Intergenerational Educational Mobility in Rural Economy: Evidence from China and India

Emran, M. Shahe and Ferreira, Francisco and Jiang, Yajing and Sun, Yan

20 May 2019

Intergenerational Educational Mobility in Rural Economy: Evidence from China and India

M. Shahe Emran[1]
IPD, Columbia University

Francisco Ferreira
World Bank

Yajing Jiang
Charles River Associates

Yan Sun
World Bank

May 20, 2019

ABSTRACT

We extend the Becker-Tomes (1986) model of intergenerational educational mobility to a rural economy characterized by occupational dualism (farm vs. nonfarm) and provide a comparative analysis of rural India and rural China. Using two exceptional data-sets, we estimate father-sons intergenerational educational persistence in farm and nonfarm households free of truncation bias due to coresidency. The sons in rural India faced lower educational mobility compared to the sons in rural China in the 1990s and earlier. Father's nonfarm occupation and education were complementary in determining a son's schooling in India, but separable in China. However, the separability observed for the older cohorts in rural China broke down for the younger cohort. Evidence from supplementary data on economic mechanisms shows that the extended Becker-Tomes model provides plausible explanations for both the cross-country heterogeneity (India vs. China), and the evolution of mobility across cohorts in China.

Key Words: Educational Mobility, Rural Economy, Occupational Dualism, Farm-Nonfarm, Complementarity, Coresidency Bias, China, India

JEL Codes: O12, J62

[1]We are grateful to Forhad Shilpi for help with REDS data and insightful comments throughout this project, and to Yang Huang for help with the CFPS data. We would like to thank the participants in Equal Chances conference 2018, Guido Neidhofer, and Hanchen Jiang for helpful comments on an earlier draft and Rakesh Gupta Nichanametla Ramasubbaiah for excellent research assistance. The standard disclaimers apply. Email for correspondence: shahe.emran@gmail.com.

(1) Introduction

Intergenerational persistence in economic status in developing countries has attracted attention of both policymakers and researchers in recent years, partly in response to growing evidence that economic reform and liberalization increased income inequality in many countries, despite significant reduction in poverty.[2] In the absence of reliable income data over the life cycle of parents and children, the focus of the recent literature on developing countries has been on intergenerational educational mobility. However, most of the recent studies are devoted to the urban households, and intergenerational mobility in rural areas remains particularly under-researched, even though the bulk of the poor lives in the villages in developing countries.

The standard single factor model widely used in the literature where parent's education is the sole indicator of family background may provide an incomplete understanding of intergenerational educational mobility in villages, as it ignores a salient feature of the rural economy: occupational dualism in the form of farm vs. nonfarm sectors. Children born into a nonfarm household may face different educational opportunities compared to the children born into a farming household even when the parents have similar educational background. At a given level of education, parent's nonfarm occupation may affect investment in children's education through two major channels. First, higher income from nonfarm occupations may relax binding credit constraints on investment in schooling.[3] Second, the probability of children getting a nonfarm job may be higher when the parents themselves are employed in nonfarm occupations because of network, referral, and role model effects (Emran and Shilpi (2011)), and this would increase the optimal investment when returns to education are higher in nonfarm occupations.

There is substantial evidence that structural change in favor of non-farm occupation is an important source of increasing income inequality in villages of many developing countries.[4] According to the estimates of Lanjouw et al. (2013) based on the data from Palanpur in the Indian state of Uttar Pradesh, the contribution of non-farm income to over-all income

[2]For recent contributions on China, see, among others, Fan et al. (2015), Park and Zou (2018), Sato and Li (2007), Emran and Sun (2015a)), on India see, among others, Azam and Bhatt (2015), Emran and Shilpi (2015), Asher et al. (2018), Ahsan et al. (2019). For cross-country analysis, see Behrman (2000), Hertz et al. (2007), and Neidhofer et al. (2018), among others. The literature on developing countries focuses primarily on educational mobility. Among the few contributions on intergenerational persistence in health, see Bhalotra and Rawlings (2013).

[3]However, in some countries, low-skilled nonfarm activities might be occupation of last resort, with low income, lower than the income of the farming households (Lanjouw and Lanjouw (2001)).

[4]For an excellent survey of the literature on rural nonfarm economy in developing countries, see Lanjouw and Lanjouw (2001). On rural China see Rozelle (1994), Yang and An (2002), and on rural India see Lnjouw et al. (2013).

inequality was only 4 percent in 1974/75, which increased to 67 percent in 2008/09.[5] The evidence on China also suggests that nonfarm income contributes to income inequality in the rural areas (Rozelle (1994), Yang and An (2002)). The rise in inequality associated with the expansion of nonfarm sector is of special concern when it reflects lower intergenerational mobility.

We develop a theoretical model in the tradition of Becker and Tomes (1986) that incorporates the role played by parental farm and nonfarm occupations in shaping children's educational opportunities, and yields an estimating equation consistent with the specification widely used in the literature.[6] An important insight is that, to understand the differences in educational mobility across farm and nonfarm households, it is necessary to analyze the differences in the intercepts of the intergenerational regression equations. This deserves attention because the focus in much of the existing literature has been on the slope-based measures of mobility such as intergenerational regression coefficient (IGRC) and intergenerational correlation (IGC). However, a credible empirical analysis of the role of nonfarm occupations in intergenerational educational persistence needs to address two major challenges highlighted in the recent literature on intergenerational mobility: (i) truncation bias due to coresidency restrictions in surveys, and (ii) spurious intergenerational persistence due to genetic correlations.

Most of the available household surveys, especially in developing countries, suffer from serious sample truncation as household membership is defined in terms of coresidency.[7] Recent evidence shows that the standard measures of relative mobility used in the literature such as IGRC suffer from substantial *downward* bias in coresident samples (Emran, Greene, and Shilpi (2018)). Our empirical analysis focuses on the father-son linkage in education, and takes advantage of two exceptionally rich data sets: the rural sample from the China Family Panel Studies (2010) for China and the Rural Economic and Demographic Survey (1999) for India. Both of these surveys are unique in that they include all of the children of household head irrespective of their residency status at the time of the survey.[8] This is especially important in a comparative study such as ours, because the evidence shows

[5] The Gini coefficient of income in Palanpur was 0.253 in 1974/75 and 0.427 in 2008/09.

[6] The existing literature on intergenerational educational mobility relies on a linear-in-levels estimating equation. However, none of the published papers on intergenerational educational mobility we are aware of derive the linear estimating equation from a theoretical model. As emphasized by Mogstad (2017), in the absence of an explicit theoretical model, it is difficult to understand and interpret the economic content of the estimated intergenerational persistence.

[7] For example, the widely used surveys such as LSMS and DHS collect information only on the coresident children.

[8] Although some surveys collect limited information on the non-resident parents of the household head and spouse, we are aware of only a few surveys that include all children of the household head.

that cross-country comparisons based on coresident children samples can lead to wrong conclusions (see, for example, the analysis of India vs. Bangladesh in Emran, Greene, and Shilpi (2018)).

A longstanding concern in the literature has been whether the observed correlations are primarily mechanical, driven largely by genetic transmissions from parents to children (see, for example, the discussion by Black and Devereux (2011)). We address this issue in two ways. First, we develop a simple but plausible approach to test whether the estimated intergenerational persistence could be due solely to genetic correlations by combining recent evidence on intergenerational correlation in cognitive ability with the Altonji et al. (2005) biprobit sensitivity analysis. Second, and perhaps, more importantly, the theoretical foundation for the empirical specification allows us to use economic mechanisms as a test for the importance of parental economic choices.

The substantive conclusions of this paper can be summarized as follows. Intergenerational educational mobility was substantially lower for the sons in rural India compared to the sons in rural China for the cohorts that went to school in 1990s or earlier. The difference between farm and nonfarm households is statistically significant in rural India, but not in rural China, and this applies to both the slope and the intercept of the intergenerational educational persistence regression. The evidence suggests that while parent's education and nonfarm occupation were complementary in determining son's education in rural India in the 1970s-1990s, they were separable in rural China. As a result, the long-term variance in schooling was significantly higher for the sons born into nonfarm households in rural India, implying that structural change from agriculture to the nonfarm sector contributed to inequality of educational opportunity.[9] Altonji et al. (2005) biprobit sensitivity analysis (henceforth AET sensitivity) shows that the observed persistence in rural India cannot be accounted for by genetic correlation alone, while the estimates in China can be explained away by ability correlation of plausible magnitude.

Under the null hypothesis that the observed persistence is due to genetics, the economic mechanisms identified in the theory are unlikely to provide a coherent explanation of the pattern of mobility across countries and over time. The theory highlights the role of returns to education in parental generation in determining the slope-based mobility measures such as IGRC, while intergenerational occupational persistence is an important factor for

[9]It is important to recognize that the separability in rural China does not imply that nonfarm income did not play any role in rural income inequality; in fact, we cite a substantial literature to the contrary. The evidence in this paper suggests that intergenerational educational linkage is unlikely to be an important mechanism through which nonfarm sector influenced the observed inequality in rural China in the 1980s and 1990s.

the intercept of the schooling persistence equation. A substantial body of independent evidence on intergenerational occupational persistence in rural China and rural India is consistent with the observed differences in the intercepts. We use household income data from Chinese Household Income Project (CHIP) and National Sample Survey (NSS) of India to explore the mechanisms behind the pattern of relative mobility (the IGRCs) across farm and nonfarm households. The household-level returns to education estimates for the parental generation provide a plausible explanation for the pattern of IGRCs across farm and nonfarm households, both in rural India and rural China.

The theory also suggests that we should observe changes in the intergenerational educational persistence in rural China for the younger generation because of the effects of reform on the relevant mechanisms such as higher returns to education in nonfarm occupations. In contrast to the separability observed for the older cohorts, we find evidence of complementarity between father's education and nonfarm occupation in rural China for the younger generation (18-28 years old in 2010). The predictions from the extended Becker-Tomes model thus explains both the cross-country heterogeneity (India vs. China) and over time evolution (younger vs. older cohorts in China) of intergenerational educational mobility in a rural economy.

The rest of the paper is organized as follows. Section 2 develops a model of intergenerational persistence with credit constraint that incorporates the salient features of farm vs. nonfarm households relevant for educational attainment. The next section describes the estimating equations derived from the theory and the empirical issues in understanding potential complementarity between parent's education and nonfarm occupation in determining children's schooling. Section 4 discusses the data and section 5 reports the main empirical estimates. The following section explores the evidence on the mechanisms identified by the theory underlying the observed pattern of slope (IGRC) and intercept estimates for the cohorts who went to school in 1990s or earlier. Section 7 provides evidence on possible changes in the mobility mechanisms in the younger generation (18-28 years old in 2010), and analyzes the question whether we observe changes in the pattern of educational mobility consistent with the extended Becker-Tomes model. The paper concludes with a summary of the main results from the theoretical and empirical analysis.

(2) Intergenerational Educational Persistence in a Dualistic Rural Economy: Theory

We develop an extension of the Becker-Tomes model with credit constraint (Becker and Tomes (1986)) to understand the role played by nonfarm occupations of parents in intergenerational educational mobility of children in a rural economy. The focus is on two salient determinants of intergenerational persistence in education: credit constraints that may constrain investment in education by parents, and differences in expected returns to education. Expected returns to education in our context depends on two factors: the probability of getting a non-farm employment, and the difference between returns to education in farm vs. nonfarm occupations. The goal in this section is to derive an estimating equation that incorporates the differences in farm and nonfarm households.

The Basic Set-up

The economy consists of households with a father and a son. The father of child i is described by a pair $\left(S_i^P, O_i^p\right)$ where S_i^p is the education (years of schooling) and $O_i^p \in \{f, n\}$ with f denoting farming occupation and n denoting nonfarm occupation of the father. Given his education and occupation, the father's income is determined as follows:

$$Y_i^p = Y_0^{pj} + R^{pj} S_i^p \; ; \; j = f, n \tag{1}$$

The income determination equation assumes that the fathers with zero years of schooling working in occupation j earns $Y_0^{pj} > 0$, and the returns to education in occupation j is R^{pj} for the parental generation. The assumption that $Y_0^{pj} > 0$ is motivated by our empirical context where a substantial proportion fathers has zero years of schooling, but positive household income. It is important to underscore that the focus is on how a household's ability to invest in education changes with the education of the father. The "returns to education" relevant here thus relate to permanent household income, not an individual's labor market earnings in a given year which has been the focus of much of the literature on returns to education.[10] In general, the intercepts are likely to be different, but whether Y_0^{pn} is larger or smaller than Y_0^{pf} will depend on the quality of the nonfarm activities at low education level ($S_i^p = 0$) which is likely to vary across countries. If low-end nonfarm activities have low-productivity, then it is possible that $Y_0^{pn} < Y_0^{pf}$.

The father allocates Y_i^p to own consumption C_i^p and investment in child's education I_i; thus the budget constraint is

$$Y_i^p \geqq C_i^p + I_i \tag{2}$$

[10]This point may be especially important in rural China during 1980s and early 1990s when the labor market was still not functioning very well, and the labor market earnings would be a poor measure of a household's economic status.

The educational investment is made from a father's own income, as there is little or no financing available from the credit market for such investments in developing countries. The education production function for the child is as follows:

$$S_i^c = F(I_i) = \theta_0 + \theta_1 \phi_i + \theta_2 I_i \tag{3}$$

The a priori sign restrictions are: $\theta_0 \geq 0$, $\theta_1, \theta_2 > 0$. We would expect θ_0 to be higher when government policies such as free primary schooling (including free books and midday meals etc) are in place so that a child can get certain level of education, for example, primary schooling without any significant investment by the parents. $\phi_i \geq 1$ is the ability of child i and higher ability produces more schooling, *ceteris paribus*. The productivity of parental financial investment is represented by the parameter θ_2 which captures, among other things, the quality of schools available to a family. The differences in productivity of financial investment are likely to be more pronounced when the private education market is well-developed and parents can buy better quality education by paying higher tuition and donation for admission. In contrast, when schooling is primarily provided by the government free of charge, the role played by parent's investment in children's education is expected to be rather limited, making θ_2 small.[11] Note that the access to better quality schools does not depend on a parent's occupation in the formulation in equation (3) (i.e., θ is not indexed by j).[12]

Parent's Optimization

The consumption sub-utility function of the parent is given by:

$$U(C^p) = \alpha_1 C^p - \alpha_2 (C^p)^2 \tag{4}$$

Denote the expected income of a child i with education S_i^c at the time of the parental investment choice by $E(Y_i^c \mid S_i^c)$. The parent's optimization problem is (denoting the

[11] However, the "free schooling" offered by the governments may not be free especially for the poor households because of corruption when the enforcement system is not unbiased and impersonal. Emran, Islam, and Shilpi (2018) show that, in Bangladesh, the poor parents are more likely to pay bribes for admission into "free" public schools.

[12] One could, however, imagine a scenario where the value of θ_2 is correlated with parent's occupation. If the high income households are primarily engaged in nonfarm activities and the private schools are located in areas with high income and nonfarm concentration, then the nonfarm children are more likely to have access to better quality private schools, while the farmer's children go to low quality public schools. This effectively results in $\theta_2^n > \theta_2^f$.

Lagrange multiplier on the budget constraint by λ):

$$Max_{C_p,I} V^p = U\left(C^p\right) + \sigma E\left(Y_i^c \mid S_i^c\right) + \lambda\left[Y_i^p - C_i^p - I_i\right] \tag{5}$$

subject to (1) and (3). In this formulation, the parameter σ is the degree of parental altruism. The expected income of the child $E\left(Y_i^c \mid S_i^c\right)$ depends on the probability of getting a nonfarm job, and is given as follows:

$$E\left(Y_i^c \mid S_i^c\right) = \left[\pi_i^{nj} R^{cn} + \left(1 - \pi_i^{nj}\right) R^{cf}\right] S_i^c \tag{6}$$

where $\pi_i^{nj} \geq 0$ is the probability that the child i gets a nonfarm job when the father is employed in occupation $j = n, f$. To simplify notation, we write $\pi_i^n\left(O_i^p = j\right) \equiv \pi_i^{nj};\ j = n, f$. If there is intergenerational persistence in non-farm occupations then the probability that a child gets a nonfarm job is higher if the parent is also in the nonfarm occupations, i.e. $\pi_i^{nn} > \pi_i^{nf}$. This may reflect learning by doing at parent's workplace through informal apprenticeship, referral and network effects in the labor market, and role model effects.

The first order conditions for parent's optimization are:

$$\begin{gathered} \alpha_1 - 2\alpha_2 C^p - \lambda = 0 \\ \sigma\theta_2\left\{\pi_i^{nj} R^{cn} + \left(1 - \pi_i^{nj}\right) R^{cf}\right\} - \lambda = 0 \end{gathered} \tag{7}$$

The first order conditions and the budget constraint together yield the following solution for the optimal investment in a son's education:

$$I_i^* = \chi_0^j + R^{pj} S_i^p \tag{8}$$

where

$$\chi_0^j = Y_0^{pj} + \frac{1}{2\alpha_2}\left[\sigma\theta_2\left\{\pi_i^{nj} R^{cn} + \left(1 - \pi_i^{nj}\right) R^{cf}\right\} - \alpha_1\right] \tag{9}$$

Intergenerational Persistence Equation

Combining equations (3) and (8) above, we get the following relationship between the education of the father and that of a son, determined by the optimal investment decision:

$$S_i^{cj*} = \psi_0^j + \psi_1^j S_i^p + \tilde{\varepsilon}_i \tag{10}$$

where

$$\begin{aligned} \psi_{0i}^{j} &= \theta_0 + \theta_2 \chi_0^{j} \\ \psi_1^{j} &= \theta_2 R^{pj} \qquad ; \tilde{\varepsilon}_i = \theta_1 \phi_i \end{aligned} \tag{11}$$

Equation (10) is consistent with the almost universally used specification for intergenerational schooling persistence in the literature, but allows for possible differences in educational opportunities across the farm and nonfarm households. Some examples of studies that use this specification are: Neidhofer et al. (2018), Narayan et al. (2018) and Hertz et al. (2007) on cross-country analysis, Azam and Bhatt (2015) and Emran and Shilpi (2015) on India, and Fan et al. (2015) on China. However, none of these studies or the other studies on intergenerational educational mobility in developing countries we are aware of use an explicit model to derive the estimating equation. Even when there is a theoretical model, the link between the theory and the estimating equation may be tenuous. For example, theoretical models that use a homothetic production function for education (e.g., Cobb-Douglas) implies that the intercept term in the schooling regression is zero, but the empirical specification includes a constant term in all of the studies we are aware of.[13] The estimating equation (10) is also consistent with the common assumption in the literature that the omitted ability is captured in the error term of the intergenerational persistence regression, and can lead to ability bias in the OLS estimates of the parameters.

An important implication of equation (10) is that the children in farm and nonfarm households may face different educational opportunities both in terms of the slope and the intercept of the persistence equation, although the existing literature focuses largely on the slope (IGRC) as a measure of relative mobility.[14] The intercept term may be especially important in developing countries where a significant proportion of the households have parents with zero years of schooling in the data. In the empirical analysis, we thus pay close attention to the estimated intercepts across farm and nonfarm households in addition to the standard relative mobility measures based on slopes.

Equally important, equations (10) and (11) help improve our understanding of the economic mechanisms behind the observed pattern of mobility. For example, consider the

[13]It is standard to assume homothetic functional forms in the analysis of intergenerational income mobility, as the estimating equation is log-linear (see Solon (2004)). However, the educational persistence regression used in the literature is linear in levels (years of schooling). This partly reflects the fact that a substantial proportion of fathers have zero years of schooling. This is especially relevant in developing countries such as India where about 40 percent of fathers have zero years of schooling.

[14]For example, none of the 13 studies on educational mobility in developing countries summarized in Emran, Greene, and Shilpi (2018) report estimates of intercepts. Some of the more recent works report measures of absolute mobility that combines both the slope and the intercept effects, but do not report the intercept estimates separately.

factors that determine the intercepts across farm and nonfarm households. The intercept is, *ceteris paribus*, higher (lower) for the nonfarm children when the income of the parents with zero schooling is higher (lower) in the nonfarm occupations. These nonfarm occupations are, however, likely to be unskilled. In some countries, the low-skilled nonfarm occupations may yield very low income, lower than the income of the farmers (Lanjouw and Lanjouw (2001), World Bank (2011)), making the intercept for the nonfarm household smaller. Another important implication, noted before, is that intergenerational persistence in occupational choices is likely to affect the relative magnitudes of the intercept terms. When $\hat{\pi}_i^{nn} > \hat{\pi}_i^{nf}$, it is more likely to have $\hat{\psi}_0^n > \hat{\psi}_0^f$, ceteris paribus, assuming that $R^{cn} > R^{cf}$. Conversely, if $\hat{\pi}_i^{nn} > \hat{\pi}_i^{nf}$ but $R^{cn} < R^{cf}$, then it is more likely to have $\hat{\psi}_0^n < \hat{\psi}_0^f$, *ceteris paribus*.

The relative magnitudes of the slope parameters (IGRC) across farm and nonfarm households depend on the household returns to education in the parental generation (R^{pj}) according to equation (11). Thus, $R^{pn} > R^{pf}$ generates complementarity between parent's education and occupation in determining children's schooling.[15]

(3) The Empirical Approach

Equation (10) above suggests the following estimating equation for the combined farm and nonfarm sample which we take as a benchmark:

$$S_i^c = \psi_0 + \psi_1 S_i^p + \varepsilon_i \tag{12}$$

where $\varepsilon_i = \tilde{\epsilon}_i + \eta_i = \theta_1 \phi_i + \eta_i$, and η_i captures exogenous idiosyncratic shocks to children's schooling. We normalize so that $E(\eta_i) = 0$. The corresponding estimating equations for the farm and nonfarm households are:

$$S_i^{cf} = \psi_0^f + \psi_1^f S_i^p + \varepsilon_i^f \quad \forall i \ \ni O_i^p = f \tag{13}$$

$$S_i^{cn} = \psi_0^n + \psi_1^n S_i^p + \varepsilon_i^n \quad \forall i \ \ni O_i^p = n \tag{14}$$

Estimating equations (13) and (14) separately may result in loss of efficiency because of splitting of the sample. To avoid this, we define an occupational dummy $D_i^p = 0$ when the father of child i reports agriculture as the main occupation (corresponding to $O_i^p = f$), $D_i^p = 1$ otherwise. We estimate the following equation using the combined sample of farm

[15] The analysis shows that different roles are played by the parental returns to education and the *expected returns* to education in children's generation, a point not recognized in the current literature, to the best of our knowledge. It is important to appreciate that the children's *expected returns* to education at the time of the investment decision do not affect the slope (IGRC), their effects are mediated only through the intercept of the AR (1) persistence regression.

and nonfarm households:

$$S_i^c = \psi_0^f + \psi_1^f S_i^p + \mu_0 D_i^P + \mu_1 \left(S_i^p * D_i^p\right) + \Gamma X_i + \varepsilon_i \tag{15}$$

So we have $\mu_0 = \psi_0^n - \psi_0^f$ and $\mu_1 = \psi_1^n - \psi_1^f$ and we allow for other covariates X which may include age controls for the child and/or parents.[16]

It is important to appreciate that a comparison of farming and nonfarming households based on the most widely used measure of mobility, i.e., IGRC ($\hat{\psi}_1$), may be misleading. The caveat that IGRC or other measures of relative mobility such as intergenerational correlation (IGC) may be misleading in comparing mobility across groups has been emphasized by Mazumder (2014) in an interesting analysis of racial (black-white) differences in intergenerational income mobility in USA, but it has not been adequately appreciated in the literature on intergenerational mobility, both in economics and sociology (see also the analysis of black-white differences by Hertz (2005)).[17] This is especially so in developing countries, as is evident from the fact that most of the available studies on China and India we are aware of focus exclusively on relative mobility measures such as IGRC, IGC (intergenerational correlation) and IRC (rank correlation).

To see the pitfalls in relying on IGRC in our context, it is instructive to consider the case where $\psi_1^n > \psi_1^f$ so that intergenerational persistence is higher in nonfarm households (see figure 1). However, whether this higher persistence leads to convergence or divergence in schooling attainment of children born into farm and nonfarm households depends on the relative magnitudes of the intercepts. When the intercepts are $\psi_0^n > \psi_0^f$, the expected schooling is higher for children born into nonfarm households across the distribution of parental schooling, and the gap between the two groups widen as parental education increases. On the other hand, we can have two sub-cases when the intercepts are: $\psi_0^n < \psi_0^f$ (see figure 2). If the IGRC in nonfarm group is high enough, the children born to lower educated but nonfarm households are disadvantaged compared to the children of low-educated farmer parents, but at the higher end of parental education distribution they are relatively advantaged (see nonfarm(a) line in figure 2). When the difference between IGRC estimates are small enough, then the farmers children are better off in educational attainment over the entire distribution, and only in this special case, the conclusion based on the IGRC that nonfarm children face lower mobility is valid (see nonfarm(b) line in figure 2).

[16]Solon (1992) includes quadratic age controls for both the child and the parent in his analysis of income mobility. However, for our main estimates, we follow Chetty et al. (2014) and do not include any controls.

[17]See the discussion on this point by Torche (2015) in the context of Sociological literature on mobility.

While most of the existing studies on intergenerational educational mobility in developing countries rely on years of schooling as the indicator of educational attainment, following the influential contribution of Chetty et al. (2014), the recent literature has increasingly adopted the rank-based mobility measures where the indicator of educational status is the percentile rank in the relevant distribution (see, for example, Fan et al. (2015) on China). A growing literature shows that the rank-based measures of mobility are significantly more robust to data limitations when compared to the measures based on years of schooling.[18] Denote r_i^c as the percentile rank of child i in the over-all (including both farm and nonfarm) schooling distribution of children, and r_i^p the percentile rank of the father of i in the over-all schooling distribution in fathers generation. For the rank-based estimates, the estimating equations are as follows:

$$r_i^c = \delta_0 + \delta_1 r_i^p + \xi_i \;\; \forall i \tag{16}$$

$$r_i^{cf} = \delta_0^f + \delta_1^f r_i^p + \xi_i^f \;\; \forall i \;\; \ni O_i^p = f \tag{17}$$

$$r_i^{cn} = \delta_0^n + \delta_1^n r_i^p + \xi_i^n \;\; \forall i \;\; \ni O_i^p = n \tag{18}$$

$$r_i^c = \delta_0^f + \delta_1^f r_i^p + \kappa_0 D_i^P + \kappa_1 \left(r_i^P * D_i^P \right) + \Psi X + \xi_i \tag{19}$$

Again, we estimate equation (19) for estimates of the parameters in equations (17) and (18) with $\kappa_0 = \delta_0^n - \delta_0^f$ and $\kappa_1 = \delta_1^n - \delta_1^f$ to avoid the reduction in sample size. The estimated slope parameter from the regression equations (16)- (19) provides us intergenerational rank correlation (IRC, for short) which is a measure of relative mobility similar to IGRC. However, there are important differences between IGRC and IRC as measures of mobility. Since rank correlation is a copula, it provides a measure of fundamental dependence between the father and son that is not affected by the changes in the marginal distributions. In contrast, the IGRC estimates reflect both the Pearson correlation and the changing marginal distributions across generations.

Interaction Between Parent's Education and Occupation: Complementary, Substitutes or Separable?

An important advantage of the empirical models discussed above is that it provides a simple way to test the nature of interaction between parent's occupation and education in determining intergenerational persistence in schooling. Consider, for example, the equa-

[18]Nybom and Stuhler (2017) find that rank-based measures are much less affected by attenuation bias due to measurement error in income, and Emran and Shilpi (2018) show that the truncation bias due to coresidency restrictions in surveys is significantly lower in rank-based measures compared to the most widely used measure IGRC in the context of educational persistence.

tions (13) and (14). From the theoretical analysis in section (2), it is straightforward to derive conditions under which the interaction can be complementary $\left(\psi_1^n > \psi_1^f\right)$, substitutes $\left(\psi_1^n < \psi_1^f\right)$, or separable $\left(\psi_1^n = \psi_1^f\right)$. The prevailing view among many observers is that nonfarm occupation and education are likely to be complementary in determining children's education leading to cumulative forces of inequality in educational attainment and income in villages (see, for example, Rama et al. (2015)). The theoretical analysis shows that such complementarity requires $R^{pn} > R^{pf}$.[19] Yet, to the best of our knowledge, there is no evidence in the literature on the potential interaction between parent's education and occupation in determining children's educational attainment. Also, without a formal model, the economic mechanisms behind the hypothesized complementarity cannot be tested with data.

(4) Data

For our main empirical analysis, we use two exceptionally rich surveys that collected data on children irrespective of their residency status at the time of the survey. The data for rural India come from the Rural Economic and Demographic Survey (REDS) carried out by the National Council for Applied Economic Research, and the source of the data for rural China is the China Family Panel Studies (CFPS) implemented by the Institute of Social Science Survey unit of Peking University.[20] This is an important advantage for the empirical analysis, as most of the evidence on intergenerational educational mobility in India and China currently available are based on data that suffer from truncation due to coresidency restrictions used to define household membership. Emran, Greene, and Shilpi (2018) summarize 13 studies on intergenerational educational mobility in developing countries, only one of which use data free of coresidency bias.[21]

We use the 1999 survey in REDS and the first round of the CFPS survey in 2010. From REDS data, we obtain the relevant information for our analysis on all father-son pairs irrespective of residency status at the time of the survey. For the CFPS data, we restrict to

[19] If private school locations are motivated by higher income associated with nonfarm activities, then school quality may also play a role making the productivity of parental investment θ_2 correlated with occupation, i.e., $\theta_2^n > \theta_2^f$.

[20] One might wonder why we chose not to use the IHDS 2012 round survey for India which would provide a survey year close to the survey year of CFPS in China. There are important differences between the CFPS and IHDS surveys. The IHDS provides a *random sample of adult children* about 85 percent of whom can be matched with the father with education information. In contrast, CFPS provides *a random sample of parents* with information on all their children irrespective of the residency status of a child at the time of the survey. The only survey in India we are aware of that also provides random sample of parents with information on all children similar to CFPS is REDS.

[21] The exception is Fan et al. (2015) that uses the same CFPS data we use on China in this paper. The focus of their analysis is to understand intergenerational mobility over time.

rural communities subsample, given our focus on intergenerational mobility in rural areas, and use the family roster to obtain a complete list of father-son pairs that includes all sons of the household head irrespective of their residency status at the time of the survey.

The main samples for our analysis consist of children aged 18 - 54 in the 1999 REDS survey, and 29 - 65 in the 2010 CFPS survey. This ensures that we focus on the same age cohorts of children who went to school mostly during 1980s and 1990s.[22] The observations with fathers aged over 100 years or missing, or sons aged over 65 years are excluded from the samples used in the empirical analysis.

In each data set, we observe the education level and an indicator of whether the main occupation is agriculture or nonfarm for both the father and the son. Our main analysis of educational mobility is based on years of schooling as the measure of educational attainment. Father's schooling is used as the indicator of parental education to avoid complications from many missing observations on mother's schooling. In our data sets, the maximum of parental education coincides with the education level of the father in most of the cases. We define an occupational dummy $D_i^p = 0$ when the father of child i reports agriculture as the main occupation (corresponding to $O_i^p = f$ in the theoretical model), $D_i^p = 1$ otherwise. This means that the households who are primarily engaged in farming with some nonagricultural sources of income are classified as agricultural occupation. While for our main analysis, the focus is on father's occupation, we will utilize the information on children's occupation when exploring the link between occupational persistence and educational persistence highlighted in the theoretical analysis in section (2) earlier.

Appendix Table A.1 shows the descriptive statistics of our main data samples from REDS and CFPS. In REDS sample, we have about 6887 observations, and the children are aged 29 on average in the survey year 1999. Fathers are aged at 60 on average. About half of the children's main occupation is agriculture, while 60% of the fathers also reported agriculture as their main occupation. The children attain significantly higher level of education than the fathers, when comparing their average years of schooling (7.4 vs. 4.1.)

In CFPS sample, a similar pattern is observed. We have 3,305 father-son pairs, and children's age is about 39 years in the survey year, 2010 (28 years in 1999, comparable to 29 years for India in 1999). Fathers are aged 68 on average in 2010. About half of the fathers work in the agricultural sector. Children receive 7.10 years of schooling on average, significantly higher than their fathers (less than 4 years).

[22]It is important to recognize that such an analysis for the overlapping age cohorts is meaningful for education, as most of the children under focus (29-65 years old in 2010) in China have completed their schooling by 1999, even though the information was gathered later in 2010.

While our main empirical analysis is based on CFPS 2010 and REDS 1999, we take advantage of a number of additional data sets for exploring the economic mechanisms identified by the theoretical analysis. To understand how the relation between father's education and household income vary by farm and nonfarm occupation in rural China we utilize the data from Chinese Household Income Project (CHIP) 1995 and 2002. To estimate the relation between father's education and household income in rural India, we use the data on household total expenditure from National Sample Survey 1993. For the analysis of the changing economic mechanisms in the younger generation in rural China, we use three rounds of CFPS: 2010, 212, 2014.

(5) Empirical Results

(5.1) Evidence on Relative Mobility and Test of Complementarity

Table 1 reports the estimates of relative mobility using two measures: intergenerational regression coefficient (IGRC) and intergenerational rank correlation (IRC). In addition to the separate estimates for sons born into farm and nonfarm households, we report the estimates from the combined farm and nonfarm sample as a benchmark.

The point estimates of IGRC show that, both in rural India and rural China, intergenerational persistence in schooling is consistently higher for the sons born into nonfarm households, but the estimates for farm and nonfarm households are similar in magnitude in China. A son of a father with 1 year more schooling in India is expected to gain 0.49 year of schooling if the father is a farmer, while the expected gain increases to 0.56 year of schooling when the father is employed in nonfarm occupation (column 2 of Table 1). The corresponding estimates for rural China are 0.31 year (farm) and 0.32 year (nonfarm) of additional schooling for the sons born to a father with 1 year of more schooling (column 1 of Table 1). Another important conclusion from the evidence in Table 1 is that all of the estimates of IGRCs are smaller in rural China compared to the corresponding estimates in rural India, suggesting that the sons in rural China who went to school in the 1990s or earlier enjoyed substantially more relative mobility in schooling. The conclusions above remain valid when we include age controls in the specifications (see Table 3A).[23]

The estimates of intergenerational rank correlation (IRC) reported in columns 3 and 4 of Table 1 also tell a similar story; the point estimates of the effect of father's schooling rank on the son's schooling rank are higher for the nonfarm households, both in China and India. Again, the effect of parental education does not vary substantially between

[23] As noted earlier, we follow Chetty et al. (2014) for the main specification in Tables 1-2 and do not include any control variables in the regressions.

farm and nonfarm household in rural China, but there is substantial difference in rural India. The magnitudes of IRCs are consistently smaller in rural China compared to that in India, reinforcing the conclusion from the IGRC estimates that the sons in rural India faced lower educational mobility. The conclusions from the IRC estimates remain intact when we include age controls in the specification (see Table 3B).

The contrasting evidence in China vs. India suggests that father's education and nonfarm occupation are likely to be complementary in India, but are separable in China. We formally test the null hypothesis of separability $\left(H_0 : \psi_1^f = \psi_1^n\right)$; the results are reported in the lower panel of Table 1. The evidence from both IGRC and IRC estimates show that, in rural China, the null hypothesis of separability cannot be rejected at the conventional significance levels; the F statistic for IGRC estimates is 0.017 with a P-value of 0.90, and the corresponding numbers for IRC are 0.15 (F statistic) and 0.70 (P-value). In contrast, in rural India, the null hypothesis of separability is rejected at the 5 percent level for both the IGRC (F=5.12, P-value=0.02) and IRC (F=8.75, P-value=0.003). Since the estimated effect of parental schooling is larger in the nonfarm households in rural India, the results suggest complementarity between nonfarm occupation and father's education in determining a son's schooling.

Relative Mobility and Long-term Variance in Schooling

When interpreted as a dynastic model of evolution of schooling across generations, a higher IGRC implies that the long-term variance in schooling would be higher.[24] To see this, note that for the IGRC equation (1), we can write the long-term variance of education as:

$$\sigma_s^2 = \frac{1}{(1-\psi_1^2)}\sigma_\varepsilon^2 \tag{20}$$

where σ_s^2 is the long-term variance of education and σ_ε^2 is the long-term variance of the error term capturing all idiosyncratic factors unrelated to father's schooling. This shows the multiplier effect of family background on the impact of the idiosyncratic shocks to education. Using equation (20) and the estimates of ψ_1^f and ψ_1^n reported in Table 1, we have the following estimates for sons in farm and nonfarm households in rural India:

$$\sigma_{s,If}^2 = 1.31\sigma_\varepsilon^2 \quad (farm)$$
$$\sigma_{s,In}^2 = 1.44\sigma_\varepsilon^2 \quad (nonfarm)$$

[24] For a discussion on the dynastic interpretation of the model and the implications for long-term variance, see Acemoglu and Autor (undated).

The subscripts I and s denote India and schooling, respectively, and as before n=nonfarm and f=farm. The long-term variance of education of sons in farming sample is 31 percent higher than the variance due to idiosyncratic factors alone (i.e., σ_ε^2), and is 44 percent higher in the nonfarm sample. Thus the contribution of family factors to the long-term variance is 13 percentage points higher in nonfarm households, a straight-forward but important implication of which is that the expansion of nonfarm sector increased the variance of men's education in the 1970s-1990s, contributing to a higher educational inequality.

The long-term variances in schooling for the farm and nonfarm households in China are:

$$\sigma^2_{s,cf} = 1.107\sigma^2_\varepsilon \quad (farm)$$
$$\sigma^2_{s,cn} = 1.111\sigma^2_\varepsilon \quad (nonfarm)$$

The multiplier effect of family background is much smaller in the case of China; the long-term variance in schooling is only about 10 percent higher than the variance of idiosyncratic shocks, and the estimates are virtually identical across farm and nonfarm samples. An important implication of this evidence is that structural change in favor of the nonfarm sector in rural China is unlikely to be an important factor in explaining the variance in schooling in the decades of 1970s-1990s.

(5.2) The Intercepts and Steady States

As noted earlier, measures of relative mobility give us an incomplete, and sometimes misleading, picture of intergenerational mobility across groups such as farm and nonfarm households. A simple but important reason is that different groups may be converging to different steady states due to different intercepts in the intergenerational persistence equations. The theory in section (2) also suggests that factors such as expected returns to investment in schooling for children work through the intercept, leaving relative mobility measured by IGRC and IRC largely unaffected. Thus it is necessary to analyze the estimates of intercepts across farm and nonfarm households and the steady state level of schooling.

The estimated intercepts of equations (13)-(15) and (17)-(19) above are reported in Table 2. The point estimates show that the intercept for nonfarm households is a bit larger in magnitude in rural China, but the difference is not statistically significant (P-value 0.15). In contrast, the intercept in India is significantly *higher* for sons born into the *farm* households. When considered along with the evidence that the slope estimates (IGRC and IRC) are smaller for the farm households in India, the evidence implies a set of interesting conclusions. First, whether the sons born to fathers in farm or nonfarm occupation enjoy educational advantage depends on a switching threshold of father's schooling (about 9-10 years of schooling). An interpretation of the evidence is that the national public examination administered at 10th grade (known as Matriculation examination, or all India Secondary School Examination (SSC)) represents a bifurcation point. The children of non-farm fathers with Matriculation or more schooling are expected to achieve better schooling attainment when compared to the children of farmer fathers with similar educational credential, but the children of nonfarm fathers with lower education (and likely unskilled nonfarm jobs) are likely to be worse-off when compared to the children of low educated farmer fathers (who likely own land). Please see figure 3. Second, the steady state level of education is not substantially different in terms of magnitudes across farm and nonfarm households: 10.81 years of schooling (farm) and 11.20 years of schooling (nonfarm). This reflects the fact that the sons born into nonfarm households gain more from a father with higher schooling, although they start from a lower level of schooling attainment. This highlights the importance of taking into account both the intercept and slope estimates; an exclusive focus on the standard IGRC or IRC (slope) estimates as done in many existing studies would suggest that the children born into farm households enjoy better educational opportunities, as they face lower intergenerational persistence.

The picture for rural China is very different (please see figure 4). The evidence in Table 2 shows that there is no statistically significant difference across the farm and nonfarm households in the intercepts of the intergenerational persistence regressions. When combined with the evidence on IGRC and IRC in Table 1, this implies that the schooling attainment of the sons in rural China converges to virtually the same steady state (8.53 years of schooling) irrespective of whether the father is a farmer or is engaged in nonfarm occupation.[25]

For robustness, the estimates with quadratic age controls are reported in Tables 3A and 3B. Tables 3A shows the results for the years of schooling (equations (13)-(16)) and 3B for the rank-rank specification (equations (17)-(20)). The top panel reports the estimates with son's age and age squared as controls, and the bottom panel with both son's and father's age and age squared as controls. A comparison of the estimates in Tables 1 and 2 with the corresponding estimates in Tables 3A and 3B shows that the age controls do not affect the estimates of the slope parameters (IGRC and IRC), but the estimated magnitudes of the intercepts are affected substantially. The conclusions regarding the relative magnitudes of the intercepts in farm and nonfarm households above remain intact for India when we

[25]The estimate of the steady state is based on the combined farm and nonfarm sample. Although they are not statistically different, the point estimates differ numerically across farm and nonfarm subsamples.

include quadratic age controls. The evidence on China is not as robust, as the conclusion depends on the controls included in the regression and the significance level chosen. The null hypothesis that the intercepts are equal in China cannot be rejected at the 5 percent level for both the IGRC specification and rank-rank regressions.

(5.3) Coresidency and Truncation Bias in the Estimates for Rural China: CFPS 2010 vs CHIP 2002

An important advantage of the data used in this study is that the estimates are free of truncation bias that arises from using coresidency to define household membership in a survey. Emran, Greene, and Shilpi (2018) provide an in-depth discussion on the magnitude of truncation bias in the context of rural India. Their estimates show that the IGRC estimates from coresident sample are on average 18 percent smaller in rural India. To the best of our knowledge, there is no similar evidence on truncation bias in the context of rural China in the existing literature. To understand the extent of truncation bias in the context of rural China, we compare the estimates free of truncation in Tables 1 and 2 with the corresponding estimates using data from Chinese Household Income Project (CHIP 2002). This may be of independent interest to many researchers as CHIP data sets have been widely-used to study intergenerational mobility in China.

Using CHIP 2002 data, appendix Table A.2 report estimates for two age ranges: (i) the same age cohorts as in Tables 1 and 2 discussed above (21-57 years old in 2002),[26] and (ii) the full sample with 18-65 years old children. The estimates of IGRC from CHIP 2002 are about 25 percent lower on average compared to the CFPS 2010 estimates (taking the CHIP 2002 estimate as the base). The estimates of the intercepts are, in contrast, biased upward in CHIP 2002, about 15-18 percent higher than the corresponding estimate from the CFPS data. The evidence that coresident sample causes substantial downward bias in the slope estimates, but upward bias in the intercept estimates from CHIP 2002 data is consistent with the evidence from India and Bangladesh provided by Emran, Greene and Shilpi (2018), and Emran and Shilpi (2018). The substantive conclusions are also less robust; the test of separability shows different results for IGRC and IRC for the age cohorts overlapping with the main estimation samples used in Tables 1 and 2. While the null hypothesis of separability cannot be rejected for IGRC estimates at the 10 percent level, the IRC estimates reject separability at the 5 percent level. An analysis based on the coresident sample thus can lead to wrong conclusions about the interaction between

[26] This ensures that the age cohorts in CHIP 2002 overlap with the 29-65 age cohorts used for CFPS 2010 data.

parent's education and occupation.[27]

(6) Economic Mechanisms: Towards an Explanation of the Differences Between Rural China and Rural India

A major concern in the literature has been whether the observed pattern of intergenerational linkages are primarily driven by omitted variables bias due to unobserved genetic correlations between parents and children. An obvious approach to this question is to correct the estimates for possible positive bias due to genetic correlations in cognitive ability. We develop a simple but plausible approach by taking advantage of the recent evidence on intergenerational correlation in cognitive ability from economics and behavioral genetics. There is substantial evidence that intergenerational correlation in cognitive ability (denoted as ρ) falls in a narrow interval, $\rho \in [0.20, 0.40]$.[28] We use this information in a biprobit sensitivity analysis as developed by Altonji et al. (2005) to check if the estimates of intergenerational persistence in schooling remain positive and statistically significant for plausible values of intergenerational correlation in ability.[29] The details of this approach are provided in the online appendix. The results from this exercise are reported in appendix Table A.3. The evidence suggests that, the estimated intergenerational schooling persistence in India is very strong, and the estimates remain statistically significant and numerically substantial even when we impose $\rho = 0.40$ in the biprobit model. In contrast, the estimates turn negative in the case of rural China when $\rho = 0.30$, suggesting that the observed persistence could be explained away by plausible magnitude of ability correlation between parents and children. This evidence strengthens substantially the conclusions that educational mobility was much lower in India in the 1990s and earlier, and that economic forces are likely to be important in explaining the differences between India and China. The advantage of this approach is that it is easily implementable, and thus could be used fruitfully by other researchers. However, it is also important to appreciate the limitations of such an atheoretical approach. For example, the evidence that the persistence in rural China could be explained by genetic correlations alone does not necessarily imply that economic forces were not at play. The theoretical analysis in section (2) provides us with a way to explore the question by focusing on the economic mechanisms behind the pattern

[27] A full analysis of CHIP 2002 data is presented in an unpublished work by Emran and Sun (2015b). The evidence and conclusions in this paper supersedes those in Emran and Sun (2015b).

[28] See, for example, Black et al. (2009), Bjorklund et al. (2010) on economic literature, and Plomin and Spinath (2004) on behavioral genetics literature.

[29] This approach relies on binary indicators of educational attainment for both the father and sons. We use a dummy for higher than primary schooling for fathers. For sons in rural China a dummy for higher than 9 years of schooling, and for sons in rural India, a dummy for more than 10 years of schooling are used.

of the slope and intercept estimates across farm and nonfarm households.

Under the null hypothesis that genetic transmission is the main force at work, we should not expect the economic mechanisms identified in the model to offer a consistent explanation of the observed pattern of intergenerational persistence across India and China.[30] If economic forces are important, the theory provides us with testable implications even in the case of rural China; the equality of the slopes (IGRCs) across the farm and nonfarm households in this case implies equality of the returns to education for the farm and nonfarm parents.

(6.1) The Differences in the Slopes (IGRCs)

The estimates of IGRC in Table 1 imply the following (denoting an estimate by a hat):

$$\begin{array}{ll} (China) & \hat{\psi}_1^f \approx \hat{\psi}_1^n \Rightarrow \theta_2 R^{pf} \approx \theta_2 R^{pn} \\ (India) & \hat{\psi}_1^f < \hat{\psi}_1^n \Rightarrow \theta_2 R^{pf} < \theta_2 R^{pn} \end{array}$$

The theoretical analysis thus highlights the importance of returns to schooling at the household level in the father's generation across occupations for understanding the pattern of relative mobility. We have $\hat{\psi}_1^f - \hat{\psi}_1^n = \theta_2 \left(R^{pf} - R^{pn}\right)$, and the effects of a widening gap in returns to education for household income between farm and nonfarm households would be low if θ_2, the productivity of financial investment in children's education, is low. We would expect θ_2 to be low when the private market for education is not well developed. To see this clearly, consider the polar case where schooling is provided only by the government free of charge and there is no private schools (or private tutoring). In this case, the scope for parental financial investment to improve a child's educational attainment is effectively nonexistent, making $\theta_2 \approx 0$.

It is important to recognize that the "returns to education" above (i.e., R^{pj}) differ from most of the available estimates of returns to education for three reasons. First, we are interested in the household income rather than the individual income. Second, the focus is not on just the labor market returns, but permanent total income of a household. Third, father's education in our analysis is a summary statistic for a family's socio-economic status and captures the other determinants of economic condition that are correlated with the education level of the father, including mother's education (assortative matching in

[30] As noted by Mogstad (2017), many recent studies of intergenerational mobility do not employ an explicit model, and thus, it is difficult to interpret the evidence. This is especially true for the recent literature on educational mobility in developing countries. None of the 13 studies on developing countries summarized in Emran, Greene, and Shilpi (2018) derive the estimating equation for intergenerational persistence in schooling from a theoretical model.

marriage).[31]

Fortunately, the Chinese Household Income Project (CHIP) provides high quality household income data for rural households for multiple years (5 years in CHIP 2002, and 3 years in CHIP 1995).[32] Unlike China, the data on household income in rural India are, however, more limited; we are not aware of any household survey data set that has good quality income information for consecutive multiple years, similar to CHIP data on China. We thus take household expenditure reported in National Sample Survey as our measure of household permanent income.

Rural China

Table 4 (panel A) provides estimates of R^{pn} and R^{pf} in rural China and tests the null hypothesis that $R^{pn} = R^{pf}$ using data from two rounds (1995 and 2002) of Chinese Household Income Project (CHIP) survey. The estimates based on the 5-year average income of a household in CHIP 2002 data show that the null hypothesis cannot be rejected with a P-value equal to 0.32. The evidence from the 1995 data (three year average income) also delivers a similar conclusion: the null hypothesis cannot be rejected with a P-value of 0.24. This is consistent with the absence of complementarity between nonfarm occupation and father's education in determining son's schooling in rural China as found earlier in Tables 1 and 3A.

Also, the magnitude of θ_2 is likely to be low in rural China during the relevant period (the children who went to school during 1970s-1990s) which would reduce the impact of any emerging advantage in favor of nonfarm households in returns to education. In China, the availability of private schools was limited; in 1996, only 4 percent of the schools in China were private (Kwong (1996)). Most of the private schools in rural areas in 1990s were primary schools with limited facilities and equipment, and they catered to children from the low-income households. At the secondary level, the private schools primarily met the demand by the students who were unsuccessful in the admission test given after grade 9 to screen for the senior secondary public schools (Lin (1999)). This implies that, in contrast to many other countries, any quality advantage in education in rural China is associated with better quality public schools. While local financing and various types of

[31] The available estimates on Mincerian labor market returns to education at the individual level in China show low returns in the early years after the reform, but there is evidence of increasing returns in the later years, as one would expect with the deepening of the labor market. The evidence also suggests higher labor market returns in nonfarm occupations (DeBrauw and Rozelle (2008)).

[32] Note that the estimates of the effects of father's education on household permanent income using CHIP data do not suffer from truncation bias, unlike the estimates of intergenerational persistence; whether some of the children were nonresident at the time of the survey is not relevant for this analysis.

fees increasingly played a role in public schools after the fiscal decentralization, it is unlikely to create a significant impact on the magnitude of θ_2 for the following reason: the share of private expenditure remained small compared to the public expenditure during the 1980s and 1990s; for example, tuition and other fees paid by the parents amount to only 4.42 percent of total educational expenditure in 1991 and 10.72 percent in 1995 (see Table 7.2 in Hannum et al. (2008)).

Rural India

For the estimates of IGRCs across farm and nonfarm households in India to be consistent with the extended Becker-Tomes model of section (2), the returns to schooling in nonfarm households need to be *higher* than that in the farming households in the parental generation. Table 4 (panel B) reports the estimates of household-level returns to education in rural India using household expenditure data from the NSS 1993 survey (the employment and unemployment round). The returns to education is, in fact, *higher* in nonfarm occupations and the difference is significant at the 1 percent level.

The available evidence also suggests that the magnitude of θ_2 is likely to be much higher in rural India when compared to that in rural China. A higher value of θ_2 would act as a multiplier for higher returns to schooling in nonfarm activities for the parents, and amplify the difference between farm and nonfarm slopes (IGRCs). This can lead to the complementarity we found earlier in Table 1 above. In India, private schools have historically been more important than in rural China, and they have become more important over time, especially after the liberalization in 1991. Muralidharan and Kermer (2006) report that, in 2003, 28 percent of rural households had access to fee-charging private schools. They also provide evidence that private schools are more likely to be established in places where public school quality is low, and the students in private schools perform better academically.[33] Thus, the relative quality of private and public schools in rural India is opposite to that in rural China. This suggests that the higher income (and better educated) households can take advantage of the high-quality private schools making θ_2 higher. Since the private schools are more likely to locate in villages where the public school quality is low, the differential effects of school quality are likely to be strong in rural India, as the better educated nonfarm parents with high income send children to private schools, and the other children (including the children of low-educated and low-skilled nonfarm parents) go to low

[33] Private schools have more teachers with college degree and teacher absenteeism is less of a problem compared to the public schools. Azam et al. (2016) find that the students in private secondary schools in rural Rajasthan scored about 1.3 standard deviation (SD) higher than their counterparts in the public schools in a comprehensive standardized math test.

quality public schools.

(6.2) The Differences in the Intercepts

According to the theory, the estimated intercepts in Table 2 discussed above imply the following relations (using a hat to denote an estimate):

$$\begin{array}{ll} (China) & \hat{\psi}_0^f \approx \hat{\psi}_0^n \Longrightarrow Y_0^{pf} + \frac{1}{2\alpha_2}\left[\sigma\theta_2 E\left(RI^{cf}\right) - \alpha_1\right] \approx Y_0^{pn} + \frac{1}{2\alpha_2}\left[\sigma\theta_2 E\left(RI^{cn}\right) - \alpha_1\right] \\ (India) & \hat{\psi}_0^f > \hat{\psi}_0^n \Longrightarrow Y_0^{pf} + \frac{1}{2\alpha_2}\left[\sigma\theta_2 E\left(RI^{cf}\right) - \alpha_1\right] > Y_0^{pn} + \frac{1}{2\alpha_2}\left[\sigma\theta_2 E\left(RI^{cn}\right) - \alpha_1\right] \end{array} \tag{21}$$

where $E\left(RI^{cj}\right) = \left\{\pi_i^{nj} R^{cn} + \left(1 - \pi_i^{nj}\right) R^{cf}\right\}$ is the expected return to financial investment in son's education when the father is employed in occupation $j = n, f$.

Rural China

The following observations are important for understanding the role played by occupational persistence in educational mobility in rural China. First, when $\pi_i^{nn} \simeq \pi_i^{nf}$, we have $E\left(RI^{cn}\right) \simeq E\left(RI^{cf}\right)$, irrespective of whether $R^{cn} > R^{cf}$ or $R^{cn} \leq R^{cf}$. Since expected returns to education for the children do not vary significantly across farm and nonfarm households in this case, we would expect parental investment in education and thus educational mobility to be similar also. The second observation is that when there is low or no intergenerational persistence in nonfarm (or farm) occupations, we have $\pi_i^{nn} \simeq \pi_i^{nf}$.

A substantial body of independent evidence, in fact, suggests that, for the relevant cohorts, there was no significant intergenerational persistence in nonfarm occupation choices ($\pi_i^{nn} \simeq \pi_i^{nf}$) in rural China. Wu and Treiman (2007) use 1996 national probability sample of Chinese men and show that there is high degree of *mobility into agriculture*; the sons of nonfarm parents also face a substantial probability of becoming a farmer. They identify the geographic restrictions on mobility of rural people because of the Hukou registration system as the primary factor behind this weak intergenerational persistence in nonfarm occupations.[34] Using CHIP 2002 data, Emran and Sun (2015) report evidence supporting Wu and Treiman (2007) finding.

The evidence that $E\left(RI^{cn}\right) = E\left(RI^{cf}\right)$, along with equation (21), above implies that a sufficient condition for the equality of the intercepts of the intergenerational persistence equations is that $Y_0^{pn} = Y_0^{pf}$, i.e., the intercepts of the returns to education function in

[34]The link between restrictions on geographic mobility of rural people and a lack of intergenerational occupational persistence (farm/nonfarm) is, however, not unique to China, similar evidence is available on Vietnam where Ho Khau registration system has been in place since 1964; see the evidence and the analysis in Emran and Shilpi (2011). This enhances the credibility of the Wu and Treiman (2007) analysis that the Hukou restrictions played an important role in the low occupational persistence in rural China.

parent's generation are the same across farm and nonfarm households. We would expect $Y_0^{pn} = Y_0^{pf}$ when the fathers with zero schooling have similar income (permanent income) and face similar credit constraint, irrespective of their occupation.

The estimates in panel A of Table 4 (with controls for number of children and province fixed effects) show that the null hypothesis $Y_0^{pn} = Y_0^{pf}$ cannot be rejected at the 10 percent level with a p-value of 0.98 for the CHIP 2002 data on five-year average income. The evidence from 1995 data is also similar (p-value is 0.29).[35]

The evidence above is also consistent with other available studies on the nonfarm sector and rural industries (TVEs) in rural China. The income gap between the farm and nonfarm households was mitigated in the early years of reform by two factors: the household responsibility reform increased farmer's income, and, in many cases, the people employed on the farm were paid wages similar to the wages paid to workers in the TVEs, thus the growing TVE sector in effect subsidizing the agricultural employment (Peng, 1998). This also reflects in part the lingering effects of policies during cultural revolution that were successful in eliminating any significant differences between peasants and the non-peasants in rural China (Hannum et al. (2008)).

Rural India

In contrast to China, a substantial body of independent evidence on occupational mobility in rural India suggests strong intergenerational persistence in farm/nonfarm occupations (Reddy (2015), Motiram and Singh (2012), Azam (2015), Hnatvoska et al. (2013)).[36] Hnatvoska et al. (2013) show that there is strong persistence in rural occupations both in 1983 and 2004-2005; the son of a farmer is highly likely to be a farmer himself. Using IHDS (2005) survey, Motiram and Singh (2012) also provide similar evidence. The fact that there was significant persistence in farm/nonfarm occupations implies that the expected returns to investing in children's education are likely to differ across farm and nonfarm households. But whether the intercept in the nonfarm households would be higher or lower depends partly on the expected relative returns to education in the children's generation, i.e., whether $R^{cn} > R^{cf}$ or $R^{cn} < R^{cf}$.[37] Note that even when $R^{cn} > R^{cf}$, the intercept for the nonfarm households can be smaller as we find in the empirical analysis above (Table 2),

[35] The conclusions remain robust if we do not include any controls, or include finer controls such as number of sons and daughters as separate variables.

[36] There are no policy restrictions on geographic mobility in India.

[37] It is much more difficult, if not impossible, to test the role played by *expected returns* to education for children, as there may be behavioral biases in expectation formation that are correlated with parent's education. Credible data on parental expected returns at the time of investing in a child's education are not easy to find.

if the households with zero (or very low) parental schooling have sufficiently lower income in nonfarm occupations, i.e., $Y_0^{pn} < Y_0^{pf}$.

Unlike China, the data on household income in rural India are, however, more limited; we are not aware of any household survey data set that has good quality income information for consecutive multiple years, similar to CHIP data on China. We thus take household expenditure reported in National Sample Survey as our measure of household permanent income. The estimates of Y_0^{pn} and Y_0^{pf} from the NSS 1993 round (employment and unemployment round) are reported in panel B of Table 4. The estimates control for number of children and state fixed effects. The estimated intercept is *larger* for the farm households and the difference is statistically significant at the 1 percent level. This evidence is consistent with the economic mechanisms in the extended Becker-Tomes model in section 2.[38]

The evidence in panel B of Table 4 also accords well with a substantial body of related evidence available on the nonfarm activities in India. Note that it is possible to have $Y_0^{pn} < Y_0^{pf}$ if the low-end nonfarm occupations are primarily low productivity residual activities and provide the last resort for the poorest households. Lanjouw and Murgai (2011) use three rounds of NSS data (1983, 1993/94, and 2004/2005) and show that nonfarm employment is positively associated with rural poverty in India, consistent with the observation that nonfarm employment involves primarily low productivity economic activities (see also World Bank (2011)).

(7) Evolution of Mobility: Evidence on the Younger Generation in Rural China

In this section, we ask the question: when policy changes and other economic forces affect the relevant mechanisms, do we see changes in the intergenerational educational persistence across cohorts in a country consistent with the extended Becker-Tomes model? To this end, we take advantage of two aspects of rural China: (i) the rural economy and educational policy in China went through significant changes in the recent decades; and (ii) there are high quality income data available for multiple years for the early 2010s from CFPS. The focus in this section is on the educational mobility of the younger generation: the 18-28 years old children in 2010 CFPS survey, who were excluded from the main sample used for the empirical analysis in Tables 1-3B.

[38]Similar to the evidence on China, again, this conclusion is robust to alternative sets of controls or no controls.

Rising Returns to Education in Nonfarm and Relative Mobility in the Younger Generation in Rural China

We provide estimates of household returns to schooling (equation (1) above) in farm and nonfarm occupations using the CFPS panel data for 2010, 2012, and 2014 in Table 5 (see panel 5B). These estimates are then compared with the CHIP 1995 (3 years income data) and CHIP 2002 (5 years income data) estimates reported earlier in Table 4. We treat the average of 2010, 2012, and 2014 as a measure of parent's permanent income relevant for the younger generation in CFPS 2010 survey.[39] Panel 5B of Table 5 shows a different picture compared to the evidence presented earlier in Table 4; household returns to schooling in the nonfarm occupation are higher $\left(R^{pn} > R^{pf}\right)$, and the difference between farm and nonfarm households is statistically significant at the 10 percent level (P-value = 0.08). The difference in the magnitudes between farm and nonfarm households is striking; the estimated R^{pn} is about 90 percent higher than the estimated R^{pf}.

The available evidence also suggests that the value of θ_2 has gone up in recent years in rural China. Private expenditure in children's schooling has become more important in the decade of 2000s; the share of tuition and miscellaneous fees in educational expenditure rose from 4.42 percent in 1991 to 18.59 percent in 2004 (Hannum et al. (2008). The spread of better quality public schools to the rural areas has accelerated. All these would increase the magnitude of θ_2 for the younger generation.

If the extended Becker-Tomes model in section (2) is a good description of the economic process generating intergenerational persistence in schooling, the evidence on the mechanisms above suggests that the separability observed in the case of the older cohorts analyzed earlier may be breaking down. To check this, we report estimates of IGRCs and IRCs for education for the 18-28 years age cohorts of children in the CFPS 2010 survey. The estimates reported in Table 6 show that, in fact, the IGRC and IRC for the nonfarm households are larger in magnitude, and the difference $\theta_2\left(R^{pn} - R^{pf}\right)$ is significant at the 10 percent level. The evidence thus suggests that there is emerging complementarity between parent's education and nonfarm occupation in determining the children's schooling in the younger generation. This is in sharp contrast to the strong evidence of separability for the older cohorts in Tables 1-3.

The Intercepts in the Younger Generation in Rural China

Panel 5A of Table 5 reports the intercept estimates of the household returns to schooling

[39] The income data for 2010, 2012, and 2014 provide us limited information on the permanent income of the children who were 18-28 in 2010 because of the life-cycle effects.

equation (1) for the farm and nonfarm occupations using the average household income from CFPS 2010, 2012, and 2014 (see the first two columns). The estimates show that the intercept for the nonfarm households is larger in magnitude $\left(Y_0^{pn} > Y_0^{pf}\right)$, and the difference is statistically significant at the 1 percent level. However, the magnitude of the difference is much smaller at about 20 percent (compare this with the 90 percent larger estimate of R^{pn} discussed above).

The available evidence also indicates that despite some relaxation of the Hukou over the years, restrictions on geographic mobility from rural to urban areas remain important (Li et al. (2017)). We would thus expect that intergenerational persistence in nonfarm occupation might be becoming more important for the younger generation, but the effect may not be strong enough yet. Using the occupation information in CFPS 2010 survey, we test this hypothesis.[40] The probability of getting a nonfarm job is 11 percentage points higher if the father is in nonfarm for the households with older cohorts of sons (29-65 years old in 2010), and it increases to 16 percentage points in the households with younger sons (18-28 years of age in 2010), and the difference across generations is significant at the 10 percent level (see Panel 6B of Table 6). Thus the evidence is broadly consistent with the Wu-Treiman hypothesis, but the difference between the farm and nonfarm households remains small.

The evidence on mechanisms discussed in the preceding two paragraphs suggests that the forces in favor of a higher intercept of the intergenerational educational persistence equation for the nonfarm households are gaining ground, but they are not as strong as the changes in the forces underlying the IGRC (slope). The intercept estimates reported in Table 6 do not differ in any significant way between the farm and nonfarm households for the 18-28 years sample (i.e., $\psi_0^n = \psi_0^f$).[41]

(8) Conclusions

This paper develops a model of intergenerational educational persistence in a rural economy taking into account the role of parental farm vs. nonfarm occupations, and derives a theoretically-grounded estimating equation which we take to the data from rural India and rural China. We use two unique data sets that include the required information for all of the children of the household head irrespective of their residency status at the time of

[40] Note that while the intergenerational persistence in occupations observed in 2010 is likely to provide useful information about parental estimate of probability of nonfarm occupation for the younger generation, it can be misleading for the occupation of the older cohorts of children analyzed in Tables 1-3 who went to school in 1990s or earlier.

[41] The evidence that economic liberalization resulted in lower educational mobility in China is consistent with the findings of Fan et al. (2015).

the survey; thus eliminating the truncation bias common in the existing studies based on the standard surveys that use coresidency criteria to define household membership.

The empirical analysis delivers the following conclusions for the sons who went to school in the 1990s or earlier: (i) the intergenerational educational mobility in rural China was significantly higher compared to that in rural India, (ii) the farm/nonfarm occupations did not play any significant role in the intergenerational schooling linkage in rural China, and this is true for both the intercept and the slope of the intergenerational persistence regressions, (iii) both the slopes and intercepts were significantly different across farm and nonfarm households in rural India. The estimates suggest that father's education and nonfarm occupation were complementary in determining son's schooling in rural India, but separable in rural China. Evidence from biprobit sensitivity analysis of Altonji et al. (2005) shows that the observed educational persistence in rural India is unlikely to be due solely to mechanical transmission of ability across generations, while the persistence in rural China could be explained by genetic correlations alone.

We analyze whether the economic forces identified in the extended Becker-Tomes model provide a coherent explanation of the observed pattern of educational mobility across countries (rural China vs. rural India) and over time (older vs. younger cohorts in rural China). A lack of intergenerational persistence in nonfarm occupations in rural China because of the Hukou restrictions seems to have played an important role in making the intercepts similar in rural China, but strong intergenerational occupational persistence in rural India resulted in significant differences between farm and nonfarm households. In rural India, the observed complementarity can be explained by higher returns to education in nonfarm occupation in the parental generation in terms of permanent household income. The separability between father's education and occupation in rural China was, in contrast, driven by the absence of any significant differences in the household-level returns to education across farm and nonfarm occupations. However, because of economic forces unleashed by the policy reform in China, the returns to education in nonfarm occupations for parents have increased substantially in more recent years, which, according to the theory, should tighten the link between father's education and son's schooling in the nonfarm sector. Indeed, we find that the separability between father's education and occupation broke down for the 18-28 years old sons, implying that structural change in favor of nonfarm sector is increasingly contributing to educational inequality in rural China.

References

Acemoglu, D, and D. Autor (undated), Lectures in Labor Economics, Book Manuscript, MIT.

Ahsan, R, A. Chatterjee, and M. Shahe Emran (2019), “Are Markets Substitutes for Better Educated Parents? Evidence from Intergenerational Educational Mobility in Rural India”, Paper presented at the Royal Economic Society Annual Conference, 2019, University of Warwick.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2005). “Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools.” Journal of Political Economy 113, no. 1, pp. 151-84. doi:10.1086/426036.

Asher, S, P. Novosad, and C. Rafkin (2018), “Intergenerational Mobility in India: Estimates from New Methods and Administrative Data”, Working Paper, Dartmouth College.

Azam, Mehtabul, and Vipul Bhatt. (2015). “Like Father, Like Son? Intergenerational Educational Mobility in India. Demography 52(6):192959.

Azam, Mehtabul & Geeta Kingdon & Kin Bing Wu, (2016). ”Impact of private secondary schooling on cognitive skills: evidence from India,” Education Economics, Taylor Francis Journals, vol. 24(5), pages 465-480, September.

Bardhan, Pranab. (2014). “The State of Indian Economic Statistics: Data Quantity and Quality Issues. Unpublished.

Becker, Gary S Tomes, Nigel, 1986. ”Human Capital and the Rise and Fall of Families,” Journal of Labor Economics, University of Chicago Press, vol. 4(3), pages 1-39, July.

Behrman, J., E. Hannum, M. Wang, and J. Liu (2008): Education in the Reform Era, in Brandt and T. Rawski Ed: *China's Great Economic Transformation*, Cambridge university Press.

Behrman, Jere, A. Gaviria and M. Szekely (2001), “Intergenerational Mobility in Latin America, Economía, Vol. 2 (1): 1 44.

Bhalotra, Sonia, and Samantha Rawlings. (2013). “Gradients of Intergenerational Transmission of Health in Developing Countries.” Review of Economics and Statistics 95(2):66072.

Bjorklund A and K. Salvanes. (2011). ”Education and Family Background: Mechanisms and Policies,” Handbook in the Economics of Education vol 3, E A Hanushek, S Machin and L Woessmann (es.), pp. 201-247.

Black, S. E. and P. Devereux (2011). “Recent Developments in Intergenerational Mobility”, Handbook of Labor Economics.

Black, S. E, Paul J. Devereux, and Kjell G. Salvanes (2009), “Like father, like son? A note on the intergenerational transmission of IQ scores”, Economics Letters, Volume 105, Issue 1, 2009, Pages 138-140.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. (2014). “Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States. The Quarterly Journal of Economics 129(4):1553123.

de Brauw, Alan, and Scott Rozelle, (2008), Reconciling the Returns to Education in Rural China, Review of Development Economics 12(1): 57-71.

Emran, M. Shahe, and Forhad Shilpi. (2011). “Intergenerational Occupational Mobility in Rural Economy: Evidence from Nepal and Vietnam.” Journal of Human Resources 46(2):42758.

Emran, M. Shahe, and Forhad Shilpi. (2015). “Gender, Geography and Generations: Intergenerational Educational Mobility in Post-Reform India.” World Development 72:36280.

Emran, M Shahe, & William Greene, & Forhad Shilpi, (2018). ”When Measure Matters: Coresidency, Truncation Bias, and Intergenerational Mobility in Developing Countries,” Journal of Human Resources, University of Wisconsin Press, vol. 53(3), pages 589-607.

Emran, M. Shahe, and Sun Yan. (2015a). “Magical Transition? Intergenerational Educational and Occupational Mobility in Rural China: 19882002.” World Bank Policy Research, Working Paper 7316.

Emran, M. Shahe & Sun,Yan (2015b). “Are the children of uneducated farmers doubly disadvantaged? farm, nonfarm and intergenerational educational mobility in rural China,” Policy Research Working Paper Series 7459.

Emran,M. Shahe, & Shilpi,Forhad J., (2018). “Estimating intergenerational mobility with incomplete data : Coresidency and truncation bias in rank-based relative and absolute mobility measures,” Policy Research Working Paper Series 8414, The World Bank.

Emran. M Shahe, & Asadul, Islam & Forhad, Shilpi, (2018). “Distributional Effects of Corruption When Enforcement is Biased: Theory and Evidence from Bribery in Schools in Bangladesh,” MPRA Paper 84637, University Library of Munich, Germany.

Fan, Yi, Junjian Yi, and Junsen Zhang. (2015). “The Great Gatsby Curve in China: Cross-Sectional Inequality and Intergenerational Mobility. Working Paper. Hong Kong: CUHK.

Hertz, Tom, Tamara Jayasundera, Patrizio Piraino, Sibel Selcuk, Nicole Smith, and Alina Veraschagina. 2007. “The Inheritance of Educational Inequality: International

Comparisons and Fifty-Year Trends.” The B.E. Journal of Economic Analysis and Policy: Advances 7(2).

Knight, John, Terry Sicular, and Yue Ximing. (2013). Educational Inequality in China: the Intergenerational Dimension. in Rising Inequality in China: Challenge to the Harmonious Society, eds. Li Shi, Luo Chuliang, and Terry Sicular, ch.4. Cambridge and New York: Cambridge University Press.

Lanjouw, P, & Rinku Murgai, & Nicholas Stern, (2013). “Nonfarm diversification, poverty, economic mobility, and income inequality: a case study in village India,” Agricultural Economics, vol. 44(4-5), pages 461-473, July.

Lanjouw, P, & Rinku Murgai, (2009). “Poverty decline, agricultural wages, and nonfarm employment in rural India: 1983-2004,” Agricultural Economics, vol. 40(2), pages 243-263, March.

Lanjouw, Jean O. & Lanjouw, Peter, (2001). “The rural non-farm sector: issues and evidence from developing countries,” Agricultural Economics, Blackwell, vol. 26(1), pages 1-23, October.

Lefgren, Lars, & Matthew J. Lindquist, & David Sims, (2012). ”Rich Dad, Smart Dad: Decomposing the Intergenerational Transmission of Income,” Journal of Political Economy, University of Chicago Press, vol. 120(2), pages 268-303.

Li, Hongbin, Prashant Loyalka, Scott Rozelle, and Binzhen Wu. (2017). “Human Capital and China’s Future Growth.” Journal of Economic Perspectives, 31 (1): 25-48.

Lin, Jing (1999), Social Transformation and Private Education in China, Praeger, CT, USA.

Mazumder, Bhashkar, (2014). “BlackWhite Differences in Intergenerational Economic Mobility in the U.S,” Economic Perspectives, Federal Reserve Bank of Chicago, issue Q I, pages 1-18.

Mogstad, M (2017). “The Human Capital Approach to Intergenerational Mobility,” Journal of Political Economy, University of Chicago Press, vol. 125(6), pages 1862-1868.

Motiram, Sripad Singh, Ashish, (2012). “How Close Does the Apple Fall to the Tree? Some Evidence on Intergenerational Occupational Mobility from India,” WIDER Working Paper Series 101, World Institute for Development Economic Research (UNU-WIDER).

Narayan, A, & Roy Van der Weide, & Alexandru Cojocaru, & Christoph Lakner, & Silvia Redaelli, & Daniel Gerszon Mahler, & Rakesh Gupta N. Ramasubbaiah, & Stefan Thewissen, (2018). “Fair Progress? Economic Mobility across Generations Around the World,” World Bank Publications, The World Bank, number 28428, March.

Neidhöfer, G, Joaquín Serrano, Leonardo Gasparini (2018), “Educational inequality and intergenerational mobility in Latin America: A new database”, Journal of Development Economics, Volume 134, 2018, Pages 329-349.

Park, Albert, and X. Zou (2018), One Child Policy and Intergenerational Mobility, Working paper, HUST, Hongkong.

Peng, Yusheng (1998), “Agriculture, Rural Industries, and Peasant Income in China”, Development and Society, June 1998.

Rama, M, & Tara Béteille, & Yue Li, & Pradeep K. Mitra, & John Lincoln Newman, (2015). “Addressing Inequality in South Asia,” World Bank Publications, The World Bank, number 20395, March.

Reddy, A. Bheemeshwar, (2015), “Changes in Intergenerational Occupational Mobility in India: Evidence from National Sample Surveys, 19832012”, World Development, 76, issue C, p. 329-343.

Rozelle, Scott. 1994. “Rural Industrialization and Increasing Inequality: Emerging Patterns in Chinas Reforming Economy.” Journal of Comparative Economics, Vol. 19, Iss. 3, pp. 362-391

Sato, Hiroshi and Shi Li. 2007. Class origin, family culture, and intergenerational correlation of education in rural China. IZA Discussion Paper series No. 2642.

Solon, Gary. 1992. “Intergenerational Income Mobility in the United States. American Economic Review 82(3):393408.

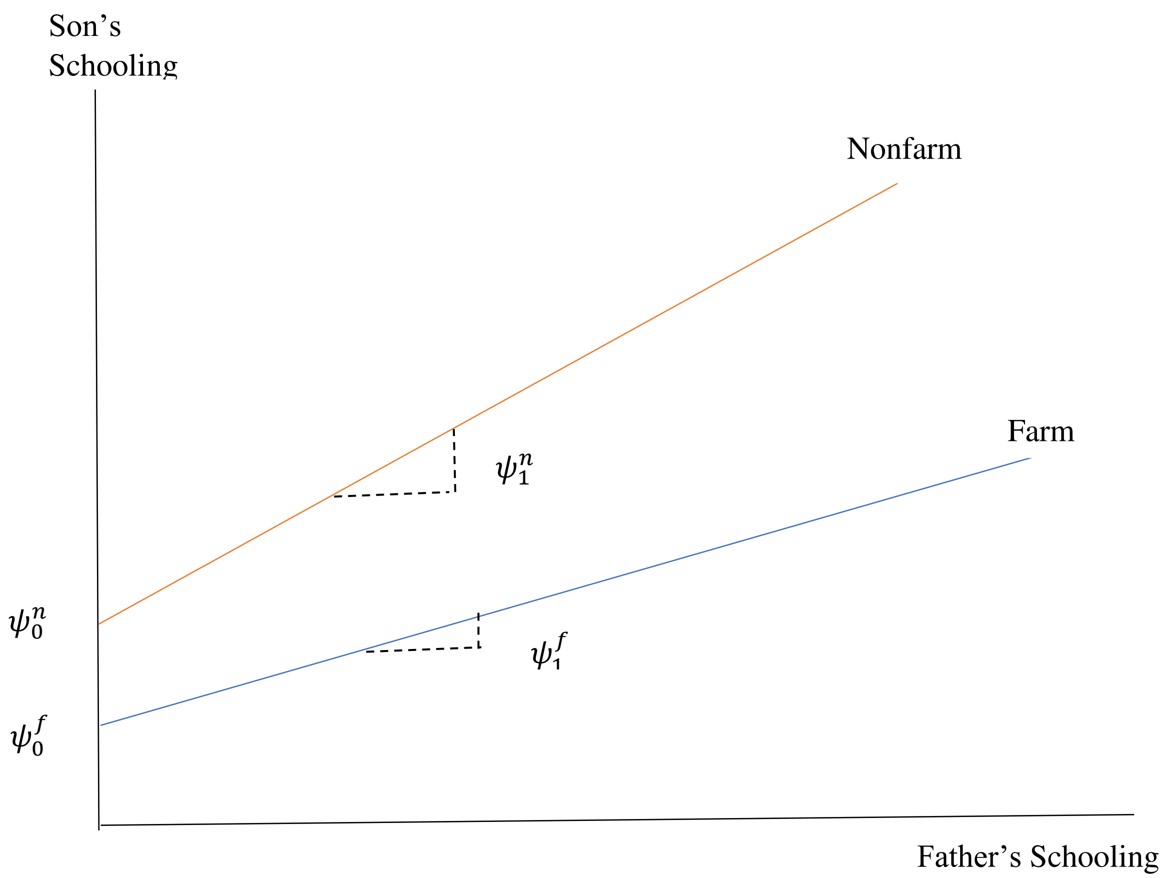
Solon, Gary. 1999. Intergenerational Mobility in the Labor Market. In Handbook of Labor Economics, Vol. 3, ed. O. Ashenfelter and D. Card, Elsevier: Amsterdam, North Holland.

Torche, Florencia. (2015). “Intergenerational Mobility and Equality of Opportunity, European Journal of Sociology 56(3): 343371.

Yang, Dennis Tao and An, Mark Yuying, 2002. Human capital, entrepreneurship, and farm household earnings, Journal of Development Economics, Elsevier, vol. 68(1), pages 65-88, June.

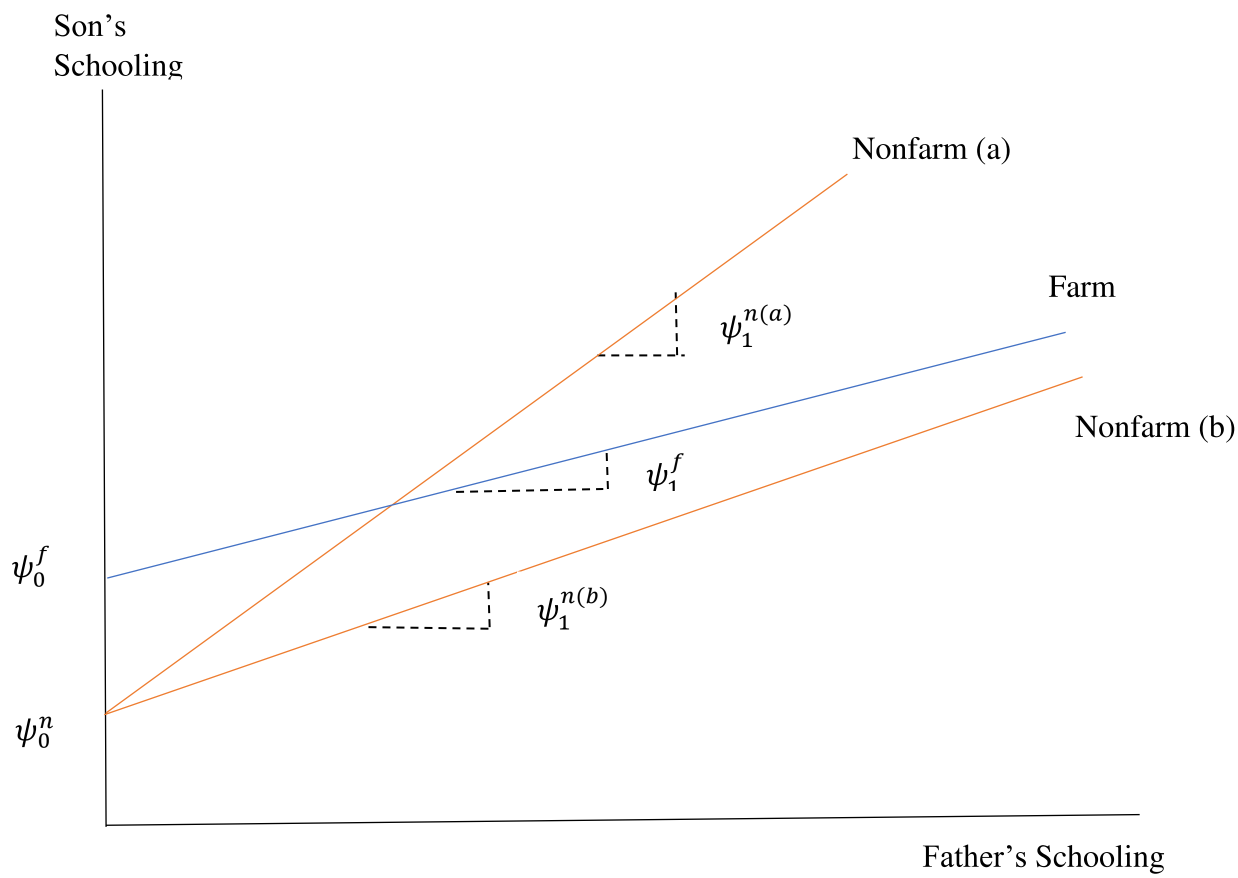
Wu, Xiaogang, and Donald J. Treiman. (2007), “Inequality and Equality under Chinese Socialism: The Hukou System and Intergenerational Occupational Mobility.” American Journal of Sociology 113, no. 2 (2007): 415-45.

Figure 1



Son's Schooling
Nonfarm
Farm
ψ_1^n
ψ_1^f
ψ_0^n
ψ_0^f
Father's Schooling

Figure 2



Son's
Schooling
Nonfarm (a)
Farm
Nonfarm (b)
$\psi_1^{n(a)}$
ψ_1^f
$\psi_1^{n(b)}$
ψ_0^f
ψ_0^n
Father's Schooling

Table 1: Relative Mobility and Test of Complementarity: Rural China and Rural India

	IGRC (ψ_1^j)		IRC (δ_1^j)	
	CHINA	**INDIA**	**CHINA**	**INDIA**
Combined Sample	**0.313**	**0.519**	**0.337**	**0.457**
	(0.016)	(0.016)	(0.017)	(0.014)
Farm	**0.311**	**0.488**	**0.331**	**0.421**
	(0.024)	(0.021)	(0.024)	(0.019)
Nonfarm	**0.316**	**0.56**	**0.344**	**0.506**
	(0.022)	(0.024)	(0.024)	(0.022)

Test of Complementarity (Farm/Nonfarm)

H_0: Farm and Nonfarm Coefficients are Equal

	IGRC($\psi_1^n = \psi_1^f$)		IRC ($\delta_1^n = \delta_1^f$)	
	CHINA	**INDIA**	**CHINA**	**INDIA**
F Statistic	**0.017**	**5.12**	**0.15**	**8.75**
P-Value	**0.90**	**0.02**	**0.70**	**0.003**

Notes: (1) IGRC stands for Intergenerational Regression Coefficient, and IRC stands for Intergenerational Rank Correlation. (2) The numbers in parenthesis are robust standard errors. (3) The number of observations for China: Combined (3305), Farm (1662), Nonfarm (1643), and for India: Combined (6887), Farm (4024), Nonfarm (2863).

Table 2: Estimates of Intercepts and Test of Equality

	IGRC Intercept (ψ_0^j)		IRC Intercept (δ_0^j)	
	CHINA	**INDIA**	**CHINA**	**INDIA**
Combined Sample	**5.86**	**5.33**	**0.381**	**0.339**
	(0.103)	(0.109)	(0.010)	(0.009)
Farm	**5.71**	**5.62**	**0.371**	**0.365**
	(0.153)	(0.145)	(0.015)	(0.012)
Nonfarm	**6.01**	**4.93**	**0.391**	**0.303**
	(0.141)	(0.162)	(0.014)	(0.013)

Test of Equality (Farm/Nonfarm)

H_0: Farm and Nonfarm Intercepts are Equal

	IGRC Intercepts ($\psi_0^n = \psi_0^f$)		IRC Intercepts ($\delta_0^n = \delta_0^f$)	
	CHINA	**INDIA**	**CHINA**	**INDIA**
F Statistic	**2.06**	**9.95**	**0.918**	**11.96**
P-Value	**0.15**	**0.002**	**0.34**	**0.001**

Notes: (1) The numbers in bold in the upper panel are estimates of the intercepts from intergenerational persistence regression using years of schooling (Called IGRC intercepts), and from rank-rank regressions (called IRC intercepts). (2) the numbers in parenthesis are robust standard errors. (3) The number of observations correspond to those reported in Table 1.

Table 3A: Evidence on Complementarity and Intercept Differences with Quadratic Age Controls (Years of Schooling)

	Estimates with Son's Age and Age Squared as Controls			
	China		India	
	Farm	Nonfarm	Farm	Nonfarm
IGRC (ψ_1^j)	0.306	0.308	0.488	0.560
H_0 : Farm = Nonfarm ($\psi_1^n = \psi_1^f$)				
F Statistic	0.005		4.968**	
P-value	0.945		0.026	
Intercept (ψ_0^j)	7.502	7.884	5.111	4.437
H_0 : Farm = Nonfarm ($\psi_0^n = \psi_0^f$)				
F Statistic	3.22		9.448	
P-value	0.073		0.002	

	Estimates with Both Son's and Father's Age and Age Squared			
	China		India	
	Farm	Nonfarm	Farm	Nonfarm
IGRC (ψ_1^j)	0.301	0.314	0.495	0.572
H_0 : Farm = Nonfarm ($\psi_1^n = \psi_1^f$)				
F Statistic	0.162		5.629	
P-value	0.687		0.018	
Intercept (ψ_0^j)	14.43	14.797	3.965	3.140
H_0 : Farm = Nonfarm ($\psi_0^n = \psi_0^f$)				
F Statistic	2.796		13.890	
P-value	0.095		0.000	

NOTES: (1) IGRC stands for Intergenerational Regression Coefficient. (2) H_0 : Farm=Nonfarm denotes the Null Hypothesis that the farm and nonfarm parameter estimates are equal.

Table 3B: Evidence on Complementarity and Intercept Differences with Quadratic Age Controls (Schooling Rank)

	Estimates with Son's Age and Age Squared as Controls			
	China		India	
	Farm	Nonfarm	Farm	Nonfarm
IRC (δ_1^j)	0.328	0.349	0.440	0.529
H$_0$: Farm = Nonfarm ($\delta_1^n = \delta_1^f$)				
F Statistic	0.347		9.294	
P-value	0.556		0.002	
Intercept (δ_0^j)	0.424	0.445	0.279	0.215
H$_0$: Farm = Nonfarm ($\delta_0^n = \delta_0^f$)				
F Statistic	0.952		13.04	
P-value	0.329		0.000	
	Estimates with Both Son's and Father's Age and Age Squared			
	China		India	
	Farm	Nonfarm	Farm	Nonfarm
IRC (δ_1^j)	0.322	0.358	0.448	0.542
H$_0$: Farm=Nonfarm ($\delta_1^n = \delta_1^f$)				
F Statistic	1.031		10.34	
P-value	0.31		0.001	
Intercept (δ_0^j)	0.868	0.884	0.172	0.098
H$_0$: Farm=Nonfarm ($\delta_0^n = \delta_0^f$)				
F Statistic	0.515		17.25	
P-value	0.473		0.000	

NOTES: (1) IRC stands for Intergenerational Rank Correlation. (2) H$_0$: Farm=Nonfarm denotes the Null Hypothesis that the farm and nonfarm parameter estimates are equal.

Table 4: Father's Education and Household Income

Panel A: Estimates for Rural China

	Intercept		Slope	
	Farm	**Nonfarm**	**Farm**	**Nonfarm**
CHIP 2002	**11575.77**	**11141.05**	**208.41**	**246.52**
	(2177.51)	(1029.08)	(46.94)	(70.72)
CHIP 1995	**989.28**	**3383.64**	**-7.95**	**70.86**
	(519.66)	(466.96)	(47.25)	(30.91)

Test of Equality Between Farm and Nonfarm

	H_0: Intercepts are Equal	H_0: Slopes are Equal
CHIP 2002		
F Statistic	**0.01**	**0.98**
P-value	**0.98**	**0.32**
CHIP 1995		
F Statistic	**1.12**	**1.40**
P-value	**0.29**	**0.24**

Panel B: Estimates for Rural India

	Intercept		Slope	
	Farm	**Nonfarm**	**Farm**	**Nonfarm**
NSS 1993	**1388.66**	**1360.52**	**62.02**	**71.72**
	(96.73)	(88.73)	(2.49)	(3.21)

Test of Equality Between Farm and Nonfarm

	H_0: Intercepts are Equal	H_0: Slopes are Equal
F Statistic	**19.62**	**10.11**
P-value	**0.00**	**0.001**

Notes: (1) The dependent variable for Rural China is the average household income (total). CHIP 2002 is the average of the last 5 years of total household income, and CHIP 1995 is the average of the last 3 years of household income. The dependent variable for India is total household expenditure. (2) The numbers in parenthesis are standard errors. (3) H_0 stands for Null Hypothesis.

Table 5: Mechanisms: Evidence on Younger Generation in Rural China (18-28 Years Old in 2010)

5A: Intergenerational Persistence in Occupations (CFPS 2010)

	18-28 Years Age Cohort		**29-65 Years Age Cohort**	
	Father's Occupation		**Father's Occupation**	
	Farm	*Nonfarm*	*Farm*	*Nonfarm*
Prob. of Nonfarm Occupation of Son	**0.542**	**0.705**	**0.299**	**0.414**
	(0.024)	(0.024)	(0.019)	(0.021)

5B: Effects of Father's Education on Household Income (Young Sample)

	Intercept $[\boldsymbol{Y_0^{pj}}]$		**Slope** $[\boldsymbol{R^{pj}}]$	
	Farm	*Nonfarm*	*Farm*	*Nonfarm*
	26573.7	**32352**	**988**	**1921**
	(611.7)	(2293.6)	(133.0)	(515.9)

Test of Equality Between Farm and Nonfarm

	H_0: Intercepts are Equal $[\boldsymbol{Y_0^{pn}} = \boldsymbol{Y_0^{pf}}]$	H_0: Slopes are Equal $[\boldsymbol{R^{pn}} = \boldsymbol{R^{pf}}]$
F Statistic	**6.714**	**3.08**
P-Value	**0.01**	**0.079**

NOTES: Household income is the average of the income from 2010, 2012 and 2014 rounds of CFPS survey. (2) $\boldsymbol{R^{pj}}$ is the returns to father's education in terms of permanent household income. (3) Numbers in parenthesis are standard errors.

Table 6: Intergenerational Persistence in Education (18-28 Age Cohort, CFPS)

Panel A: Estimates Based on Years of Schooling

	Intercept (ψ_0^j)		IGRC (ψ_1^j)	
	Farm	**Nonfarm**	**Farm**	**Nonfarm**
	6.99	**7.17**	**0.27**	**0.34**
	(0.19)	(0.25)	(0.024)	(0.028)

Test of Equality Between Farm and Nonfarm

	H0: Intercepts are Equal ($\psi_0^n = \psi_0^f$)	H0: IGRCs are Equal ($\psi_1^n = \psi_1^f$)
F Statistic	**0.305**	**2.917**
P-Value	**0.581**	**0.087**

Panel B: Estimates Based on Schooling Ranks

	Intercept (δ_0^j)		IRC (δ_1^j)	
	Farm	**Nonfarm**	**Farm**	**Nonfarm**
	0.34	**0.35**	**0.29**	**0.36**
	(0.014)	(0.019)	(0.025)	(0.029)

Test of Equality Between Farm and Nonfarm

	H0: Intercepts are Equal [$\delta_0^n = \delta_0^f$]	H0: Slopes are Equal ([= δ_1^f]
F Statistic	**0.517**	**3.204**
P-Value	**0.472**	**0.074**

NOTES: (1) IGRC stands for Intergenerational Regression Coefficient, and IRC for Intergenerational Rank Correlation. (2) Numbers in parenthesis are standard errors.

Figure 3: Regression of Fathers' Years of Schooling against Sons' Years of Schooling in Rural India

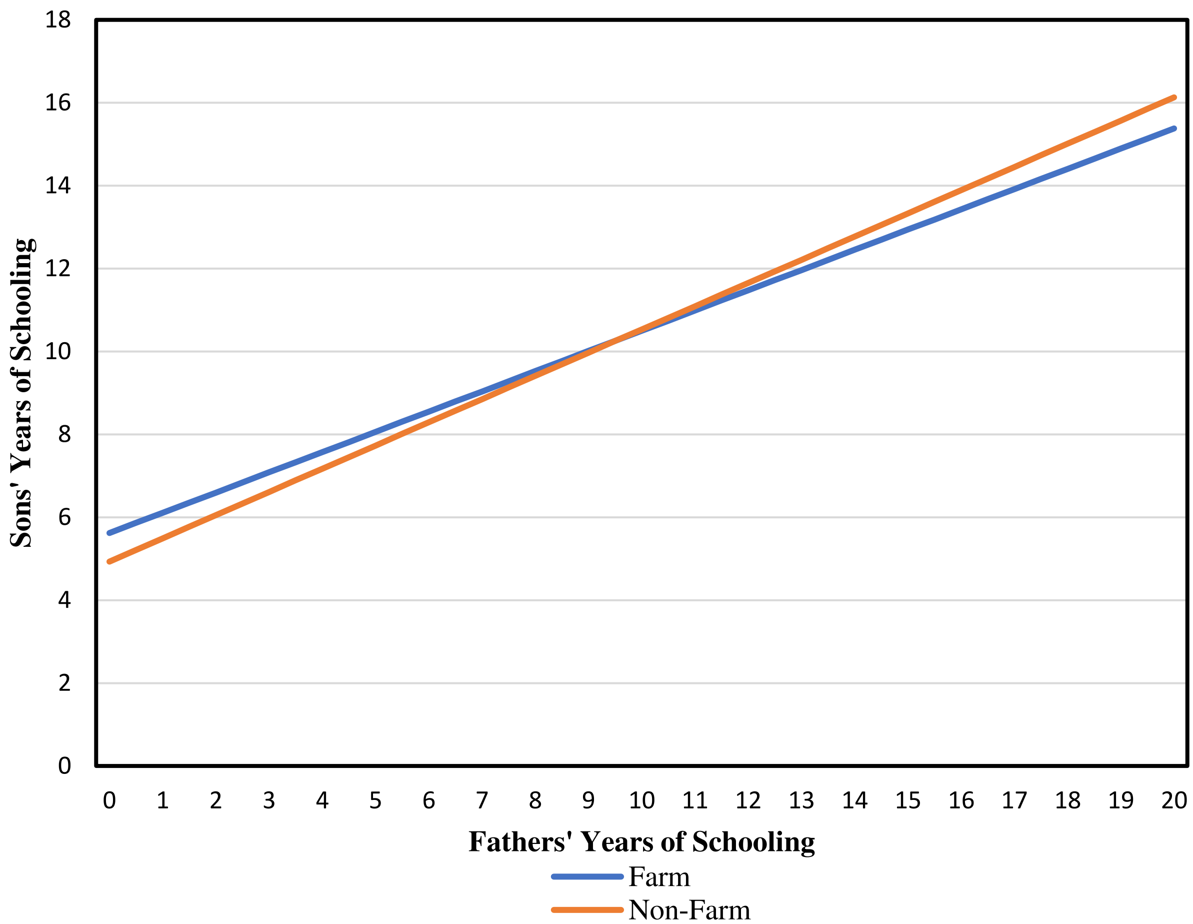


Figure 4: Regression of Fathers' Years of Schooling against Sons' Years of Schooling in Rural China

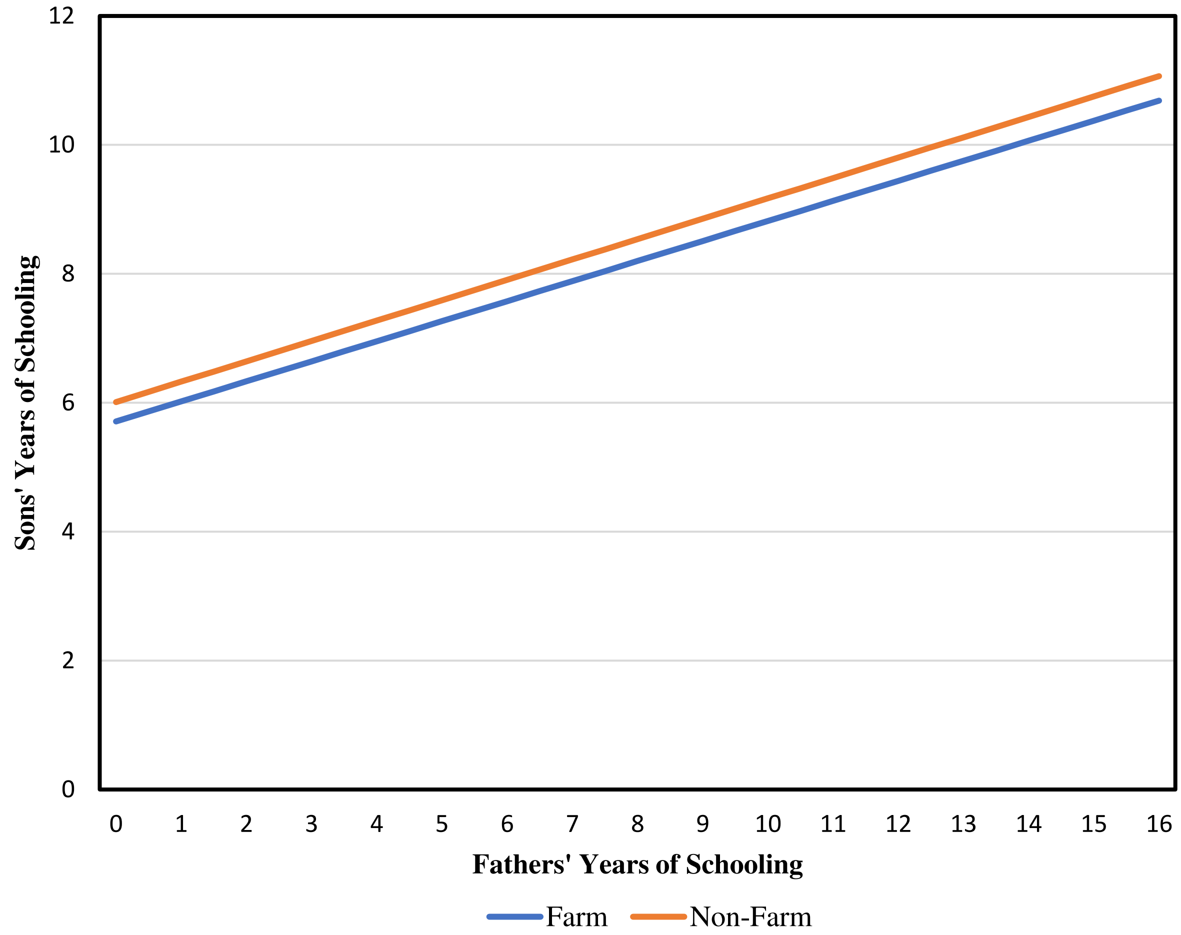
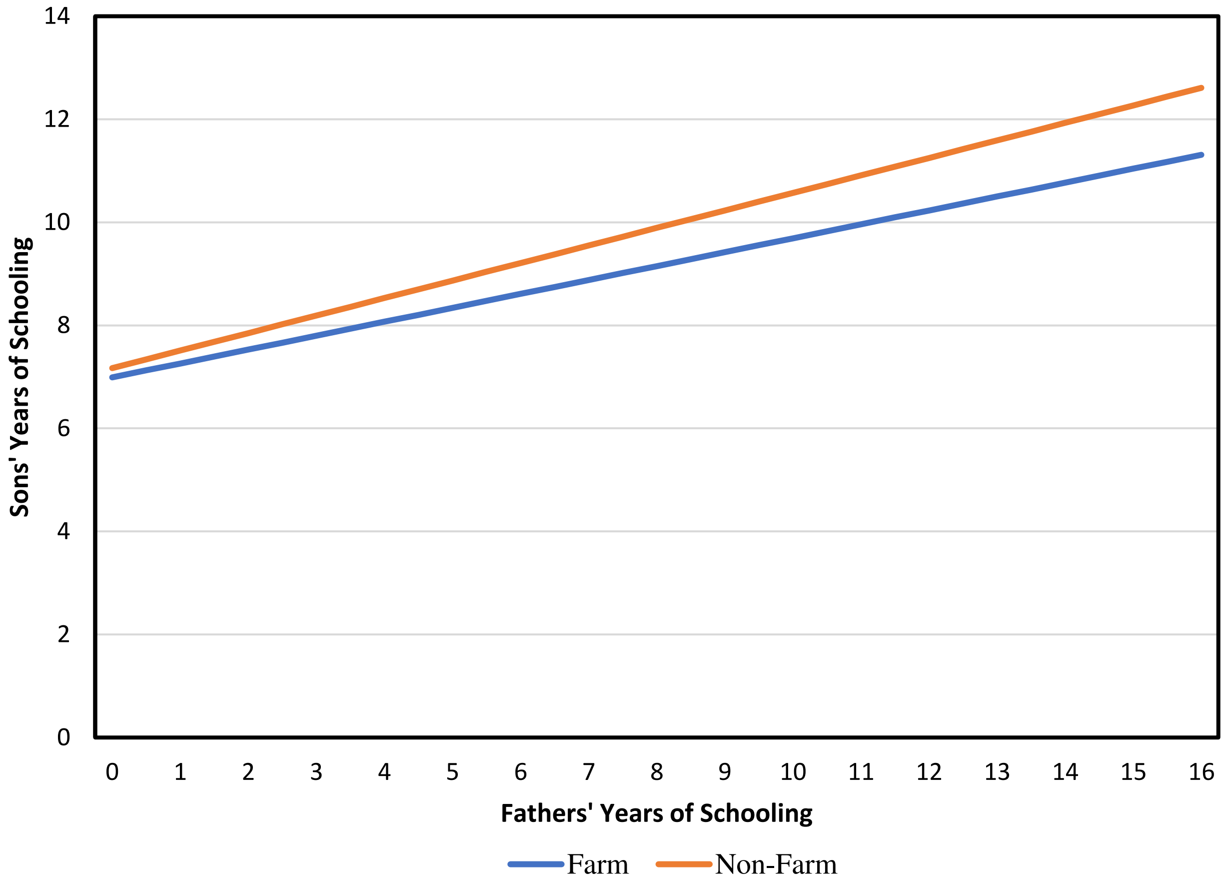


Figure 5: Regression of Fathers' Years of Schooling against Sons' Years of Schooling for the Younger Generation in Rural China



Online Appendix: An Approach to Nature vs. Nurture

The approach developed here exploits the restrictions implied by the recent estimates of interegenerational correlation in cognitive ability from economics and behavioral genetics in a triangular biprobit model a la Altonji et al. (2005), and performs sensitivity analysis over a narrow interval of the correlation parameter. This approach requires binary classification of educational attainment. We define a dummy D_i^{Sp} that takes on the value 1 when the father of a child has more than primary schooling and zero otherwise. Analogously, we define a binary variable for children's education D_i^{Sc} which takes on the value of 1 when a child's schooling years is higher than a threshold (junior high schooling for China and secondary schooling for India).[1] This means that we have a $[2 \times 2]$ occupation and education set-up. Consider the following triangular model of children's and parent's education:

$$\begin{aligned} Pr\left(D_i^{Sc}=1\right) &= \Phi\left(\lambda_0^j + \lambda_1^j D_i^{Sp} + X_i'\Pi^j + \varsigma_i\right) \\ Pr\left(D_i^{Sp}=1\right) &= \Phi\left(\gamma_0^j + X_i'\mathit{\Gamma}^j + \epsilon_i\right) \end{aligned}$$

where Φ is the normal CDF and superscript j refers to parental occupation, i.e., $j \in \{f, n\}$. The error terms capture the unobserved factors including ability, part of which is genetically transmitted from father to son in our application.

The choice of the educational cut-offs described above is based on the following considerations. For parental generation, the cut-off is primary schooling, which equals 5 years of schooling in India and 6 years in China. For children in India, the cut-off we chose is 10 years of schooling that correspond to the completion of secondary schooling. The 10-year is a natural focal point for India as the students take one of the most important public examination at the end of 10th grade. For China the cut-off used is junior high schooling which corresponds to 9 years of schooling. The 9-year cut-off is a focal point in China because of the 9-year compulsory schooling policy adopted by the government in 1986. While a lump in the distribution of children's schooling attainment at the 9 years of schooling may be driven by government policy, whether a child goes beyond 9 years of schooling would reflect more faithfully the effects of family background. Thus we define all the dummies as strict inequalities; for example, for rural China, we set $D_i^{Sc} = 1$ when a child attains *higher* than 9 years of schooling and zero otherwise. The conclusions below, however, do not depend on the precise cut-off chosen for the educational attainment dummies.[2]

[1] For more details on the choice of the educational cut-offs, please see the discussion below.

[2] As part of robustness checks, we estimated biprobit models for China using 5 years cut-off for father

It is useful to decompose the error terms in the triangular model into two parts, one genetically transmitted (denoted as ϕ_i) and the other orthogonal to the genetic component:

$$\varsigma_i = \phi_i^c + \tilde{\varsigma}_i$$
$$\epsilon_i = \phi_i^p + \tilde{\epsilon}_i$$

So $Cov\left(\varsigma_i, \epsilon_i\right) = Cov\left(\phi_i^c, \phi_i^p\right) + Cov\left(\tilde{\varsigma}_i, \tilde{\epsilon}_i\right)$. The focus is on the role played by $Cov\left(\phi_i^c, \phi_i^p\right)$.

We take advantage of a substantial literature in economics and behavioral genetics that provides estimates of correlation between parents and children in cognitive ability. The correlation between parent's and children's cognitive ability is between 0.35 and 0.38 according to the estimates reported by Black et al. (2009) and Björklund et al. (2010). A meta-analysis of behavioral genetic studies by Plomin and Spinath (2004) reports a correlation of 0.40. Let $\rho = Corr\left(\varsigma_i, \epsilon_i\right)$. We estimate the bivariate probit model above by imposing $\rho = 0.10, 0.20, 0.30, 0.40$.[3]

It is also important to appreciate that the estimates of intergenerational schooling persistence from the sensitivity analysis with $\rho = 0.40$ can be interpreted as the lower bounds on the true intergenerational effects due to economic and social factors. The estimates of ability correlations in the literature discussed above are likely to be biased upward as measures of *genetic correlations at birth* because they partly capture the dynamic interactions between family environment and genetics up to the age when the ability measurements are taken.[4] For example, the careful recent analysis by Gronqvist et al. (2017) uses measures of cognitive ability taken at age 13.

The results from the biprobit sensitivity analysis are reported in online appendix Table A.3 (the first two columns for India and the last two columns for China). We report the marginal effects of switching the parental educational dummy from zero (primary or below) to one (more than primary) which implies that the estimates of intergenerational

and 10 years cut-off for children, so that the educational attainment dummies in China match exactly those in India in terms of years of schooling. The estimates are very close to those reported in appendix Table A.3 below. The details are available from the authors.

[3] In an interesting recent paper, Gronqvist et al. (2017) show that the estimates of ability correlation may be biased downward because of measurement error, and they report estimates in the range of 0.42-0.48. However, note that the educational attainment as measured by years of schooling is also usually measured with error. It thus seems reasonable to use 0.40 as the upper bound for our analysis, assuming that the measurement errors in schooling and cognitive ability largely offset each other.

[4] This includes the in-utero effects on a child's health which is found to be of substantial magnitude according to a large literature. Please see the survey by Almond and Currie (2011). Recent evidence shows that socioeconomic status a child born into affects the development of brain in a significant way (Noble et al. (2015)).

persistence depend on all of the probit coefficients in the model, including the intercept term.[5]

The Effects of Positive Ability Correlations in Rural India

The estimates from univariate probit model for India reported in row 1 of Table A.3 shows that the pattern of the effects is broadly similar to that found in the estimates based on years of schooling in Tables 1-2 in the main text. The sons born to fathers with more than primary schooling enjoy a higher probability of attaining more than secondary schooling, and this effect is larger for the children with father in nonfarm occupation.

The more important and interesting for our purpose is how the estimates are affected when we relax the assumption of $\rho = 0$ imposed in the univariate probit estimates. Consistent with *a priori* expectation, the magnitude of the estimated effects declines monotonically with higher values of intergenerational ability correlation ρ. However, the estimated effect of having a better educated father remains positive and statistically significant at the 1 percent level across the board even when we set the value of ρ at its upper bound of 0.40. This can be interpreted as strong evidence that the estimated effects in India are not likely to be driven exclusively by mechanical effects of genetic transmission of ability.

The Effects of Positive Ability Correlations in Rural China

The estimates of father's effect in rural China for alternative values of genetic correlation in ability are reported in the last two columns of Table A.3. The estimates from the univariate probit model under the assumption that $\rho = 0$ show that the effects for both farm and nonfarm households in China are much smaller in magnitude when compared to the corresponding estimates for India. This confirms the conclusion based on years of schooling as a measure of educational attainment that the sons in rural China enjoy much higher educational mobility compared to the sons in rural India. The more important is the evidence that the estimated effects become very small in China when we set $\rho = 0.20$. The advantage due to the higher educated father declines effectively to zero when we set $\rho = 0.30$, as the estimated effects turn negative for both the farm and nonfarm households. The evidence thus indicates that the estimates of intergenerational persistence in China reported in Tables (1)-(3) in the main text could be entirely driven by genetic correlations in ability. This suggests high intergenerational educational mobility during the decades of 1980s and 1990s in rural China, for the sons of both the farmer and non-farmer fathers.

[5]The AET sensitivity analysis including the quadratic age controls yield similar conclusions to those based on Table A.3. The results are available from the authors upon request.

References not Cited in the Manuscript

Almond, Douglas & Currie, Janet, (2011). “Human Capital Development before Age Five,” Handbook of Labor Economics, Elsevier.

Anger, S, & Guido Heineck, (2010). “Do smart parents raise smart children? The intergenerational transmission of cognitive abilities,” Journal of Population Economics, Springer;European Society for Population Economics, vol. 23(3), pages 1105-1132, June.

Björklund Anders, & Hederos Eriksson Karin, & Jäntti Markus, (2010). “IQ and Family Background: Are Associations Strong or Weak?,” The B.E. Journal of Economic Analysis Policy, De Gruyter, vol. 10(1), pages 1-14, January.

Grönqvist, E, & Björn Öckert, & Jonas Vlachos, (2017). “The Intergenerational Transmission of Cognitive and Noncognitive Abilities,” Journal of Human Resources, University of Wisconsin Press, vol. 52(4), pages 887-918.

Noble, Kimberly G and others (2015), “Family income, parental education and brain structure in children and adolescents”, Nature Neuroscience, 18, pages 773778 (2015).

Plomin, R, and F. Spinath (2004), “Intelligence: Genetics, Genes, and Genomics”, Journal of Personality and Social Psychology, Vol 86(1), Jan 2004, 112-129.

ONLINE APPENDIX TABLES

Appendix Table A.1: Summary Statistics
(Main Overlapping Samples)

	Mean	SD	Min	Max
		CFPS 2010		
Son's Schooling (years)	7.1	3.94	0	19
Father's Schooling (years)	3.94	4.18	0	16
Father in Agriculture (dummy)	0.50	0.50	0	1
Son's Age (years)	39.4	7.63	29	65
Father's Age (years)	67.6	8.75	45	96
		REDS 1999		
Son's Schooling (years)	7.44	5.08	0	21
Father's Schooling (years)	4.07	4.4	0	20
Father in Agriculture (dummy)	0.58	0.49	0	1
Son's Age (years)	28.82	7.95	18	54
Father's Age (years)	59.57	9.86	35	98

NOTES: (1) CFPS stands for China Family Panel Studies and REDS stand for Rural Economic and Demographic Survey. (2) SD stands for standard deviation. (3) No. of observations for CFPS is 3305, and for REDS 6887.

Appendix Table A.2: Coresidency and Truncation Bias in China

Estimates of Intergenerational Educational Persistence in Rural China from CHIP 2002

	Panel A: Children 18-65 Years			
	SLOPE		INTERCEPT	
	IGRC (ψ_1^j)	IRC (δ_1^j)	(ψ_0^j)	(δ_0^j)
Combined	**0.265**	**0.295**	**7.105**	**0.357**
	(0.015)	(0.016)	(0.112)	(0.009)
Farm	**0.245**	**0.263**	**7.075**	**0.353**
	(0.022)	(0.022)	(0.158)	(0.012)
Non-farm	**0.266**	**0.305**	**7.29**	**0.376**
	(0.021)	(0.022)	(0.166)	(0.014)

	Test of Separability		Test of Equality	
	($\psi_1^n = \psi_1^f$)	($\delta_1^n = \delta_1^f$)	($\psi_0^n = \psi_0^f$)	($\delta_0^n = \delta_0^f$)
F-statistics	0.45	1.771	0.873	1.574
P-value	0.502	0.183	0.35	0.21

	Panel B: Children of 21-57 years age in 2002			
	SLOPE		INTERCEPT	
	IGRC (ψ_1^j)	IRC (δ_1^j)	(ψ_0^j)	(δ_0^j)
Combined	**0.262**	**0.283**	**7.074**	**0.360**
	(0.018)	(0.018)	(0.126)	(0.011)
Farm	**0.226**	**0.237**	**7.127**	**0.361**
	(0.027)	(0.026)	(0.182)	(0.015)
Non-farm	**0.277**	**0.310**	**7.180**	**0.372**
	(0.025)	(0.025)	(0.184)	(0.016)

	Test of Separability		Test of Equality	
	($\psi_1^n = \psi_1^f$)		($\psi_0^n = \psi_0^f$)	
F-statistics	1.946	3.992	0.042	0.271
P-value	0.163	0.046	0.838	0.603

Appendix Table A.3:

AET (2005) Sensitivity Analysis for Ability Correlations

The Effects of Father's Higher Education on the Probability of Higher Education of Sons.

	CHINA		INDIA	
	Farm	**Nonfarm**	**Farm**	**Nonfarm**
ρ=0	**1.72**	**2.83**	**8.71**	**10.14**
	(0.38)	(0.46)	(0.44)	(0.46)
ρ=0.10	**1.17**	**2.14**	**7.66**	**9.61**
	(0.44)	(0.51)	(0.47)	(0.49)
ρ=0.20	**0.38**	**1.2**	**6.28**	**8.80**
	(0.50)	(0.57)	(0.51)	(0.53)
ρ=0.30	**-0.66**	**-0.02**	**4.53**	**7.62**
	(0.57)	(0.63)	(0.55)	(0.59)
ρ=0.40	**-1.99**	**-1.52**	**2.38**	**6.02**
	(0.64)	(0.68)	(0.58)	(0.64)

Notes: (1) AET (2005) stands for Altonji, Elder and Taber (2005, Journal of Political Economy) biprobit sensitivity analysis. (2) **ρ** stands for correlation in cognitive ability of father and son. Estimates in the first row with ρ=0 are the univariate Probit estimates. (3) The numbers in bold are percentage points increase in the probability of higher education of sons when the father has higher education. (3) Higher education for parents implies more than primary, and for sons in India more than 10 years of schooling, for sons in China more than 9 years of schooling. (4) The numbers in parenthesis are standard errors.