection bias in a traditional regression analysis. However, as can be seen in our methodology section, this is not a standard regression analysis, but rely on econometric technique and instrumental variables to identify the "channel" in which Intergenerational income transmission is passed down.

It is noteworthy that approximate a three-quarters of the sample children are males. The severe disproportion of gender is caused by the design principles of CFPS. Since CFPS does not survey the incomes of non-resident fathers, we have to select sample fathers who live together with their children or other headed-children. However, it's conventional for Chinese women to leave parents after marriage, which means that we can hardly simultaneously observe incomes of fathers and daughters when the latter is married. Hence the exodus of married women brings about overwhelming of males in the sample.

As can been seen from the Theoretical Model, this study depends critically on the instrumental variables. These instrument variables need to have high correlation with father's permanent income while orthogonal to transitory shocks in current income for both fathers and children, which is actually a cozy job since the transitory shocks in Eq. (1) are uncorrelated with all factors that are correlated with fathers' income. Based on these conditions, we selected four instruments: years of schooling, level of education, social status and international socio-economic index (ISEI). There should be little argument that they all have a strong correlation with father's permanent income and human capital, and at most a weak correlation to the father's "luck".

Years of schooling is accurately calculated based on the detailed measure for educational level and other factors such as the type of schools, grade, and graduation statuses, and so on. Educational level is a categorical variable with five tiers: illiterate/semi-illiterate, primary school, junior middle school, senior middle school, college or above. Social status is coded using the Erikson and Goldthorpe's Class Categories(EGP), we use the following nine categories: I-Higher controllers, II-Lower controllers, III-Routine non-manual, IV-Self-employed with employees, V-Self-employed without employees, VI-Manual supervisor, VII-Skilled manual, VIII-Semi-unskilled manual, IX-Self-employed agricultural workers. International Socio-Economic Index of Occupational Status is based on average level of education and income, thus it is correlated to father's permanent income

III. EMPRICAL ESTIMATES AND ROBUSTNESS CHECKS

We will now start with the empirical estimates:

5.1 . IV estimates

We start with the estimation of Eq. (1) regressing the four instruments (which are highly correlated with the permanent income of the father, y_{0i}) on current income. The results are shown in Table 2. As can be seen, the estimates are very consistent with the lowest estimate (0.358) coming from using "ISEI" as the IV for permanent income, while the highest (0.433) based on the IV of "level of education". The p-value is 0.716, so we can't reject the null hypothesis that the four IV estimates are identical. However, 'fail to reject' a null hypothesis is not the same as 'accept'. Our sample size is too small and lacks the statistical power to detect difference in estimates (Lefgren *et al*., 2012). However, we can safely conclude that "nepotism" plays an important role in Chinese society and that the impact of paternal human capital on child's income, π_2 , is unlikely to be zero.

Regardless, according to Section 3.2, the closer the four IV estimates, the smaller the π_2 ; and indeed, if the different IV estimates are the same, then π_2 = 0. Given that the four IV estimates are relatively similar, and the rather high p-value suggests that even if the four IV estimates are not identical, the difference is quite small. This suggests that, at least, π_2 is smaller than π_1 in magnitude, which means that the father's investment is the primary causal mechanism in the intergenerational transmission of income. This result seems not in line with Qin *et al.* (2016), who find that direct transfer of parents' human capital has great impact on the intergenerational transmission of income in China. However, Qin *et al.* (2016) measure human capital only by education and health and there are lots of omitted variables in the OLS regression. In other words, the estimate is actually not the causal effect of the transmission of human capital. On the other hand, Qin *et al.* (2016)'s research doesn't involve comparison between the effect of father's income and human capital whereas our research focus on the relative importance of father's income to human capital , and we don't deny the importance of father's human capital.

Table 2. Different IV Estimates of the IIE

	INSTRUMENTS			
	Father Years of Schooling	Father Level of Education	Father Social Status	Father ISEI
Fathers' current income	0.416 (0.087)	0.433 (0.081)	0.381 (0.049)	0.359 (0.059)
Over-identification test (p-value)	0.716			
Observations	735	735	735	735

NOTE：Robust standard errors in brackets. All IV estimates are significant at the 1% level.

5.2. Intergenerational income elasticity

Theoretically, if $\pi_2 = 0$, we can get a consistent estimate of the IIE using IV procedure and current income. Though $\pi_2 \neq 0$ here, given the small value of π_2 , we can still obtain a rough estimate of the IIE. Unfortunately, due to lack of relevant research on China, we cannot get the magnitude of κ without λ_t and λ_s[6]. To remedy this, we performed a back-of-the-envelope estimate of the κ using the λ estimates that Haider and Solon (2006) obtained over life cycle in the U.S. We present the values of κ and λ in Tables 3 and Table 4, respectively.

We can see that $E\lambda_t$ and $E\lambda_s$ are equal to 0.458 and 0.791, respectively, which leads to κ = 0.579, suggesting that an IV estimate of the IIE using current income will produce about 40% downward bias. Therefore, we divide the estimates in Table 2 by 0.579, and the "adjusted" IIE estimates range from 0.620 (using "ISEI" as the IV) to 0.748 (with "level of

Table 3. Estimates of λ (Haider and Solon, 2006)

Age	λ		Age	λ	
	Coefficient	Std. Error		Coefficient	Std. Error
20	0.237	0.033	41	1.144	0.075
21	0.251	0.042	42	0.948	0.075
22	0.171	0.05	43	0.821	0.056
23	0.284	0.061	44	0.818	0.062
24	0.317	0.041	45	0.86	0.058
25	0.405	0.046	46	0.86	0.064
26	0.432	0.03	47	0.904	0.073
27	0.541	0.036	48	0.764	0.061
28	0.508	0.033	49	0.722	0.059
29	0.643	0.05	50	0.725	0.064
30	0.76	0.055	51	0.756	0.073
31	0.835	0.06	52	0.762	0.07
32	0.945	0.063	53	0.788	0.071
33	0.993	0.071	54	0.776	0.069
34	1.27	0.078	55	0.77	0.069
35	0.869	0.05	56	0.776	0.071
36	0.947	0.058	57	0.799	0.076
37	0.812	0.046	58	0.763	0.074
38	0.981	0.053	59	0.723	0.072
39	1.062	0.06	60	0.704	0.068
40	1.17	0.069			

NOTE：In Haider and Solon (2006), ages are derived from years minus 1932, which gives the

[6] λ_t and λ_s denote the same time-dependent variable that leads to life-cycle bias. We use different subscripts here to differentiate between father and child as they are at both ends of the life-cycle. To avoid misunderstanding, we use unified symbol, λ, to indicate this variable later in the paper.

approximate age of the 1931-1933 cohort. Hence the mismatch between the range of their sample's age (19-59) and ours (20-60) will not make difference.

Data source：www.e-aer.org/data/sept06/20040284_data.zip.

Table 4. Estimates of the IIE and κ

	Median	Mean	Std. Error
λ_t	0.405	0.458	0.242
λ_s	0.770	0.791	0.064
$\kappa = E\lambda_t / E\lambda_s$	0.579		
$\beta = p\lim\left(\hat{\beta}^{IV}_{\text{current}}\right) / \kappa$			
Years of schooling	0.718		
Level of education	0.748		
Social status	0.658		
ISEI	0.620		

education" as the IV). These values are relative high, but consistent with Gong *et al*. (2012) and Long and Wang (2014).

Obviously, since Haider and Solon (2006) is based on U.S. data, whether it can be directly applied to China is clearly a question that needs to be raised. In the absence of direct replication of their study using Chinese data, this question cannot be addressed at present. However, the literature on life-cycle bias in different countries (Haider and Solon, 2006; Bohlmark and Lindquist, 2006; Brenner, 2010) show that the variation of λ over the life cycle shows a consistent pattern: λ is low when individuals are in their twenties (as low as 0.2 in the U.S. before age 25), and then rise to close to 1 when the individual reach thirties and remain high until their late forties, and by their late fifties, λ declines to about 0.6. This pattern is quite robust across countries, and hence we feel our approach is reasonable given the circumstances and that the "adjusted" IIE estimates should be in the neighborhood of the true value; at the minimum, China's IIE is no lower than the 0.358 shown in Table 2.

5.3 Robustness Check

It is customary to carry out robustness tests to see if the key results are stable when small changes are made. We implemented three such tests.

Table 5. IV Estimates after Removing Extreme Values

	INSTRUMENTS			
	Father Years of Schooling	Father Level of Education	Father Social Status	Father ISEI
Fathers' current income	0.399 (0.087)	0.421 (0.083)	0.387 (0.051)	0.355 (0.061)
Over-identification test (p-value)	0.662			
Observations	723	723	723	723

NOTE：Robust standard errors in brackets. All IV estimates are significant at the 1% level.

Outliers

By structure there is a large difference between the ages of the child relative to the father, and hence the pair may suffer from very different stochastic factors; thus raising the potential issue of outliers. To check for the robustness of the estimates, we removed the 0.5% of the upper and lower extreme values of the fathers' income and child's income, respectively. The re-estimated IIE are reported in Table 5. With the sample size trimmed to 723, both the magnitude and the pattern of the four IV estimates remain. The P-value of over identifying restriction test is still at a robust 0.662, with which we can't reject the null hypothesis that the four IV estimates are identical.

Life-cycle bias

Due to the data restriction that fathers still earn a positive wage income, most of our sample children are in the early stage of their life cycle[7], where λ is significantly below 1. This indicates that life-cycle bias is relatively large in our estimates. As a robustness check, we *successively* remove children with the age of 20, 21, 22, 23, 24 and 25 from our sample, which gradually increases the minimum age of the children and thus reducing the life-cycle bias. In each round, we re-estimate the IIE based on the four IVs. By doing so we can check the robustness as the impact of life-cycle bias diminishes; the results are shown in Table 6.

As can be seen, the estimates exhibit a rising trend as the minimum age of "children" in the sample increases; this is true across the four IV estimates. As the age of children rise, it will increase $E\lambda_t$ while leaving $E\lambda_s$ unaffected, which leads to a rise in κ . Eq. (13) clearly predicts that the IV estimates will rise as well, which is exactly what we see here. As for the test of over-identifying restrictions, we can see that p-values are in general more than large enough such that we can't reject that they are the same.

Table 6. IV Estimates with Decreasing Life-cycle Bias

		Minimum age of sample children					
		21	22	23	24	25	26
IV estimates	Years of schooling	0.371	0.374	0.409	0.385	0.386	0.423
		(0.088)	(0.089)	(0.087)	(0.092)	(0.094)	(0.103)
	Level of education	0.389	0.344	0.358	0.357	0.308	0.339
		(0.082)	(0.082)	(0.076)	(0.080)	(0.079)	(0.086)
	Social status	0.389	0.385	0.396	0.408	0.422	0.449
		(0.051)	(0.052)	(0.052)	(0.056)	(0.058)	(0.060)
	ISEI	0.342	0.314	0.337	0.344	0.339	0.387
		(0.060)	(0.062)	(0.063)	(0.066)	(0.071)	(0.074)
P-value		0.450	0.206	0.376	0.255	0.169	0.318
No of Obs.		691	628	567	474	403	336

NOTE：Robust standard errors in brackets. All IV estimates are significant at the 1% level.

Sons

In both economics and sociology, most of the studies focus on the relationship between fathers and sons. This disproportionation partly from unconscious sexism and partly from a recognition that, in a society in which married women's labor-force participation rates are lower than men's, women's earnings may often be an unreliable indicator of their economic status (Solon, 2002). However this situation has changed in recent years. The increasing number of papers has paid attention to the role of daughters in the intergenerational transmission of income (Black and Devereux, 2011). In this paper, we add daughters into our sample as well, which is motivated by following causes: First, due to the tradition of favoring sons over daughters (as the offspring of the son will carry the family, while the daughter's does not), parents are likely to invest more on sons than on daughters. This will bias the estimate of the IIE upwards when the sample is restricted to sons. Besides, Focusing only on father-son correlations may miss part of the picture. Daughters should be included if we want to know how the *average* well-being of a generation correlates with that of their parents. However, in this part, we will remove daughter from our sample to perform a parallel analysis of sons' mobility. It's not only a robustness check, but also a comparison of level of mobility with other countries.

With the sample size now 671, we re-estimate the four IV estimates for the IIE (Table 7). The variation among the IVs are smaller, 0.34 (vs. 0.74 in Table 2), and the p-value of the over-identification test is higher (at 0.955) and suggest that π_2 is still smaller than π_1 in magnitude, which is the critical element in our analysis. It is worth pointing out that in Table 2, the first two IV estimates are very similar, while the last two IVs generate a lower IIE, which is quite different with the case of Table 7. It is tempting to interpret this as indicative that the father's social status and Socio-Economic Index tend to

[7] In our sample, children age between 20-25 account for 54.29% of the total sample.

affect the son more than it does for the daughter. This certainly does not surprise anyone familiar with the Chinese social practice, and is perhaps worth a separate study to verify or refute this line of thought.

Table7. IV Estimates of the IIE for father-son pairs

	INSTRUMENTS			
	Father Years of Schooling	Father Level of Education	Father Social Status	Father ISEI
Fathers' current income	0.339 (0.119)	0.357 (0.101)	0.373 (0.058)	0.365 (0.067)
Over-identification test (p-value)		0.955		
Observations	671	671	671	671

NOTE: Robust standard errors in brackets. All IV estimates are significant at the 1% level.

Cohabitation selection bias

As stated in our data description, we limit our sample to father-child pairs who co-reside, and the reason for doing so is to assure that we have data on income for both father and child. Of course, this immediately raises a red flag as there may be sample selection bias. To be more specific, If the co-residing sample is systematically different from the non-co-residing sample, we may suffer the cohabitation selection bias. However, theoretically, our results are robust even if this selection bias exists since the methodology is based on comparing different IV estimates rather than estimating a specific coefficient, as traditional regression analysis does. In such approaches, when the "cohabitation" selection bias exists, an additional variable——Inverse Mill's ratio (IMR) will arise in the equation (12). However, since IMR can be estimated by the father's income and other variables that determine the child's choices to co-reside with parents using the probit model, it should be highly correlated with the father's human capital, which is an aggregation of all father's endowments that can affect father's income. Thus the IMR can be considered as part of father's human capital, which means that the variable HC_{oi} also includes the IMR if there is cohabitation selection bias. Therefore the method of comparing different IV estimates is still valid in theory, and the result that different IV estimates are similar will be unaffected with the cohabitation selection sample[8].
However, the specific value of the IV estimate may be biased when using cohabitation selection sample. Fortunately, CFPS provides an opportunity to correct such a bias since it asks for some socioeconomic characteristics of children who are not living with their parents. Specifically, we will use the Heckman two-stage procedures to separate the effect between father's human capital and IMR. Inspired by Deng et al. (2013) and Fan (2016), we use province level co-residence rates, age, age-squared, gender, and provincial dummies as identifying variables. Results are reported in Table 8.

Table 8. IV Estimates of the IIE after Correcting for co-residence bias

	INSTRUMENTS			
	Father Years of Schooling	Father Level of Education	Father Social Status	Father ISEI
Fathers' current income	0.460 (0.090)	0.466 (0.081)	0.386 (0.048)	0.364 (0.060)
Inverse Mill's ratio	0.379 (0.099)	0.382 (0.098)	0.342 (0.091)	0.331 (0.092)
Over-identification test (p-value)	0.56			
Censored obs.	773			
Uncensored obs.	735			
Observations	1508	1508	1508	1508

[8]Metaphorically, we can compare the heights of different people as long as they stand on the same elevation no matter they are on the top of the Everest or the bottom of the Mariana Trench.

NOTE: Robust standard errors in brackets. All IV estimates are significant at the 1% level.

In Table 8, we report the different IV estimates on intergenerational income elasticity after correcting for co-residence bias. The coefficients of the Inverse Mill's ratio are positive and statistically significant, implying a positive self-selection co-residency (which is as expected). Turning to the IIEs, the corrected estimates are a little higher that those in Table 2, but the four IV estimates are still similar, and we cannot reject the null hypothesis that they are identical with the p-value (0.56) of the Over-identification test. As the lowest IV estimate (0.364) is higher than that (0.359) in Table 2, the lower bound of the IIE is unchanged.[9]

CONCLUSIONS

Empirically, countries with more income inequality tend to be countries in which a greater fraction of economic advantage or disadvantage is passed on between parents and their children[10]. This relation ***may*** also exist in China. Before the initiation of the Economic Reform of 1978, Chinese society was relative egalitarian, but inequality has been increasing with the transition from a socialistic society to a market-oriented economy, along with which the intergenerational mobility has been declining (Fan *et al*., 2015). Large income inequality combined with low social mobility will severely degrade the equality of opportunity, which will inevitably lead to social conflicts. Such circumstances have clear policy implications, but correct policies must be built on accurate understanding of the transmission mechanisms that led to such social injustice.

In this paper, we estimate the causal effect of the father's income and human capital on the income of the child. The key finding is that the majority of the intergenerational income elasticity is attributed to the causal effect of paternal income. This result contradicts similar research (Lefgren *et al*., 2012; Cardak *et al*., 2013) in other countries where the dominate effect was via human capital. This is strong evidence of the less egalitarian nature of Chinese social institutions.

This suggests that any efforts aimed at reducing the income/wealth inequalities in China will have the added benefit of reducing the inequalities in future generations as the intergeneration transfer is mainly through paternal income. As such, though China's income distribution is very dire, if the Central government takes decisive action to correct the current inequalities, it may have a chance to significantly improve the distribution in two generations. This could be considered a ray of hope in the dark environment of China's current inequalities. In addition, by using a different method and the age specific life cycle attenuation factor found by Haider and Solon (2006) on the U.S., we obtain an estimate of 0.359 as a lower bound IIE estimate for father-child in China, which could be adjusted to a similar level of 0.6 as found by Gong et al (2012). This shows a low mobility of China compared to other developed market-oriented countries, and should be of concern for policy makers. Combined, the need for aggressive actions to improve income equality in China is even more imperative!

For those readers less familiar with China, it is natural to ask why parents' income matter so much. It is certainly a legitimate question, and that is why we decided to take the unusual step to have a more expansive discussion in this section. The sample "children" in this study are all from the 1976-1990 cohort, and can thus be characterized as born after China's Comprehensive Economic Reform. The Reform has generated enough literature to fill a small library, but what is less emphasized is the re-emergence of "money" as money (Fei and Hou, 1994). Prior to the Reform, the true "money" was the coupons (food, cloth, meat, etc.), without which one cannot purchase the goods, regardless of how much currency one has. These coupons are allocated to each individual according to the "Plan", as such a father's income has very little meaning in acquiring any instruments that may improve the standing of his child.

As we move deeper into the post-reform era, money quickly re-emerged as a medium of exchange and store of value, much like any typical market economy. This allowed the father to use his income/money to amass assets and wealth to improve the standard of living for his family, and to command resources that would benefit his child's chances of stature and wealth. This natural desire of a parent is further enhanced by the unique one-child policy of China, which was implemented in 1979 (Hou 2011). An even more intriguing line of study is to estimate the IIE for families that have more

[9]We would like to thank an anonymous referee for raising the concern regarding selection bias stemming from the co-residency requirement. Though we believe that our methodology is not a standard regression analysis and should be theoretically immune from such biases, one should always go a step further and verify it empirically. To this and we would like to thank the anonymous author again for pushing us to go this further step, and in doing so, strengthen our result with an important robustness test.

[10]This relationship, commonly referred to as the "Great Gatsby Curve", has garnered attention recently in policy debates and academic studies ever since it was coined by former Council of Economic Advisors chair, Alan Krueger, in a 2012 speech.

than one child (there are provisions where a family can legally have more than one child, though it is definitively in the minority). With the recently decision to loosen the one-child policy, future research can focus on whether this reduces China's IIE and perhaps improve social mobility.

A final warning whether the methodology of Lefgren et al. (2012) could be interpreted as "causal" as it is essentially a decomposition method. In addition, even if the indirect effect were indeed zero, it is unclear what would be the policy implications because the direct effect is still largely a black box. Future research should be aimed at identifying the causal effect of different components of the father's income and human capital.

REFERENCES

Becker, G., and N. Tomes, "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, 1979, 87(6), 1153-1189.

Becker, G. S. and N. Tomes, "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 1986, 4(32), 1-47.

Black, S., and P. Devereux.,'Recent Developments in Intergenerational Mobility,'in D. Card, and A. Orley (ed.), *Handbook of Labor Economics* (Elsevier), 2011.

Björklund, A. and M. Jäntti, "Intergenerational Income Mobility in Sweden Compared to the United States" *American Economic Review*, 1997, 87(5), 1009-1018.

Björklund, A., M. Lindahl, and E. Plug, "The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data," *Quarterly Journal of Economics*, 2006, 121(3), 999-1028.

Blanden, J., "Cross-Country Rankings in Intergenerational Mobility: A Comparison of Approaches from Economics and Sociology," *Journal of Economic Surveys*, 2013, 27(1), 38-73.

Bowles, S., and H. Gintis, "The Inheritance of Inequality," *Journal of Economic Perspectives*, 2002, 16(3), 3-30.

Bratberg, E., Ø. A. Nilsen, and K. Vaage, "Intergenerational Earnings Mobility in Norway: Levels and Trends," *Scandinavian Journal of Economics*, 2005, 107(3), 419-435.

Bratsberg, B., K. Roed ,O. Raaum, R. Naylor, M. Jantti, T. Eriksson, and E. Osterbacka, "Nonlinearities in Intergenerational Earnings Mobility: Consequences for Cross-Country Comparisons," *Economic Journal*, 2007, 117(519), 72-92.

Cardak, B., D. Johnston, and V. Martin, "Intergenerational Earnings Mobility: A New Decomposition of Investment and Endowment Effects," *Labour Economics*, 2013, 24, 39-47.

Chadwick, L., and G. Solon, "Intergenerational Income Mobility among Daughters," *American Economic Review*, 2002, 92(1), 335-344.

Corak, M. and A. Heisz, "The Intergenerational Earnings and Income Mobility of Canadian Men: Evidence from Longitudinal Income Tax Data," *Journal of Human Resources*, 1999, 34(3), 504-533.

Corcoran, M., R. Gordon, D. Laren, and G. Solon, "The Association between Men's Economic Status and Their Family and Community Origins," *Journal of Human Resources*, 1992, 27(4), 575-601.

Deng, Q., Gustafsson, B., and Li, S, "Intergenerational income persistence in urban China," *Review of Income and Wealth*, 2013, 59(3), 416–436.

Dunn, E., "The Intergenerational Transmission of Lifetime Earnings: Evidence from Brazil," *B.E. Journal of Economic Analysis and Policy*, 2007, 7(2), 1-42.

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

Fan, Y., J.J. Yi and J.S. Zhang, "The Great Gatsby Curve in China Cross-Sectional Inequality and Intergenerational Mobility," 2015, ABFER Working Paper.

Fei, J., and J. Hou, "The Comprehensive Economic Reform of The PRC (1978-)," in Shao-chuan Leng (ed.), *Reform and Development in Deng's China*, Volume IV, The Miller Center Series on Asian Political Leadership (University Press of America: New York), pp. 19-64, 1994.

Gong, H., A. Leigh, and X. Meng, "Intergenerational Income Mobility in Urban China," *Review of Income and Wealth*, 2012, 58(3), 481-503.

Grawe, N. D, "Reconsidering the Use of Nonlinearities in Intergenerational Earnings Mobility as a Test for Credit Constraints," *Journal of Human Resources*, 2004, 39(3), 813-827.

Grawe, N. D, "Life-cycle Bias in Estimates of Intergenerational Earnings Persistence," *Labour Economics*, 2006, 13(5), 551-570.

Haider, S., and G. Solon, "Life-Cycle Variation in the Association between Current and Lifetime Earnings," *American Economic Review*, 2006, 96(4), 1308-1320.

Hirvonen, L.H., "Intergenerational Earnings Mobility among Daughters and Sons: Evidence from Sweden and a Comparison with the United States," *American Journal of Economics and*

Sociology, 2008, 67(5): 777– 826.
Hou, J.W., “Economic Reform in China: Cause and Effect,” *Social Science Journal*, 2011, 48(3): 419 – 434.
Lee, C., and G. Solon, “Trends in Intergenerational Income Mobility,” *Review of Economics and Statistics*, 2009, 91(4), 766-772.
Lefgren, L. , M. Lindquist, and D. Sims, “Rich Dad, Smart Dad: Decomposing the Intergenerational Transmission of Income,” *Journal of Political Economy*, 2012, 120(2), 268-303.
Long, C., and X. Wang, “Research on China's Intergenerational Income Mobility and Transfer Mechanism,” *Journal of East China Normal University*, 2014, 5, 156-164. (in Chinese)
Mazumder, B., “Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data,” *Review of Economics and Statistics*, 2005, 87(2), 235-255.
Mocetti, S., “Intergenerational Earnings Mobility in Italy,” *B.E. Journal of Economic Analysis and Policy*, 2007, 7(2), 1-25.
Mulligan, B., “Galton versus the Human Capital Approach to Inheritance,” *Journal of Political Economy*, 1999, 107(6, pt. 2): S184-S224.
Naughton, B., *The Chinese Economy: Transitions and Growth* (Cambridge, Massachusetts: MIT Press), 2005.
Nicoletti, C., and J.Ermisch, “Intergenerational Earnings Mobility: Changes across Cohorts in Britain,” *B.E. Journal of Economic Analysis and Policy*, 2007, 7(2), 1-38.
Qin, X., T. Wang, and C. C. Zhuang, “Intergenerational transfer of human capital and its impact on income mobility: Evidence from China,” *China Economic Review*, 2016, 38, 306-321.
Roemer, J., “Equal Opportunity and Intergenerational Mobility: Going Beyond Intergenerational Income Transition Matrices” in Corak, M. (ed.), *Generational Income Mobility in North America and Europe* (Cambridge: Cambridge university Press), 2004.
Solon, G., “Intergenerational Income Mobility in the United States,” *American Economic Review,* 1992, 82(3), 393-408.
Solon, G., “Cross-Country Differences in Intergenerational Earnings Mobility,” *Journal of Economic Perspectives*, 2002, 16(3), 59-66.
Solon, G., “A model of intergenerational mobility variation over time and place,” in Corak, M. (ed.), *Generational Income Mobility in North America and Europe* (Cambridge: Cambridge University Press), 2004.
Torche, F., “Intergenerational Mobility and Inequality: The Latin American Case,” *Annual Review of Sociology*, 2014, 40, 619-642.
Wang, H., W., “Intergenerational Mobility in Chinese Income Distribution,” *Economic Science,* 2005, 2:18-25. (in Chinese)
Yang, J., and M. Qiu, “The impact of education on income inequality and intergenerational mobility,” *China Economic Review*, 2016, 37, 110-125.
Yuan, W., “The Sins of the Fathers: Intergenerational Income Mobility in China,” *Review of Income and Wealth*, 2017, 63(2), 219-233.
Yuan, Z., and L. Chen, “The Trend and Mechanism of Intergenerational Income Mobility in China: An Analysis from the Perspective of Human Capital, Social Capital and Wealth,” *The World Economy*, 2013, 36(7), 880-898.
Zimmerman, D., “Regression toward Mediocrity in Economic Stature,” *American Economic Review*, 1992, 82(3), 409-429.