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Gender Bias and Intergenerational Educational Mobility

Theory and Evidence from China and India

M. Shahe Emran
Hanchen Jiang
Forhad Shilpi

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Abstract

This paper incorporates gender bias against girls in the family, school and labor market in a model of intergenerational persistence in schooling where parents self-finance children's education because of credit market imperfections. Parents may underestimate a girl's ability, expect lower returns, and assign lower weights to their welfare ("pure son preference"). The model delivers the widely used linear conditional expectation function under constant returns and separability but generates an irrelevance result: parental bias does not affect relative mobility. With diminishing returns and complementarity, the conditional expectation function can be concave or convex, and parental bias affects both relative and absolute mobility. This paper tests these predictions in India and China using data not subject to coresidency bias. The evidence rejects the linear conditional expectation function in rural and urban India in favor of a concave relation. Girls in India face lower mobility irrespective of location when born to fathers with low schooling, but the gender gap closes when the father is college educated. In China, the conditional expectation function is convex for sons in urban areas, but linear in all other cases. The convexity supports the complementarity hypothesis of Becker et al. (2018) for the urban sons and leads to gender divergence in relative mobility for the children of highly educated fathers. In urban China, and urban and rural India, the mechanisms are underestimation of the ability of girls and unfavorable school environment. There is some evidence of pure son preference in rural India. The girls in rural China do not face bias in financial investment by parents, but they still face lower mobility when born to uneducated parents. Gender barriers in rural schools seem to be the primary mechanism.

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Gender Bias and Intergenerational Educational Mobility: Theory and Evidence from China and India

M. Shahe Emran[1]
IPD, Columbia University

Hanchen Jiang
Johns Hopkins University

Forhad Shilpi
World Bank

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[1]Email for correspondence: shahe.emran.econ@gmail.com. fshilpi@worldbank.org. hjiang15@jhu.edu.
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(1) Introduction

Gender bias against girls in developing countries has been the focus of a large and growing economic and sociological literature. Son preference, selective abortion, genital mutilation, mobility, and social restrictions such as Purdah are widely noted. There is a broad consensus that education is a key policy instrument for tackling gender disparity and socioeconomic inequality (see, for example, Stiglitz (2012), Duflo (2012), Jayachandran (2015)). This paper provides an analysis of the gender gap in education in China and India from the perspective of intergenerational mobility.[2] Most of the studies of intergenerational mobility, both in developed and developing countries, focus on the father-son linkage, and research on women in general and on gender bias in particular remains scant.[3]

Many existing studies on intergenerational mobility, especially in developing countries, lack a well-articulated theoretical foundation. As emphasized recently by Mogstad (2017), it is thus difficult to interpret the estimates, or understand the underlying economic mechanisms. We develop a model of intergenerational educational persistence in the tradition of Becker and Tomes (1986) that captures different sources of gender bias against girls in the family, the school, and the labor market. The sources of gender bias in the family are: (i) biased estimate of academic ability, (ii) lower weight to the welfare of a daughter compared to that of a son (we call it "pure son preference"), and (iii) lower expected returns from a daughter's education. The expected returns may in part reflect biases in the labor market. These factors affect the financial investment in education of the daughters, but the daughters may also face bias in non-financial aspects such as home tutoring.[4] Moreover, unfavorable school environment, for example, the absence of bathrooms for girls, can result in dropouts when a girl reaches puberty.

[2] In most developing countries, girls have historically lagged behind boys in educational attainment. However, there is evidence that the gender gap in schooling attainment may be narrowing over time. Reverse gender gap has emerged in Latin America in educational attainment (Grant and Behrman (2010)).

[3] Among the few available contributions on intergenerational mobility of daughters, see Chadwick and Solon (2002) on United States, Azam (2016) on India, and Torche (2015b) on Mexico. But they do not study the effects of gender bias. For a discussion on gender and intergenerational mobility with a focus on persistence in gender attitude and labor market participation, see Luke (2019). For evidence on intergenerational transmission of gender attitudes in India, see Dhar et al. (2019).

[4] A better educated parent may act as a more effective home tutor, but son preference may mean that priority (and more attention) is given to sons.

The conditional expectation function (CEF) of children's education given parental education is assumed to be linear in all of the existing studies on intergenerational educational mobility we are aware of.[5] In a Becker-Tomes model with self-financing constraint, a linear and additively separable education production function delivers a linear estimating equation for intergenerational educational persistence.[6] This "linear model" of intergenerational educational mobility, however, yields strong predictions: parental bias against girls in financial investment does not affect relative mobility; the effects of parental gender bias are captured solely by the intercept of the regression function. Although the linear estimating equation has been the workhorse in the current literature, the sharp implications of the linear model for gender bias in intergenerational educational mobility have not been noted before, to the best of our knowledge.

When the education production function exhibits diminishing returns, the estimating equation for intergenerational educational mobility is concave in parental schooling, assuming that the separability holds.[7] However, separability may not be an appropriate assumption, especially in urban areas with developed education markets. As noted by Becker et al. (2015), the better educated parents may reap higher marginal returns from financial investment because they are more-efficient in such investment decision making in a complex education market, thus parental education is likely to be complementary to financial investment in such a context. This complementarity, when strong enough, can more than offset the diminishing returns in the education production function making the intergenerational educational persistence equation convex. In contrast to the linear model,

[5]Functional form assumptions are usually not tested in much of the literature on intergenerational mobility, both in the developed and developing countries. For an important recent exception see the discussion in Chetty et al. (2014) on the instability of the log-linear model of intergenerational income mobility in the United States.

[6]This, in particular, implies that (i) there are constant returns to financial investment in education, and (ii) the financial investment and the direct effects of parental education are separable.

[7]To our knowledge, the quadratic intergenerational educational persistence equation was first derived by Becker et al. (2015). Their set-up is different from ours in terms of modeling the credit constraint. They assume that low income parents pay a higher interest rate, but can borrow as much as they want given the interest rate. We assume that parents cannot borrow from the credit market to finance educational investment and thus use part of their income for such investment. The credit market model we adopt is similar to Becker (1991). Given that the education loan markets are practically non-existent for most of the parents in India and China, we believe this is an appropriate modeling choice. Becker et al. (2015) do not explore gender differences in intergenerational mobility.

parental gender bias affects both relative and absolute mobility when diminishing returns and/or complementarity are important.

A credible empirical analysis of the above ideas, however, depends critically on the quality of the data available.[8] Most of the existing household surveys use coresidency criteria to define household membership and thus miss children from the sample in a non-random fashion. This results in truncation bias in the estimates of widely used measures of intergenerational mobility such as the intergenerational regression coefficient (IGRC). As reported by Emran et al. (2018), the truncation bias due to coresidency can vary significantly across gender and countries, making it doubly hazardous to rely on the coresident sample for a comparative study of gender bias in China and India. We take advantage of rich household surveys from China and India that do not suffer from coresidency bias for our analysis. Since the theory yields interesting predictions regarding the effects of gender bias on educational investment, our empirical analysis estimates both the intergenerational persistence equation (using IHDS 2012 for India, and CFPS 2016 for China) and the investment equation (using IHDS 2005 and NSS1995 for India, and CFPS 2010 for China).

The main conclusions from the empirical analysis are as follows. In India, the intergenerational mobility equation is *concave* irrespective of gender and geographic location, rejecting the almost universally used linear specification in the existing literature. The concavity suggests that the complementarity between financial investment and parental education emphasized recently by Becker et al. (2018) may not be important in India. There are strong diminishing returns to both financial investment and parental direct inputs in education for girls in rural India. Girls face significantly lower relative and absolute mobility when the father is uneducated, but the gender difference becomes negligible when the father is college educated.[9] The relative magnitudes of the estimated parameters of the

[8] A large literature on intergenerational income mobility in the context of developed countries emphasizes the attenuation bias in the intergenerational income elasticity estimates due to measurement error in yearly income data. See, for example, the seminal analysis by Solon (1992). Measurement error is likely to be less of a concern in education data (Deaton (1987)).

[9] If one relies on the linear CEF estimates, s/he would miss the gender convergence at the right tail of the father's schooling distribution.

investment and mobility equations across gender are combined with substantial evidence of higher returns to education for girls in urban and rural India to sort out the mechanisms. The evidence suggests that parents systematically underestimate the academic ability of daughters, and girls also face disadvantages in school. There is evidence of pure son preference in rural India.

In urban China, the CEF is *convex* for sons, while we cannot reject linearity for daughters. The evidence of convexity for sons is interesting, providing the first evidence in favor of the complementarity hypothesis of Becker et al. (2015, 2018) in the context of a developing country. Similar to urban India, daughters of uneducated fathers face significantly lower mobility, in terms of both absolute and relative measures. There is evidence of gender convergence in absolute mobility for the most educated households, but, unlike urban India, there is a widening gender gap in relative mobility at the right tail of the father's schooling distribution. The main mechanisms at work are, however, similar to those in urban India noted above.

The results on rural China are different: the evidence is largely consistent with a linear model with no significant diminishing returns or complementarity. The IGRC estimate is larger for girls, while the intercept is lower. Girls face lower expected years of schooling when the fathers have less than 14 years of schooling, but the advantage flips in the households with higher schooling of fathers. The estimates of educational investment show that girls consistently enjoy an advantage. The constraints girls face in school is a major factor behind the observed pattern of the estimates, but the evidence cannot reject the null hypothesis of no parental bias. An important advantage of the approach developed in this paper is that the inferences regarding the nature of gender bias and its implications for intergenerational educational mobility pertain to the whole population of interest, not a subset as is usually the case with estimates based on an instrumental variables approach or a regression discontinuity design.

The rest of this paper is organized as follows. In section 2, we develop a theoretical model in the tradition of Becker and Tomes (1986) that incorporates gender bias in both financial investment and nonfinancial inputs by parents, and also gender bias in the labor market (returns to education) and school. The next section provides a discussion on the data sets used for the empirical analysis. Section 4 reports and discusses the estimates of the investment and mobility equations for the urban households, along with an analysis of how the estimated parameters can help sort out the mechanisms driving the observed pattern of educational investment and intergenerational mobility. Section (5) then discusses the corresponding results for the rural households. Section (6) concludes with a summary of the main findings and the methodological contributions of the paper.

(2) Related Literature

The literature on intergenerational mobility in developed countries is well-developed, with many fundamental theoretical and empirical contributions. For excellent surveys of the literature, please see Solon (1999), Black and Devereux (2011), and Bjorklund and Salvanes (2011). The focus of this literature has been on intergenerational (permanent) income persistence, and a lot of effort has been devoted to understanding the biases that arise from measurement error and life-cycle effects. Also, most of the studies deal with father-son linkages, and, as noted above, research on women, and in particular on gender bias is lacking.

In contrast, research on intergenerational economic mobility in developing countries remains relatively neglected. This partly reflects the data constraints. Good quality income data for long enough time periods to calculate permanent income remain rare. As a result, the focus of the research on developing countries has been on intergenerational educational persistence. For a discussion on the methodological challenges and data constraints in research on intergenerational mobility in developing countries, see Emran and Shilpi (2019). Recent surveys of this literature include Iversen et al. (2019), Behrman (2019) and Torche (2019). For cross-country evidence, please see Hertz et al. (2008), Narayan et al. (2018) and Bhalotra and Rawlings (2013). The recent studies on India include Azam and Bhatt (2015), Azam (2016), Emran and Shilpi (2015), Asher et al. (2018), Maitra and Sharma (2010), and Ahsan and Chatterjee (2017). On intergenerational mobility in China, see, among others, Fan et al. (2019), Golley and Kong (2013), Emran and Sun (2015), Gong et al. (2012), Park and Zou (2017), and Knight et al. (2011). Most of the studies on India and China focus on intergenerational schooling persistence based on a linear CEF, but none of them derives the estimating equation from theory.

(3) Sons vs. Daughters: A Model of Gender Bias in Intergenerational Educational Mobility

The economy consists of households with a parent and a child (son denoted by s) or daughter (denoted by d). The parent of child i has schooling H_i^p. Given the education level, the parent's income is determined as follows (similar to the specification adopted by Solon (2004), and Becker et al. (2015)):

$$Y_i^p = Y_0^p + R^p H_i^p \tag{1}$$

Since our empirical work focuses on father's education because of data constraints, in what follows, we couch the discussion in terms of father as the parent. The income determination equation assumes that the fathers with zero year of schooling earn $Y_0^p > 0$, and the return to education is R^p in the parental generation.[10] The assumption that $Y_0^p > 0$ reflects our empirical context where 15-40 percent of fathers have zero year of schooling, but all the households report positive income.

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

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

The budget constraint assumes that there is no credit market where the father can borrow to finance children's education, thus has to pay from his own income. As noted earlier, this is a plausible assumption in the context of developing countries where the student loan market (public or private) is underdeveloped or nonexistent.

Following Becker et al. (2015), we assume that the education production function exhibits three features: (i) diminishing returns to financial investment, (ii) complementarity between the financial investment, and parental education (iii) the direct effect of parent's

[10]We ignore the gender differences in parental income, as our empirical analysis focuses on the effects of father's education due to substantial missing observations on mother's education.

education capturing non-financial aspects such as "cultural capital":

$$H^c = \delta_0 + \delta_1^j I - \delta_2^j I^2 + \delta_3^j H^p - \delta_4^j \left(H^p\right)^2 + \delta_5^j I H^p \tag{3}$$

where $j = s, d$ is the gender index (s for son, and d for daughter). We assume that $\delta_0, \delta_1^j, \delta_3^j > 0$ and $\delta_2^j, \delta_4^j, \delta_5^j \geq 0$. The last inequalities are weak to allow for the possibility that over the relevant range the education production function is approximately linear. The direct effect of parental education can be concave or linear. The direct effect captures nonfinancial aspects of parental influences including home tutoring and role model effects as noted before.[11] When the complementarity effect is ignorable, we have $\delta_5^j = 0$. The intercept term (δ^0) captures the common family and school factors that affect a child's education irrespective of gender and thus is not indexed by j. The slope parameters determining the effects of financial investment are specified as below:

$$\begin{aligned} \delta_1^j &= \delta_1^0 + \gamma_1 q^j + \gamma_2 \phi \\ \delta_2^j &= \delta_2^0 - \omega_1 q^j - \omega_2 \phi \end{aligned} \tag{4}$$

where q denotes the institutional quality such as schools, and ϕ is the ability of a child. The specifications in (4) imply that higher ability and better school quality increase the marginal returns to educational investment by both increasing the linear coefficient δ_i^j and by reducing the degree of diminishing returns through a lower δ_2^j. Note that the ability parameter in the production function is not gender-specific, but the institutional quality depends on gender because of factors such as role model effects of female teachers, school policy on gender bias and its enforcement, and the availability of appropriate infrastructure such as separate restrooms for women, which becomes an important factor for girls, especially after puberty (see the discussion by Adukia (2017) in the context of India). When there are few or no female teachers and no restroom in the school, we would expect $q^d < q^s$. The assumption that ability is not indexed by gender reflects substantial evidence that cognitive ability does not depend on the gender of a child in a systematic manner,

[11]These are part of the family endowment transmission across generations in Becker and Tomes (1979), Becker and Tomes (1986), and Becker (1991).

ceteris paribus.

But it is important to appreciate the distinction between the true ability of a child ϕ and a parent's estimate of a child's ability denoted as $\tilde{\phi}^j$. The investment choices of parents are determined by the estimated ability $\tilde{\phi}^j$, and given an investment level, the actual educational attainment is determined by the true ability of a child ϕ. In societies where son preference is strong, it is likely that the parents would overestimate a son's ability and underestimate a daughter's ability, implying that $\tilde{\phi}^s > \phi > \tilde{\phi}^d$.[12] The expected schooling (denoted as $\tilde{H}^c$) for a given level of financial investment can be written as:

$$\tilde{H}^{cj} = \delta_0 + \tilde{\delta}_1^j I - \tilde{\delta}_2^j I^2 + \delta_3^j H^p - \delta_4^j \left(H^p\right)^2 + \delta_5^j I H^p \tag{5}$$

where $\tilde{\delta}_1^j = \left(\delta_1^0 + \gamma_1 q^j + \gamma_2 \tilde{\phi}^j\right)$ and $\tilde{\delta}_2^j = \left(\delta_2^0 - \omega_1 q^j - \omega_2 \tilde{\phi}^j\right)$ In contrast to the true production function (3), ability is gender specific in equation (5), with $j = s, d$.

The income function for the children is:

$$Y_i^{cj} = Y_0^{cj} + R^{cj} H_i^c \tag{6}$$

The returns to education are gender specific; when return to education is lower for girls, we expect $R^{cs} > R^{cd}$. There is substantial evidence that returns to education in the labor market may be higher for women. In their extensive cross-country study, Psacharopoulos and Patrinos (2018) find that, in about 66 percent cases, returns to education in the labor market are higher for women. Higher returns for girls are also observed in India and China during the 1980s and 1990s (see, for example, the estimates reported by Bargain et al. (2009)).[13] Pitt et al. (2012), and Rosenzweig and Zhang (2013) suggest that the higher

[12] If gender bias in the household is strong enough to systematically discriminate against girls in food and medical care, especially in the early years of a child's life, girls may end up with lower academic ability. There is evidence that the development of a child's brain is significantly affected by socioeconomic conditions (Noble et al. (2015). In this case, the inequality above will reflect both the actual differences in cognitive ability generated by gender bias, and also biased estimate given a certain level of cognitive ability.

[13] The estimated coefficients for the higher secondary schooling in 2002-2004 from the Mincer equation are: 1.09 (women, India), 0.55 (men, India), 0.51 (women, China), and 0.26 (men, China) (see Table A3 in Bargain et al. (2009)). They use CHIP data from China and NSS data for India. Their estimates are at the national level, they do not present separate estimates for rural and urban areas. We discuss the

returns to education for girls reflect women's comparative advantage in skill-intensive occupations as opposed to brawn-intensive occupations and structural change in the economy in favor skill-intensive occupations. However, the evidence also consistently shows that there is a substantial gender wage-gap against the women due to the fact that $Y_0^{cd} < Y_0^{cs}$ in most of the cases. It is well-known in the literature that return to education plays a prominent role in intergenerational educational persistence (Becker (1991), Solon (1999), Solon (2004)). As we will see below, in contrast, the intercept Y_0^{cj} matters much less.[14]

For the main analysis of the mechanisms underlying intergenerational persistence in schooling, we assume that the parents are aware of the fact that the labor market returns are higher for girls. We are not aware of any studies on eliciting parental belief about returns to education for sons vs. daughters in our study countries.[15] In fact, data on what parents state (which may differ from the true belief) when asked about relative returns to education in a survey are also not available in the major data sets we are aware of in India (such as NSS, IHDS, REDS, NHSF) and China (CHIP, CFPS, CHNS). The only data set we are aware of is the Gansu Survey of Children and Families in China. An analysis of the Gansu survey shows that about 55 percent of mothers disagree that returns to education (in terms of higher income) are higher for sons. We also explore the implications of the alternative assumption where parents believe that the returns to education are lower for girls notwithstanding the evidence noted above. This alternative assumption, however, leads to implausible conclusions, as we discuss below in the context of urban India in section (4.1). The consumption sub-utility function of the parent is given by:

$$U\left(C^{p}\right)=\alpha_{1} C^{p}-\alpha_{2}\left(C^{p}\right)^{2} \tag{7}$$

available evidence on rural and urban areas below which is consistent with the national-level results of Bargain et al. (2009).

[14]This refers to educational mobility; the wage gap clearly has important implications for income and poverty.

[15]In a widely-cited study, Jensen (2010) shows that parents in the Dominican Republic underestimate the returns to education, but he does not analyze possible gender differences in parental belief. In a related study in the context of India, Jensen (2012) finds that women's education responds positively to labor market opportunities, providing a basis for the argument that labor market returns are important for parental decisions regarding women's education in India.

(3.1) Optimal Educational Investment

The parent's optimization problem is (denoting the Lagrange multiplier on the budget constraint by λ):

$$Max_{C^p,I} V^p = U\left(C^p\right) + \sigma^j E\left(Y_i^{cj}\right) + \lambda\left[Y_i^p - C_i^p - I_i\right] \tag{8}$$

where σ^j is the degree of parental altruism, and son preference implies that $\sigma^s > \sigma^d$, and parents use production function (5) to estimate the expected income of children $E\left(Y_i^{cj}\right)$.

The first order conditions are:

$$\begin{gathered} \alpha_1 - 2\alpha_2 C^p - \lambda = 0 \\ \sigma^j R^{cj}\left(\tilde{\delta}_1^j - 2\tilde{\delta}_2^j I + \delta_5^j H^p\right) - \lambda = 0 \end{gathered} \tag{9}$$

Using the first order conditions and equations (1) and (2) above, we solve for the optimal investment in a child's education as a function of parental education:

$$I^{*j} = \theta_0^j + \theta_1^j H^P \tag{10}$$

where

$$\theta_0^j = \frac{2\alpha_2 Y_0^p + \tilde{\delta}_1^j \sigma^j R^{cj} - \alpha_1}{2\left\{\alpha_2 + \tilde{\delta}_2^j \sigma^j R^{cj}\right\}} \tag{11}$$

$$\theta_1^j = \frac{2\alpha_2 R^p + \delta_5^j \sigma^j R^{cj}}{2\left\{\alpha_2 + \tilde{\delta}_2^j \sigma^j R^{cj}\right\}} \tag{12}$$

It is important to note some of the implications of equations (11) and (12) which are not well-appreciated in the current literature where linearity is a maintained assumption. As we discuss below, the intergenerational mobility equation is necessarily linear when the education production function is linear ($\delta_2^j = \delta_4^j = \delta_5^j = 0$). In this case, gender bias in the form of pure son preference *(i.e.,* $\sigma^d < \sigma^s$*)*, lower returns to education for girls *(i.e.,* $R^{cd} < R^{cs}$*)*, low estimate of academic ability of girls *(i.e.,* $\tilde{\phi}^d < \tilde{\phi}^s$*)*, and bias against girls in schools *(i.e.,* $q^d < q^s$*)* implies that $\theta_0^d < \theta_0^s$, but $\theta_1^d = \theta_1^s$. The result that such gender bias does not affect the slope parameter is especially striking, and suggests that we should be careful in interpreting the evidence from the investment equation (10) above. Without the benefit of the theory, most researchers would interpret the finding that the data do not reject $\theta_1^d = \theta_1^s$ as evidence against gender bias in educational expenditure. This is compounded by the fact that the focus of the analysis usually is on the slope parameter, and many studies do not report the intercept estimates which should be the focus of an analysis of gender bias if the linear model is correct.

(3.2) Intergenerational Persistence in Education

The optimal education of a child can be written as follows:

$$H^{cj^*} = \delta_0 + \delta_1^j I^{*j} - \delta_2^j \left(I^{*j}\right)^2 + \delta_3^j H^p - \delta_4^j \left(H^p\right)^2 + \delta_5^j I^{*j} H^p \tag{13}$$

where I^* is given by equation (10) above.

Since optimal investment I^* is a linear function of parental education H^p, H^{cj^*} is a quadratic function of parental education H^p even when $\delta_4^j = 0$ and $\delta_5^j = 0$. The estimating equation for intergenerational persistence implied by equation (10) and (13) above is as follows:

$$H^{cj^*} = \psi_0^j + \psi_1^j H^p + \psi_2^j \left(H^p\right)^2 \tag{14}$$

where

$$\psi_0^j = \delta_0 + \theta_0^j \left[\delta_1^j - \delta_2^j \theta_0^j\right]$$
$$\psi_1^j = \theta_1^j \left(\delta_1^j - 2\delta_2^j \theta_0^j\right) + \delta_3^j + \delta_5^j \theta_0^j; \quad \psi_2^j = \theta_1^j \left(\delta_5^j - \delta_2^j \theta_1^j\right) - \delta_4^j$$

(3.3) Sorting Out the Mechanisms

A comparison of the two estimating equations (investment equation (10) and mobility equation (14)) above shows that the parental gender bias in ability estimate and pure son preference are reflected in the parameters of the investment equation, while the estimated mobility parameters are useful in understanding the role played by biases in the direct impact of parents on children's education. As we will see below in the empirical analysis section, both in India and China, the evidence, in general, suggests an important role for the bias arising from direct (nonfinancial) impact of parents through, for example, homework help and role model effects.

The estimated parameters from the investment equation (10) and the mobility equation (14) provide us 5 binary relations, which impose restrictions on the potential explanations, and help sort out the existence and mechanisms of gender bias when combined with information on gender differences in returns to education.[16] In particular, combining information about returns to education with the estimated *intercepts* of the investment equation can help infer whether the parents underestimate a girl's ability and whether girls face constraints in school. This can be seen by considering the intercept as a function of returns to education, i.e., the function $\theta_0^j(R^{cj})$. It is easy to check that $\theta_0^d = \theta_0^s < 0$ when $R^{cd} = R^{cs} = 0$, implying that the intercept of the function $\theta_0^j(R^{cj})$ is negative and does not depend on the gender of a child. As we discuss in the online appendix, $\theta_0^j(R^{cj})$ is an increasing function of returns to schooling, i.e., $\frac{\partial \theta_0^j}{\partial R^{cj}} > 0$ with a horizontal asymptote equal to $\frac{\tilde{\delta}_1^j}{2\tilde{\delta}_2^j}$. More importantly, if $\theta_0^j > 0$, the slope $\frac{\partial \theta_0^j}{\partial R^{cj}}$ is higher when the parents have higher estimate of a child's ability, and/or when the school environment is favorable, i,e, $\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial \tilde{\phi}^j} > 0$, and $\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial q^j} > 0$.[17] The condition that $\theta_0^j > 0$ is satisfied in all the cases we consider below in India and China. The upshot of the above discussion is that when we plot two functions $\theta_0^j(R^{cj})$ for different ability and school quality, the curve corresponding to higher ability estimate and better school must lie above the other curve at each positive value of returns to schooling (see Figures F1.IU and F1.IR below).

When we superimpose the estimates of the intercepts and returns to education in this graph, we can infer whether the upper curve refers to the sons or daughters. For illustration, we consider two cases in (i) Figure F1.IU: $\hat{\theta}_0^d = \hat{\theta}_0^s$, and (ii) Figure F1.IR: $\hat{\theta}_0^d < \hat{\theta}_0^s$. For brevity, we discuss Figure F1.IU in more detail, and leave Figure F1.IR to the readers. In Figure F1.IU, the $\hat{\theta}_0^d = \hat{\theta}_0^s$ curve is drawn as a horizontal line, and it is clear that the returns

[16] It is important to appreciate that the inference about the mechanisms refer to the whole population of interest, rather than a subset.

[17] The effects of pure son preference on $(\frac{\partial \theta_0^j}{\partial R^{cj}})$, however, are not unambiguous without additional restrictions on the curvature of the consumption sub-utility function (α_2).

to education corresponding to the higher $\hat{\theta}_0$ curve must be lower. As discussed in some detail above, returns to education are lower for sons in both India and China which implies that the upper curve must refer to the sons. This implies that if the estimated intercepts of the investment equation do not vary across gender, then the evidence would imply that the parents underestimate a girl's cognitive ability, and/or the girls face significant gender-specific constraints in school.

(3.4) Discussion

Many existing studies on intergenerational educational mobility in developing countries share two features. First, all of the published empirical studies on intergenerational educational mobility we are aware of use a linear intergenerational persistence equation. Second, the implicit theoretical model assumes that the primary source of intergenerational link in educational attainment is financial investment by parents in children's schooling, with special emphasis on the roles of credit constraint and returns to education. Although a primary focus of Becker-Tomes (1979, 1986) model was the implications of optimal parental financial investment on children's education for intergenerational transmission of inequality, they also emphasized the link across generations due to factors such as cultural capital of a family. Following Becker et al. (2015, 2018), the cultural capital is represented by the direct effect of father's education on son's schooling.

The theoretical analysis above clarifies the assumptions implicit in the linear CEF used almost universally in the empirical literature on intergenerational educational mobility. A linear intergenerational persistence equation implies that $\psi_2^j = \theta_1^j \left(\delta_5^j - \delta_2^j \theta_1^j\right) - \delta_4^j = 0$. We have $\psi_2^j = 0$ when there are no diminishing returns or complementarity in the human capital production function; i.e., $\delta_5^j = \delta_2^j = \delta_4^j = 0$. We call this the "linear model", as the CEF is *necessarily* linear in this case. It is easy to check that in the linear model, parental bias against girls irrespective of the form it takes does not affect relative mobility (as measured by intergenerational regression coefficient IGRC), its effects are captured by the intercept of the linear CEF alone. However, we can also have a linear CEF as a special case of the more general quadratic model; this happens when, as a matter of chance, the convexity due to complementarity approximately cancels out the diminishing returns. When estimating intergenerational schooling persistence, significant differences in the IGRCs for sons and daughters ($\hat{\psi}_1^d \neq \hat{\psi}_1^s$) should, in general, be interpreted as evidence that the underlying model is likely to be quadratic, even though the CEF is approximately linear. If the evidence does not reject a linear CEF ($\hat{\psi}_2 = 0$), one would be more confident that this reflects an underlying linear model when the evidence from the investment equation also does not reject constant returns and separability, implying $\theta_1^d = \theta_1^s$. It is unlikely to have $\delta_5^j > 0; \delta_2^j > 0$ and then the different parameter values to align in a way to satisfy $\theta_1^d = \theta_1^s$ along with the conditions that $\psi_2^j = 0$ for $j = d, s$.[18]

When data reject the linear CEF in favor of a quadratic CEF, we do not have a constant relative mobility measure like IGRC; the marginal effect of father's education varies across the education distribution. We call it "intergenerational marginal effect" or IGME for short:

$$IGME(H^p) = \psi_1 + 2\psi_2^j H^p$$

. In the empirical analysis, we will provide estimates of IGME at focal points of father's education distribution: no schooling, primary (5 years in India, and 6 years in China), secondary (9 years in China and 10 years in India), and college (16 years of schooling). We denote the marginal effect for the children born to parents with no schooling as $IGME_0$, and so on. As a measure of absolute mobility, we provide estimates of expected years of schooling conditional on father's schooling at these focal points of father's schooling distribution.[19] The expected years of schooling for the children born to parents with no schooling is denoted as ES_0, and so on. The fathers with no schooling is an important group for our analysis, as the proportion is substantial in our data set, especially in India, and, more important, these are likely to be the poorest of the households.

[18]Note that even with constant returns and no complementarity, we can get $\psi_1^d \neq \psi_1^s$ if girls face significant constraints in the schools.

[19]This definition of absolute mobility is similar to that of Chetty et al. (2014), although the interpretation is somewhat different when the CEF is not linear. There is a different concept of absolute mobility adopted by many authors where the focus is on whether a child attains higher education than his/her parents. For a discussion of the limitations of this concept in empirical application to developing countries where 20-40 percent fathers have no schooling, please see Emran and Shilpi (2019). Equally important, we are not aware of any economic model that yields this alternative empirical specification of absolute mobility.

(4) Data

(4.1) Data for China: CFPS (2016, 2010)

The data for estimating the intergenerational mobility of education in China come from the China Family Panel Study (CFPS)- 2016 wave. In order to match children-parents pairs irrespective of residency status at the time of the survey, we take advantage of the Family Member Module, which has an innovative T-Tables design feature. As discussed in Xie and Hu (2014), the T-Tables in CFPS consist of three tables - T1, T2, and T3. Table T1 (on family members living together) and Table T2 (on immediate relatives not living together) record the basic socio-demographic characteristics of every family member and her immediate relatives (parents, children and spouses) who are not living with them. Table T2 (on relations) identifies the relations of all the family members and the corresponding relations between T1 and T3 members. Therefore, three tables jointly present a complete family network, and most importantly, allow us to avoid truncation of the sample.

More specifically, in order to identify all the children-fathers pairs, we take the following steps. For each individual currently living in the family, own education and father's education are directly available in the Family Member module irrespective of whether the father is coresident at the time of the survey. This subsumes two cases involving three generations. (i) If such an individual is the household head (or head's spouse) who lives in the family, their parents are matched, irrespective of whether they are co-resident or not. (ii) If such an individual is household head's (or head's spouse's) child, who lives in the family, the child's parents are of course matched, i.e. they are household head and head's spouse. However, step 1 misses the following case: if household head's (or head's spouse's) child is currently living outside. An important advantage of the CFPS survey is that it collected data on such nonresident children. In the second step, we include these nonresident children in the sample. Our estimation sample thus includes both the nonresident parents of household head and spouse, and also their nonresident children.

The summary statistics for various estimation samples are reported in Table T1.U for the urban households and Table T1.R for the rural households; the upper panel in each table corresponds to China, and the bottom panel to India. For China, the main estimation sample for the analysis of intergenerational mobility consists of children 18-35 years of age in 2016, and the estimation samples for the investment equation are 6-22 and 8-23 years in the 2010 round of the panel. This age range is chosen so that the age cohorts in the investment equation have substantial overlap with the age cohorts in the mobility analysis. In CFPS-2016 for the 18-35 age cohorts, the mean schooling of fathers is 7.65 in the sons sub-sample and 7.67 in the daughters sub-sample in the urban areas according to Table T1.U. The average schooling of sons is 11.17 years, and 11.18 years for daughters. However, there is a gender gap in the average schooling attainment in rural China: 9.2 (sons) years and 8.7 (daughters) (see Table T1.R, upper panel). The average education expenditure is *higher for daughters* in the urban estimation samples, but favors the sons in the rural samples.

(4.2) Data for India: IHDS (2012, 2005) and NSS (1995)

The data for estimating the intergenerational mobility of education in India come from the India Human Development Survey (IHDS)-2012. The construction of matched children and parents pairs are slightly different between sons and daughters. To generate matched son-father pairs, we follow Azam and Bhatt (2015) closely (see the Table 8 in Azam and Bhatt (2015)). The only difference is that we are using wave 2 (2012) while Azam and Bhatt (2015) use wave 1 (2005) of IHDS panel data. For all household heads, their father's education information is available directly in the household module, irrespective of a father's residency status at the time of the survey. The comparison between our sample using IHDS-2012 to Azam and Bhatt's sample using IHDS-2005 is documented in the online appendix Table A1.S. To generate matched daughter-father pairs, we follow Azam (2016) closely (see the Table 1 in Azam (2016)). Since Azam (2016) also use IHDS-2012 data, we can compare our sample precisely, as shown in the online appendix Table A1.D.

The summary statistics for our various estimation samples for IHDS-2012 (for intergenerational mobility estimation), and IHDS-2005 and NSS-1995 (for estimation of the investment equation) are reported in the lower panels of Tables T1.U (for the urban plus rural sample), T1.R (for rural sample). The mean education of fathers in urban areas is 6.64 years in the sons sub-sample, and 6.44 years in the daughters sub-sample of the main estimation sample for intergenerational mobility (18-35 year old children in 2012). The average schooling is 10 years for sons and 9.36 for daughters. In the rural sample, the average education of fathers is much lower; 3.90 years (sons sub-sample) and 3.83 (daughters sub-sample). The gender gap in average schooling is also much more pronounced in the rural areas; 8.13 years (sons) vs. 6.24 years (daughters). The average educational expenditure in IHDS-2005 is higher for sons and it is true irrespective of geographic location and for both the estimation samples (6-22 year old) and (8-23 year old). The bias in educational expenditure against girls is also observed in the NSS-1995 data.

(5) Empirical Results

The empirical estimates of the mobility and investment equations discussed below report robust standard errors. However, we also estimate the standard errors clustering at different levels: district and state levels for India, and county (only for investment) and province levels for China. We cannot cluster the standard errors at the county level for the mobility estimates for China, as the county location is not available for the non-resident members of a household. The estimated clustered standard errors are reported in the online appendix. All the main conclusions based on the robust standard errors, however, remain intact when we use clustered standard errors instead. If and when clustering makes a difference in inference, we will note that in the following discussion.

(5.I) Intergenerational Mobility in India: Evidence and Interpretations

(5.I.1) Urban India

The estimates of the effects of father's schooling on children's schooling in urban India are reported in the upper panel of Table T2.IU.[20] The first two columns contain the evidence from a linear CEF which provides estimates comparable to the existing literature where linearity is a maintained assumption. The IGRC estimate is higher for the daughters, suggesting that the daughters face significantly lower relative mobility in urban India.

Although almost all of the existing studies on India focus primarily (or exclusively) on relative mobility, it has been emphasized in the recent literature that inter-group analysis of

[20]The table numbers are indexed by country and location. For example, T2.IU stands for Table 2 for the Indian Urban sample, and so on.

intergenerational mobility based solely on relative mobility can be misleading, as different groups may be converging to different steady states defined in part by the intercept term (Hertz (2005), Mazumder (2014), Torche (2015a), Emran et al. (2020), Emran and Shilpi (2019)). The estimates for the linear CEF show that the intercept for the daughters is lower. The daughters attain lower education than the sons when the father has less than 16 years of schooling, but the gender advantage flips in favor of girls for the children of the fathers with higher education.

The estimates from a linear CEF provide suggestive evidence in favor of the widely-held notion of strong gender bias against girls in India. However, the evidence rejects the assumption of linearity; the estimates of the quadratic term in columns (4) (for sons) and (5) (for daughters) in Table T2.IU are negative and statistically significant at the 1 percent level. The quadratic coefficient is numerically larger for the daughters, but the difference is not statistically significant at the 10 percent level. Consistent with the econometric evidence, the nonparametric LOWESS plots of son's and daughter's schooling against father's schooling in urban India suggest a concave relation (see Figure F2.IU). The evidence that the CEF is concave implies that we cannot reject the null hypothesis: $\delta_5 = 0$, suggesting the absence of any significant complementarity between father's education and financial investment in urban India.

The estimated quadratic CEFs using the coefficients in Table T2.IU are plotted in Figure F3.IU and show that the expected schooling attainment conditional on father's education is higher for sons, except at the right tail of the distribution of father's schooling. As a measure of absolute mobility, we report estimated expected years of schooling conditional on a father having 0, 5, 10 and 16 years of schooling in the bottom panel of Table T2.IU. The daughters born to low educated fathers face significant disadvantage in term of expected schooling attainment (the ES_0 estimates are: 5.8 (daughters) vs. 6.8 (sons)), but there is no gender difference when the father has college education (the ES_{16} estimate is 13.8 for both daughters and sons).[21]

For relative mobility, the estimated $IGMEs$ in the bottom panel of Table T2.IU show

[21] The ES_0 estimates refer to the children of fathers with zero years of schooling. The proportion of fathers with zero schooling in urban India is 24 percent in our data.

that the persistence is much stronger for the girls born to fathers with low education ($IGME_0$ estimates are: 0.65 (daughters) vs. 0.55 (sons)), but, again, the gender difference becomes negligible when the father has college or more education: ($IGME_{16}$ estimates are: 0.33 (sons) vs. 0.35 (daughters)). Please see Figure F4.IU. The evidence on absolute and relative mobility thus favors the idea that gender difference in educational attainment may primarily be a product of low education (and thus low permanent income) of parents. This also brings into focus the incorrect conclusions from the standard linear CEF that the daughters face less relative mobility throughout the parental schooling distribution. A researcher focused exclusively on the linear CEF would completely miss the gender convergence in relative mobility at the right tail of father's schooling distribution.

Sources of Gender Bias

The extended Becker-Tomes model in section (2) above highlights parental educational investment as a major mechanism through which inequality persists across generations. Thus, it is informative to look first at the estimates of the investment equation to understand the economic mechanisms at play. The estimates of θ_0 and θ_1 for urban India are reported in Table T3.IU, using IHDS 2005 and NSS 1995 data. We report estimates for two age groups of children for each data set to ensure robustness of the conclusions.[22]

The evidence suggests strongly that $\hat{\theta}_1^d < \hat{\theta}_1^s$; the interaction of father's education with the daughter dummy is negative across the board, and is statistically significant at the 10 percent or lower level in 7 out of 8 cases.[23] The estimates for the intercept shows a contrasting picture: the daughter dummy is *not* statistically significant at the 10 percent level in 6 out of 8 cases. The evidence cannot reject the null hypothesis that $\hat{\theta}_0^d = \hat{\theta}_0^s$.

[22]We also used other age groups for estimating the investment equation. The conclusions reached in this paper are robust to such alternative age samples.

[23]This is consistent with the existing evidence on gender bias against girls in educational expenditure in India (see Kingdon (2007), Azam and Kingdon (2013)). Azam and Kingdon (2013) find significant pro-male bias for the 10 years or older children, using the IHDS 2005 data. They point out that the focus on educational expenditure misses substantial gender bias against girls in terms of schooling continuation decisions. When gender bias manifests as early drop-out of daughters from school, this is captured by lower educational attainment in our data. Datta and Kingdon (2019) use 1995 and 2014 NSS data and find that the role played by gender bias in educational expenditure (the intensive margin) has increased substantially over time in India. *Note, however, that the existing evidence while suggestive does not provide estimates of the effects of father's education on children's educational expenditure, which is the focus of the investment equation in intergenerational mobility analysis.*

The estimates for the educational investment equation and the quadratic intergenerational persistence equation can be summarized as the following binary relations (denoting an estimated parameter with a hat):

$$MOBILITY \qquad \begin{array}{l} \hat{\psi}_0^d < \hat{\psi}_0^s; \quad \hat{\psi}_1^d > \hat{\psi}_1^s \\ \hat{\psi}_2^d = \hat{\psi}_2^s; \quad \hat{\psi}_2^d, \hat{\psi}_2^s < 0 \end{array} \tag{15}$$

$$INVESTMENT \qquad \hat{\theta}_1^d < \hat{\theta}_1^s \quad \hat{\theta}_0^d = \hat{\theta}_0^s \tag{16}$$

These binary relations impose restrictions on plausible explanations for the observed differences between the sons and the daughters. We combine these with the evidence on gender differences in returns to education to understand the role played by different forms of gender bias discussed in the theoretical section.

Interpreting the Evidence: The Investment Equation

As noted earlier, the evidence on functional form fails to reject the null hypothesis that $\delta_5 = 0$ in urban India, and we trace out the implications of the binary relations in (16) above with this restriction imposed. However, some of important conclusions regarding the mechanisms of gender bias discussed below hold irrespective of whether $\delta_5 = 0$. Using equation (12) from the theoretical model, $\hat{\theta}_1^d < \hat{\theta}_1^s$ implies the following inequality:

$$\tilde{\delta}_2^d \sigma^d R^{cd} > \tilde{\delta}_2^s \sigma^s R^{cs} \tag{17}$$

A substantial body of evidence suggests that, in urban India, the returns to education in the labor market are higher for daughters, especially at the secondary and higher secondary levels (see Duraisamy (2002), Aslam et al. (2010)).[24] For a summary of the available

[24] However, there is also substantial evidence that educated women, especially married women, withdraw from the labor market and devote to home production such as child care and home tutoring (Afridi et al. (2018)). This may partly reflect the fact that there is a significant gender wage gap against women in the labor market, even though the Mincerian returns are higher, reflecting a low intercept for women. Moreover, the expected returns to education for daughters R^{cd} capture both labor market and non-market returns (expressed in shadow prices), including the returns in the marriage market, and from home production, for example, in the form of higher quality grand children. If educated women withdraw from the labor market even though the returns are higher than those of men, it implies that the shadow returns from

estimates of returns to education in urban India, please see the first two columns of Table T4.I. We focus on the returns to education at secondary (10 years of schooling) and higher secondary (12 years of schooling) levels, given that the average education in urban India in our data set is 9.93 years for the sons, and 9.43 years for the daughters.[25] Since $R^{cd} > R^{cs}$, inequality (17) is satisfied even if we assume that $\tilde{\delta}_2^d \sigma^d = \tilde{\delta}_2^s \sigma^s$. Clearly, this last equality is consistent with no gender bias by the parents.

Turning to the intercept estimates from the investment equation, the theory implies the following relation:

$$\frac{2\alpha_2 Y_0^p + \tilde{\delta}_1^d \sigma^d R^{cd} - \alpha_1}{2\left\{\alpha_2 + \tilde{\delta}_2^d \sigma^d R^{cd}\right\}} = \frac{2\alpha_2 Y_0^p + \tilde{\delta}_1^s \sigma^s R^{cs} - \alpha_1}{2\left\{\alpha_2 + \tilde{\delta}_2^s \sigma^s R^{cs}\right\}} \tag{18}$$

An immediate observation is that it is not possible to satisfy (18) if there are no gender biases (i.e, if $\tilde{\delta}_1^d = \tilde{\delta}_1^s$, $\tilde{\delta}_2^d = \tilde{\delta}_2^s$, and $\sigma^d = \sigma^s$), because $R^{cd} > R^{cs}$.

The fact that there is no significant difference in the intercepts implies that urban India corresponds to the case depicted in Figure F1.IU in section 2.3 above. An inspection of Figure F1.IU shows that the returns to education must be smaller for the curve with higher ($\tilde{\phi}^j unexpected'' inmath$) and ($q^j$). Since the returns to education is smaller for the sons (see Table T4.I), the higher curve must refer to the sons, implying that the parents have systematically higher ability estimates for the sons, and/or the girls face substantial hurdles in the schools. It is important to note that these conclusions hold irrespective of the value of δ_5.

The above analysis of the mechanisms of gender bias in the observed educational investment in urban India is based on the assumption that the parents are aware of the fact that returns to education are, in fact, higher for the daughters. One might wonder what are the implications of the alternative assumption that, despite the evidence, the parents believe that the returns from education are lower for daughters. If $R^{cd} < R^{cs}$, then an

non-market sources are even higher. Thus the expected total returns for women are likely to be higher than that suggested by the estimates of labor market returns.

[25]Most of the estimates of returns to education in India are based on NSS data, which do not provide years of schooling information, only the highest completed level (primary, secondary etc).

analysis based on Figure 3.IU suggests the following conclusions: (i) parents believe that the daughters have more academic ability, and (ii) the daughters enjoy a more favorable school environment. When we combine these with the evidence above that $\hat{\theta}_1^d > \hat{\theta}_1^s$, we get the conclusion that the parents must hold pure daughter preference. All these conclusions seem implausible given the accumulated evidence on gender bias against girls in India in the economics and sociology literature.

The discussion above suggests that the evidence on the functional form of the mobility equation, returns to education, and the investment equation taken together cannot reject the following joint null hypothesis: (i) complementarity between financial investment and father's education is not important in urban India, i.e., $\delta_5 = 0$, (ii) parents systematically underestimate the ability of daughters, and (iii) the daughters face unfavorable school environment. In what follows, we confront the estimates from the mobility equation to check whether this set of null hypotheses is sufficient to explain the pattern of the inequalities in (15) above.

Learning about Gender Bias: The Intergenerational Mobility Equation

We begin with the estimates of the quadratic coefficients. When interpreted in terms of the theoretical analysis of section (2.2) above, $\hat{\psi}_2^d = \hat{\psi}_2^s$ implies the following:

$$\delta_2^d \left(\hat{\theta}_1^d\right)^2 + \delta_4^d = \delta_2^s \left(\hat{\theta}_1^s\right)^2 + \delta_4^s \tag{19}$$

From the estimates of the investment equation, we know that $\hat{\theta}_1^d < \hat{\theta}_1^s$, which implies that equation (19) cannot be satisfied without some form of bias against daughters that works through either δ_2 and/or δ_4. It is important to recognize that δ_2 and δ_4 are the parameters of the "true" production function, and thus do not depend on parental bias, but are affected by bias in the school. However, unfavorable school environment found earlier does not help satisfy equation (19). This follows from the observation that, starting at no bias, i.e., $\left(q^d = q^s = q\right)$, a lower school quality for the girls $\left(q^d < q\right)$ reduces the value of $\delta_2^d \left(\hat{\theta}_1^d\right)^2$, while a higher school quality for the boys $(q^s > q)$ increases $\delta_2^s \left(\hat{\theta}_1^s\right)^2$. The upshot of the above discussion is that, to satisfy equation (19), we need gender bias in the form of $\delta_4^d > \delta_4^s$, implying that the diminishing returns to the direct effect of father's education are stronger for daughters. Recalling that the evidence earlier also suggests stronger diminishing returns to financial investment for daughters, the daughters in urban India thus seem to face stronger diminishing returns at double margins.

We next turn to the implications of the inequality $\hat{\psi}_1^d > \hat{\psi}_1^s$. From the theory in section (2.2), this inequality implies the following (with $\delta_5 = 0$):

$$\hat{\theta}_1^d \left(\delta_1^d - 2\delta_2^d \hat{\theta}_0^d\right) + \delta_3^d > \hat{\theta}_1^s \left(\delta_1^s - 2\delta_2^s \hat{\theta}_0^s\right) + \delta_3^s \tag{20}$$

According to the educational investment estimates discussed above, $\hat{\theta}_1^d < \hat{\theta}_1^s$ and $\hat{\theta}_0^d = \hat{\theta}_0^s$. Again, it is important to keep in mind that δ_1^d and δ_2^d are parameters of the true production function. The evidence on the investment equation discussed above shows that the girls face unfavorable school environment, i.e., $q^d < q^s$, implying that $\delta_1^d < \delta_1^s$ and $\delta_2^d > \delta_2^s$. This implies that $\hat{\theta}_1^d \left(\delta_1^d - 2\delta_2^d \hat{\theta}_0^d\right) < \hat{\theta}_1^s \left(\delta_1^s - 2\delta_2^s \hat{\theta}_0^s\right)$. It is thus necessary to have $\delta_3^d > \delta_3^s$ for inequality (20) to hold. When considered along with the evidence earlier that $\delta_4^d > \delta_4^s$, this suggests that the *marginal direct effect* of father's education $\left(\delta_3^j - 2\delta_4^j H^p\right)$ is higher for the daughters of fathers with low education, but lower when father's education is high enough.

Since $\hat{\theta}_0^d = \hat{\theta}_0^s$, the inequality of intercepts of the mobility equation, i.e., $\hat{\psi}_0^d < \hat{\psi}_0^s$ implies the following (denote the common value by $\hat{\theta}_0^c$):

$$\hat{\theta}_0^c \left[\delta_1^d - \delta_1^s\right] < \left(\hat{\theta}_0^c\right)^2 \left[\delta_2^d - \delta_2^s\right] \tag{21}$$

It is easy to check that bias in the school against girls found earlier i.e., $\left(q^d < q^s\right)$, is necessary and sufficient for inequality (21) to hold.

(5.I.2) Rural India

The estimates of intergenerational persistence in schooling in rural India are reported in Table T2.IR. The pattern of estimates from the linear CEF is similar to that in urban India; the IGRC estimate is larger for the daughters implying lower relative mobility, while the intercept is smaller. A comparison with the estimates for urban India shows that the IGRC estimates do not vary significantly across rural vs. urban areas, but the intercept for girls in rural areas is substantially lower. Also, the difference in the intercepts between sons and daughters is larger in rural areas, a 50 percent higher intercept for the sons, compared to only a 16 percent higher intercept in the urban areas. Although useful as a benchmark comparable to the existing estimates in the literature, these preliminary estimates are, however, contingent on the maintained assumption that the CEF is linear.

The estimates from the quadratic specification for rural India show that the coefficient of the quadratic term is statistically significant at the 1 percent level, for both the sons and the daughters, providing clear evidence that the null hypothesis of a linear CEF is rejected. The estimated quadratic coefficient is negative, suggesting that both the CEFs are concave, similar to what we observed in urban India (see also the Lowess plots in Figure F2.IR). However, there is an important gender difference between the urban and rural India; the degree of concavity is similar for sons irrespective of location (the estimate of the quadratic coefficient is -0.007 in both rural and urban samples), but the quadratic coefficient is substantially larger in magnitude for daughters in rural areas. In fact, the null hypothesis of equality of quadratic coefficients can be rejected in rural India at the 1 percent level, indicating that the girls face especially strong forces of diminishing returns in the villages.

The estimates of mobility in the bottom panel of Table T2.IR show that the girls face lower mobility, both in terms of absolute and relative measures, when they are born to low educated parents. The expected years of schooling remains consistently lower for girls, even when the father has college education; a girl growing up in rural India can expect a year less schooling on average. For the lowest educated households, the gender gap is almost 2 years of expected schooling. The estimates of relative mobility show that the intergenerational persistence is substantially higher for the daughters born into households with low educated fathers (compare the $IGME_0$ estimate of 0.52 (sons) with 0.64 (daughters)).[26] The gender difference in $IGME$, however, becomes negligible for the households with highly educated fathers (college educated). Please see Figure F4.IR.

Sources of Gender Bias in Rural India

The estimates of the parameters of the educational investment in Table T3.IR show that

[26] About 40 percent of fathers in rural India in our data have zero schooling.

the daughters receive significantly less educational investment in rural India; the daughter dummy is negative and statistically significant at the 10 percent or lower levels, implying that $\hat{\theta}_0^d < \hat{\theta}_0^s$. The evidence is robust across alternative data sets (IHDS 2005 and NSS 1995) and consistent with existing evidence in the context of India (Azam and Kingdon (2013)).[27]

The evidence on the marginal effect of father's higher education in Table T3.IR also suggests a smaller effect for girls; the interaction of the daughter dummy with father's schooling is negative, and significant at the 10 percent level in 5 out of 8 cases. However, the evidence is weaker than that in urban India, because only one of the estimates is significant at the 5 percent level, and the magnitude of the interaction effect is also smaller.[28] Moreover, the interaction is significant only in 4 cases when we use standard errors clustered at the district level (see Table A3.IR in online appendix).

Putting together the estimates of investment equation with those from the intergenerational mobility equation, we have the following binary relations in rural India:

$$MOBILITY \qquad \begin{array}{c} \hat{\psi}_0^d < \hat{\psi}_0^s; \qquad \hat{\psi}_1^d > \hat{\psi}_1^s \\ \left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|; \quad \hat{\psi}_2^d < 0, \hat{\psi}_2^s < 0 \end{array} \tag{22}$$

$$INVESTMENT \qquad \hat{\theta}_1^d \leqq \hat{\theta}_1^s \quad \hat{\theta}_0^d < \hat{\theta}_0^s \tag{23}$$

Since the CEF is concave for both sons and daughters, we cannot reject the null hypothesis that $\delta_5 = 0$. In what follows, the discussion assumes that this restriction holds.

Implications of the Investment Equation Estimates

We first consider the evidence on the slope of the investment function. Given the uncertainty regarding the evidence discussed above ($\hat{\theta}_1^d \leqq \hat{\theta}_1^s$), the inference regarding gender bias depends critically on one's interpretation. If one interprets the evidence as a lower slope for the girls (i.e., $\hat{\theta}_1^d < \hat{\theta}_1^s$), then we have exactly the same results as in urban India, and as

[27]Azam and Kingdon (2013) show that the gender bias against girls in education expenditure is larger in rural areas in India. We, however, restate the caveat that the existing evidence does not relate to the question of how educational expenditure varies with the education of a father.

[28]In urban India, the interaction effect is significant at the 1 percent level in 2 cases, and at the 5 percent level in 4 cases.

noted before, the slope estimates are consistent with no parental bias because returns to education are higher for girls (see Table T4.I for the evidence on returns to education in rural India).[29] In contrast, if the conclusion is that there is no strong evidence of difference in the marginal effect of father's education across gender of children, then we have $\hat{\theta}_1^d = \hat{\theta}_1^s$. This, in turn, implies $\tilde{\delta}_2^d \sigma^d R^{cd} = \tilde{\delta}_2^s \sigma^s R^{cs}$. Since $R^{cd} > R^{cs}$, we must have $\tilde{\delta}_2^d \sigma^d < \tilde{\delta}_2^s \sigma^s$. Observe that if parents underestimate a girls ability, we have $\tilde{\delta}_2^d > \tilde{\delta}_2^s$, and we can have $\tilde{\delta}_2^d \sigma^d < \tilde{\delta}_2^s \sigma^s$ only if there is pure son preference, i.e., $\sigma^d < \sigma^s$. We discuss below that the evidence on the intercepts is consistent with parents underestimating a daughter's academic ability.

$R^{cd} > R^{cs}$ when combined with $\hat{\theta}_0^d < \hat{\theta}_0^s$ provide evidence consistent with parents underestimating ability of a daughter, and girls facing constraints in the school. This case is depicted in Figure F1.IR in section 2.3 above. An inspection of the graph makes it clear that it is not possible have $\hat{\theta}_0^d < \hat{\theta}_0^s$ with $R^{cd} > R^{cs}$, if the upper curve in Figure F1.IR refers to the daughters. The evidence is consistent with only the case where the upper curve refers to sons, implying gender bias against girls in the form of lower ability estimate and/or unfavorable school environment.[30]

Implications of the Intergenerational Mobility Estimates

With $\delta_5 = 0$, the evidence that $\left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|$ implies the following inequality: $\delta_2^d \left(\hat{\theta}_1^d\right)^2 + \delta_4^d > \delta_2^s \left(\hat{\theta}_1^s\right)^2 + \delta_4^s$. From the estimates of the investment equation and the discussion above, we know that $\delta_2^d > \delta_2^s$ because of the constraints girls face in the school. Since the case with $\hat{\theta}_1^d < \hat{\theta}_1^s$ was discussed at length for urban India, here we focus on the case when $\hat{\theta}_1^d = \hat{\theta}_1^s$. In this case, the inequality above is satisfied without imposing any restrictions on the relative magnitudes of the parameters δ_4^d and δ_4^s. Similarly, it is easy to check that the inequality $\hat{\psi}_1^d > \hat{\psi}_1^s$ also is not useful to sort out the role of different mechanisms of gender bias.[31] Since $\hat{\theta}_0^d < \hat{\theta}_0^s$ and $\delta_2^d > \delta_2^s$, a sufficient condition for $\hat{\psi}_0^d < \hat{\psi}_0^s$ to hold is that $\delta_1^s > \delta_1^d$

[29] Again, if we assume that the parents are not aware of the fact that returns are higher for girls, and believe the opposite, then the evidence from the investment equation implies implausible conclusions such as parents have pure daughter preference in rural India.

[30] If the parents believe that the returns to education are in fact lower for girls, then it implies that the parents underestimate the ability of boys, and also that boys face gender-based constraints in the school.

[31] This follows from the observation that $\theta_0^d \theta_1^d < \theta_0^s \theta_1^s$ but $\delta_2^d > \delta_2^s$.

but it is not necessary. From the evidence in the immediately preceding section, we know that $\left(q^d < q^s\right)$ which implies $\delta_1^s > \delta_1^d$.

(5.C) Intergenerational Mobility in China: Evidence and Interpretations

(5.C.1) Urban China

The estimates of the effects of father's schooling on children's schooling in urban China are reported in Table T2.CU. The estimates for the linear CEF show that, similar to urban India, the intercept is lower for girls but the IGRC estimate is larger. With linearity a maintained assumption, the evidence thus suggests that the girls face lower relative mobility in urban China, but the expected level of schooling is, in fact, higher for girls when father's education is higher than 7 years of schooling.

The evidence on the null hypothesis of a linear CEF shows that it is a good approximation for the daughters in urban China, but not for the sons. The estimates in Table T2.CU show that, for sons, the quadratic term is statistically significant at the 1 percent level, and perhaps more strikingly, it bears a *positive* sign, implying that the CEF of sons' schooling is *convex*. The convexity is also apparent in the Lowess plot (please see Figure F2.CU). The evidence on functional form in urban China is thus different from the concave CEF found earlier in urban India. The estimated convex CEF using the coefficients in Table T2.CU for sons is plotted in Figure F3.CU along with the linear CEF for the daughters. The CEF plots show very different pattern of mobility when compared to the urban India case; the sons born to fathers at the tails of the schooling distribution enjoy higher expected years of schooling, while the daughters have a slight advantage in the middle of the distribution. This is reflected in the absolute mobility estimates in the bottom panel of Table T2.CU.

The relative mobility estimates in the bottom panel of Table T2.CU show a large gender difference in terms of magnitude. The intergenerational persistence is very low for the sons born to fathers with no schooling (0.09), but the daughters face much higher persistence (0.35). The pattern flips when the fathers have more than 9 years of schooling (junior secondary). The IGME estimate for sons is 0.56 when the father has college education (16 years schooling), while IGME remains the same (0.35) for daughters given the linear CEF. Please see Figure F4.CU. This is in sharp contrast to urban India where the gender difference in educational persistence becomes negligible for the most educated parents.

Sources of Gender Differences in Urban China

To understand the role played by parental financial investment in children's education, we utilize the data from the first round of the CFPS survey (2010) to estimate the parameters of the investment equation (i.e., equation (10) above) in Table T3.CU and test the equality of the coefficients across gender. The evidence in Table T3.CU is clear that parental financial investment in schooling does not depend on the gender of a child; we cannot reject the null hypothesis that $\theta_0^d = \theta_0^s$ and $\theta_1^d = \theta_1^s$. These conclusions are consistent with the other existing evidence (see, for example, Tsui and Rich (2002)).

The estimates of the parameters of the investment function and the estimates of the mobility equation discussed above can be summarized in the following binary relations for sons vs. daughters:

$$MOBILITY \qquad \begin{array}{ll} \hat{\psi}_0^d < \hat{\psi}_0^s; & \hat{\psi}_1^d > \hat{\psi}_1^s \\ \hat{\psi}_2^d < \hat{\psi}_2^s; & \hat{\psi}_2^d = 0, \hat{\psi}_2^s > 0 \end{array} \tag{24}$$

$$INVESTMENT \qquad \hat{\theta}_1^d = \hat{\theta}_1^s \quad \hat{\theta}_0^d = \hat{\theta}_0^s \tag{25}$$

We first look at the implications of the evidence on the functional form of the intergenerational schooling persistence regressions. The evidence of convexity in the case of sons (i.e., $\hat{\psi}_2^s > 0$) implies that we can reject the null hypothesis of $\delta_5^s = 0$ in favor of $\delta_5^s > 0$. This is interesting evidence for the Becker et al. (2015, 2018) hypothesis that higher educated fathers are more efficient in financial investment in education.[32] The linearity of the CEF for the daughters, however, cannot be interpreted as evidence in favor of the linear model. With $\delta_5^s > 0$, it is difficult to satisfy $\hat{\theta}_1^d = \hat{\theta}_1^s$ if $\delta_5^d = 0$.

Learning from the Investment Equation

Two pieces of evidence in urban China are similar to that in urban India: (i) the returns to education are higher for girls (see Table T4.C), and (ii) $\hat{\theta}_0^d = \hat{\theta}_0^s$. As discussed in section

[32] We are not aware of any other analysis of intergenerational educational persistence that provides such evidence in favor of the Becker et al. (2015, 2018) convexity hypothesis in a developing country.

(4.1) above, these together imply that parents underestimate a daughter's academic ability $\left(\tilde{\phi}^d < \tilde{\phi}^s\right)$, and the daughter's also face disadvantages in the school $\left(q^d < q^s\right)$.[33]

However, the evidence that $\hat{\theta}_1^d = \hat{\theta}_1^s$ does not add to our understanding without bringing in additional restrictions imposed by the estimates of the parameters of the intergenerational mobility equation. This is because, in contrast to urban India, the evidence on functional form of the CEFs reject the null hypothesis that $\delta_5 = 0$.[34] So we turn to the evidence from the intergenerational mobility equation below to see if that helps narrow down the possible explanations.

Learning from the Intergenerational Mobility Equation

Since $\hat{\theta}_1^d = \hat{\theta}_1^s$, the evidence that $\hat{\psi}_2^d < \hat{\psi}_2^s$ implies the following inequality (denoting the common value of θ_1^j by θ_1^c):

$$\left(\delta_4^s - \delta_4^d\right) < \theta_1^c \left(\delta_5^s - \delta_5^d\right) + \left(\theta_1^c\right)^2 \left(\delta_2^d - \delta_2^s\right) \tag{26}$$

Now, note that $\left(q^d < q^s\right)$ imply that $\left(\delta_2^d - \delta_2^s\right) > 0$, and from the functional form evidence we know that $\left(\delta_5^s - \delta_5^d\right) > 0$. So a sufficient condition for inequality (24) to be valid is that $\left(\delta_4^s - \delta_4^d\right) \leq 0$, but it is not necessary. This is in contrast to the evidence on urban India where it is necessary that $\left(\delta_4^s - \delta_4^d\right) < 0$.

Next, we consider the evidence $\hat{\psi}_1^d > \hat{\psi}_1^s$ which implies the following inequality when combined with the evidence that $\hat{\theta}_1^d = \hat{\theta}_1^s$ and $\hat{\theta}_0^d = \hat{\theta}_0^s$:

$$\left(\delta_3^d - \delta_3^s\right) > \theta_1^c \left(\delta_1^s - \delta_1^d\right) + 2\theta_0^c\theta_1^c \left(\delta_2^d - \delta_2^s\right) \tag{27}$$

A necessary condition for inequality (25) to be satisfied is that $\delta_3^d > \delta_3^s$ because when $\left(q^d < q^s\right)$ we have $\left(\delta_1^s - \delta_1^d\right) > 0$ and $\left(\delta_2^d - \delta_2^s\right) > 0$. This is similar to what we found earlier for urban India.[35]

[33] The implication of the alternative assumption about parental belief regarding returns to education are also the same.

[34] Note that with $\delta_5 > 0$, we cannot sign the slope of the $\hat{\theta}_1^j(R^{cj})$ function.

[35] But, unlike urban India, we cannot determine whether the *marginal direct effect* of father's education $\left(\delta_3^j - 2\delta_4^j H^p\right)$ is higher for daughters with low educated fathers because the evidence does not pin down the sign of $\left(\delta_4^s - \delta_4^d\right)$ in the case of urban China.

Finally, the inequality of the intercepts of the mobility regressions implies the following for urban China:

$$\left(\delta_1^d - \theta_0^c \delta_2^d\right) < \left(\delta_1^s - \theta_0^c \delta_2^s\right) \tag{28}$$

This is similar to what we had before for urban India, and as noted earlier, inequality (26) is satisfied when the daughters face gender-based constraints at the school, i.e., $\left(q^d < q^s\right)$.

(5.C.2) Rural China

The estimates for intergenerational persistence in schooling in rural China are presented in Table T2.CR. The first striking thing to notice is that the evidence on the functional form cannot reject the null hypothesis of linearity for both the sons and the daughters; this is in contrast to the other three cases we considered above in sections (4.1), (4.2) and (5.1). However, note that the linear CEF estimates show substantial difference in the IGRC of sons and daughters; the daughters face higher intergenerational persistence in schooling. As discussed in section (2.3) above, the estimated CEF can be approximately linear even if the underlying model is a quadratic one. Following the discussion in section (2.1), we can check the plausibility of the linear model with evidence from the investment equation: by testing whether the null hypothesis that $\theta_1^d = \theta_1^s$ is rejected by the data. The evidence on the investment equation parameters in Table T3.CR suggests that the null hypothesis cannot be rejected at the 5 percent level. This is also consistent with other available evidence on the lack of any significant gender differences in educational investment in the economic and sociology literature on rural China (Hannum et al. (2009)). Taken together, the evidence from the investment and mobility equations thus suggests that the linear model provides a plausible characterization of the data in rural China.

Given a linear CEF, the estimate of relative mobility does not vary across the distribution of parental schooling (Figure F4.CR): the IGRC is 0.27 for sons, and 0.33 for daughters, suggesting much lower relative mobility for the daughters. The estimate of absolute mobility, on the other hand, depends on the level of parental schooling. The estimated absolute mobility (expected years of schooling) in the lower panel of Table T2.CR shows that the daughters are at a disadvantage when the father's schooling is less than 13 years, but the advantage flips when the father has college education. This implies that, even though the girls face stronger intergenerational persistence across the board, they in fact leave the boys behind in terms of schooling attainment when the father is sufficiently well-educated. The estimated CEFs are plotted in Figure F3.CR.

Mechanisms of Gender Bias: Interpretations

When the correct model is, in fact, linear (no significant diminishing returns or complementarity), then the only mechanism that can lead to different relative mobility (IGRCs) for sons vs. daughters is gender-specific constraints in school. The estimates on relative mobility (IGRC) in Table T2.CR thus imply that an important source of gender bias against girls in rural China is unfavorable school environment.

However, with a linear model, the theory also implies that the effects of parental or labor market bias would be reflected in the intercept estimates of the investment and mobility equations. The estimates of the intercept of the investment equation in Table T3.CR show that $\hat{\theta}_0^d > \hat{\theta}_0^s$. Combined with the evidence that $\hat{\theta}_1^d = \hat{\theta}_1^s$, the estimates of the investment equation thus suggest no gender bias against girls in rural China, if anything financial investment favors the daughters.[36]

$\hat{\theta}_0^d > \hat{\theta}_0^s$ implies the following inequality: $\tilde{\delta}_1^d \sigma^d R^{cd} > \tilde{\delta}_1^s \sigma^s R^{cs}$. Table T4.C provides a summary of the available estimates of returns to education in rural China showing evidence in favor of $R^{cd} > R^{cs}$.[37] These two inequalities are, however, consistent with a variety of hypothesis about parental attitude towards sons vs. daughters and do not help us narrow down the explanations.

The intercept estimates of the mobility equation shows that $\hat{\psi}_0^d < \hat{\psi}_0^s$, which implies $\delta_1^d \theta_0^d < \delta_1^s \theta_0^s$. Since $\theta_0^d > \theta_0^s$, this implies that $\delta_1^d < \delta_1^s$. This last inequality holds when the girls face constraints in the school. Thus, the only conclusion we can reach is that the girls in rural China face significant bias in the schools, but do not find any evidence that the parents discriminate against girls when choosing educational investment. This

[36]This is consistent with other available evidence. See, for example, Hannum et al. (2009).

[37]The available estimates of returns to education for rural China suggest that the returns were very low during the early period of economic liberalization (deBrauw and Rozelle (2008), Meng (1998)), but the more recent evidence shows increasing returns to education with higher returns for girls (see, for example, Ren and Miller (2012)).

last conclusion, in fact, is consistent with in-depth case studies reported by Hannum et al. (2009).

(6) Robustness Checks

The empirical results on intergenerational mobility discussed so far are based on the sample of 18-35 years age cohorts of children in the survey year. To check robustness of the findings, we also estimated the mobility equation (14) in section (2) for alternative age ranges. The estimates for the age cohorts 18-30 years are reported in the online appendix; please see the Tables A2.IU.B, A2.IR.B, A2.CU.B, and A2.CR.B. The main conclusions regarding gender differences in intergenerational educational mobility remain intact.

We also check whether the conclusions are partly due to the effects of gender bias working through endogeneous fertility choices. To this end, we estimate the mobility equation using only the sub-sample of the first-born child, as the gender of the first born is usually not determined by parental preference. The CFPS survey on China is suitable for such an analysis. But we are unable to implement this for IHDS data in India, as the IHDS survey does not contain the information on the birth-order of the household head and spouse. The estimates based on the first-born sample for urban and rural China are reported in online appendix Tables A2.CU.C and A2.CR.C respectively for the 18-35 age cohorts; the main conclusions discussed in the text above are again robust. The estimates from the first=born sub-sample of the 18-30 age cohorts also support the main conclusions.

(7) Concluding Comments

This paper provides a theoretical and empirical analysis of the implications of gender bias against girls for intergenerational educational mobility in developing countries. We develop a Becker-Tomes model where the parents self-finance children's schooling because of credit market imperfections, and the girls may face bias in the family, the school, and the labor market. The model yields a linear conditional expectation function (CEF) under the assumptions of constant returns and separable education production function but delivers sharp predictions: parental bias against girls is irrelevant for relative mobility and for the marginal impact of parent's education on investment in schooling. The effects of parental bias are captured by the intercepts of the investment and mobility equations, which are usually not the focus in the existing literature relying on a linear estimating equation. When the education production function exhibits diminishing returns to financial investment and complementarity between parents' direct impact and financial investment as proposed by Becker et al. (2015, 2018), the CEF can be concave or convex depending on the strength of complementarity. With quadratic CEF, parental gender bias affects both relative and absolute mobility.

We take advantage of rich household survey data from China and India to test the above ideas. The data sets used (IHDS for India and CFPS for China) do not suffer from sample truncation due to coresidency restrictions common in household surveys in developing countries. Our estimates are thus free of severe truncation bias reported recently by Emran et al. (2018) because of coresidency restrictions. The evidence shows interesting cross-country and rural-urban differences. The CEF is concave in India irrespective of gender and location. In contrast, the CEF is convex for sons, but linear for daughters in urban China. In rural China, the CEF is linear for both sons and daughters. The evidence on functional form suggests that children face diminishing returns India, and girls in rural India face diminishing returns both in financial investment and parental direct inputs to schooling. The convexity observed in urban China for sons supports the complementarity hypothesis of Becker et al. (2018).

Girls face lower relative and absolute mobility in India when the father has low education, but there is gender convergence at the right tail of the parental schooling distribution. The relative magnitudes of the estimated parameters of the investment and mobility equations across gender when combined with the evidence of higher returns to education for girls help us sort out possible explanations for the observed pattern of mobility. The evidence on rural and urban India is consistent with the hypothesis that parents systematically underestimate the academic ability of girls, and girls also face significant bias in school. The same mechanisms can also explain the evidence in urban China, but, in rural China, the evidence indicates constraints in the school as the main mechanism at work and fails to reject the null hypothesis of no parental bias. There is some evidence that pure son preference plays a role in educational persistence in rural India.

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Figure F1.IU

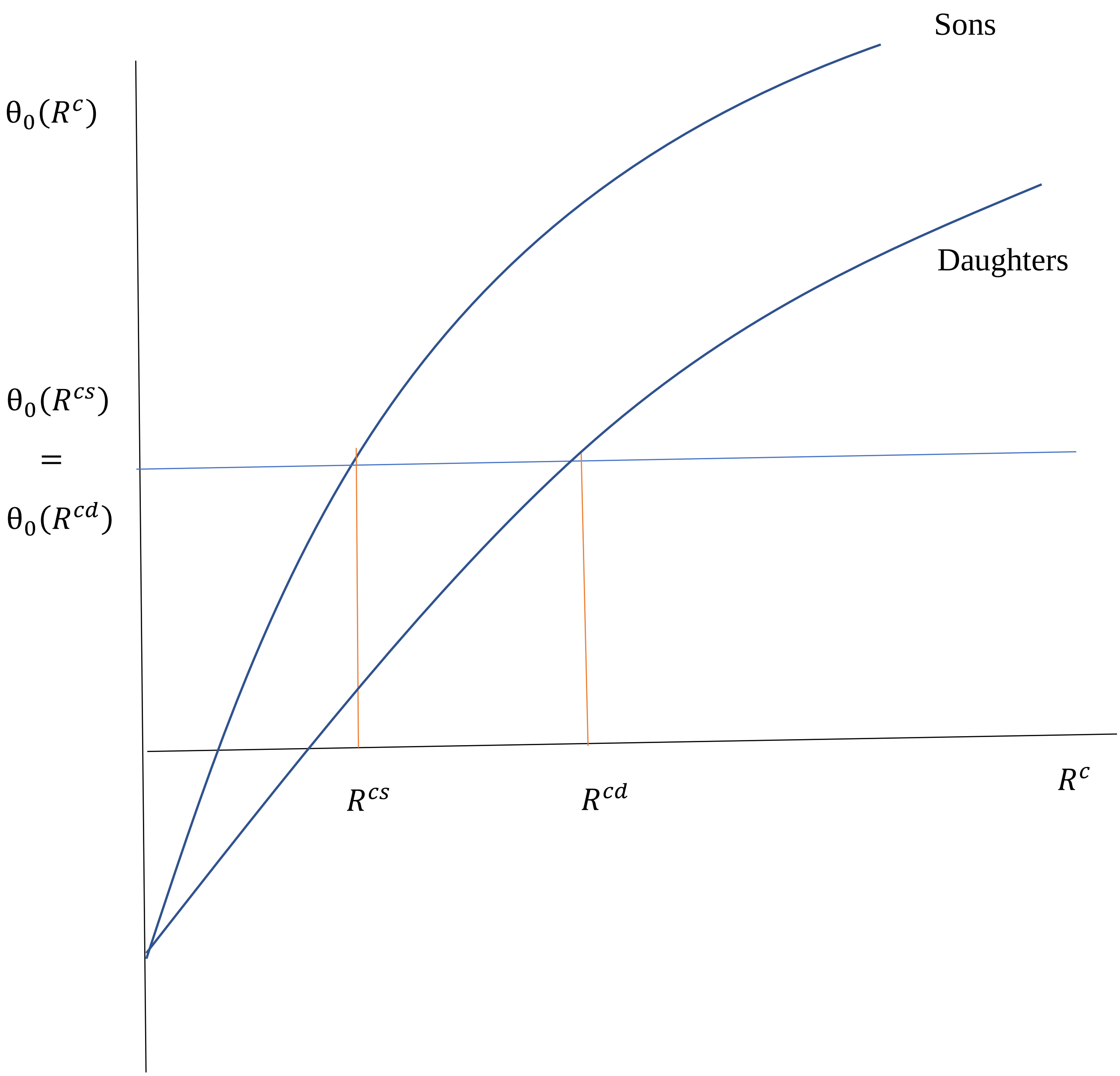


Figure 1.IR

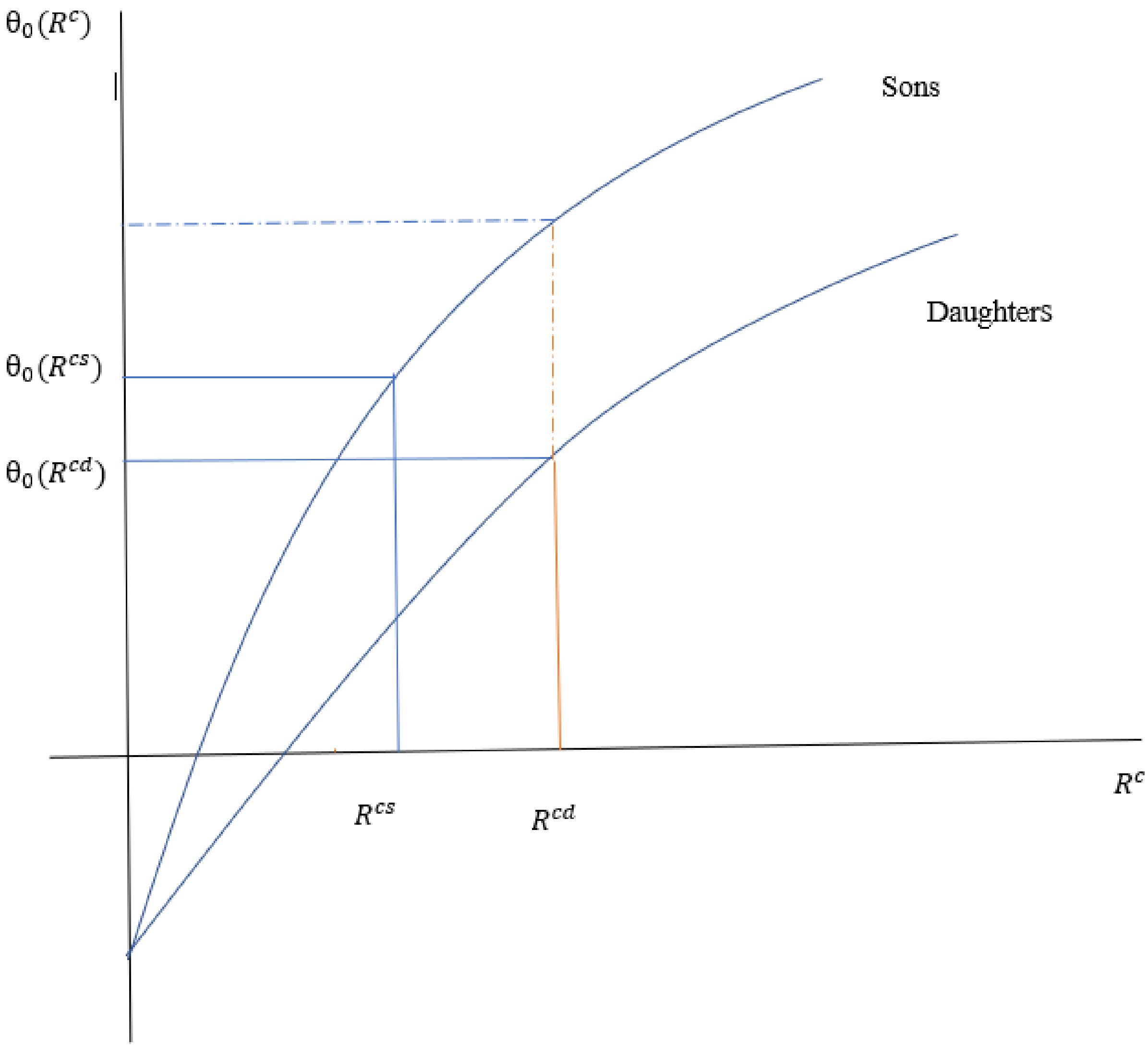


Table T1.U: SUMMARY STATISTICS (URBAN SAMPLES)

	Full		Sons		Daughters	
	Mean	SD	Mean	SD	Mean	SD
			CHINA			
CFPS 2016 (18-35)	N=6433		N=3192		N=3241	
Father's Sch.	7.66	4.27	7.65	4.32	7.67	4.23
Children's Sch.	11.17	3.88	11.17	3.85	11.18	3.9
CFPS 2016 (18-30)	N=4435		N=2230		N=2205	
Father's Sch.	7.8	4.2	7.8	4.23	7.79	4.17
Children's Sch.	11.27	3.77	11.23	3.73	11.31	3.8
CFPS 2010 (6-22)	N=2784		N=1425		N=1359	
Father's Sch.	9.35	4	9.24	4	9.48	4
Educ. Exp.	3178.11	4760.34	3014.98	4761.47	3349.16	4754.89
No. of Children	1.2	0.72	1.18	0.67	1.21	0.76
CFPS 2010 (8-23)	N=2435		N=1251		N=1184	
Father's Sch.	9.28	3.99	9.17	4.02	9.39	3.95
Educ. Exp.	3261.35	4990.48	3101.34	5093.39	3430.41	4875.83
No. of Children	1.17	0.75	1.15	0.69	1.19	0.8
			INDIA			
IHDS 2012 (18-35)	N=18519		N=9449		N=9070	
Father's Sch.	6.54	5.05	6.64	4.96	6.44	5.14
Children's Sch.	9.69	4.52	10.01	4.2	9.36	4.8
IHDS 2012 (18-30)	N=14140		N=7314		N=6826	
Father's Sch.	6.81	5	6.9	4.89	6.72	5.1
Children's Sch.	10	4.35	10.2	4.06	9.78	4.63
IHDS 2005 (6-22)	N=13086		N=6917		N=6169	
Father's Sch.	8.55	4.68	8.52	4.71	8.59	4.65
Educ. Exp.	3798.29	5349.04	4060.57	5657.13	3504.2	4965
No. of Children	2.41	1.43	2.36	1.43	2.46	1.43
IHDS 2005 (8-23)	N=11051		N=5883		N=5168	
Father's Sch.	8.58	4.68	8.54	4.7	8.61	4.66
Educ. Exp.	4082.12	5721.06	4368.01	6025.75	3756.67	5335.11
No. of Children	2.42	1.46	2.35	1.46	2.5	1.46
NSS 1995 (6-13)	N=18689		N=10071		N=8618	
Father's Sch.	5.09	2.46	5.03	2.47	5.16	2.43
Educ. Exp.	1101.84	1237.90	1145.16	1293.68	1051.22	1167.40
No. of Children	2.67	1.11	2.61	1.10	2.73	1.13
NSS 1995 (6-18)	N=27819		N=15152		N=12667	
Father's Sch.	5.24	2.44	5.16	2.46	5.33	2.42
Educ. Exp.	1338.27	1529.59	1382.00	1588.18	1285.96	1454.75
No. of Children	2.67	1.14	2.60	1.12	2.75	1.17

Notes: CFPS stands for China Family Panel Survey, IHDS stands for Indian Human Development Survey, and NSS stands for National Sample Survey.

Table T1.R: SUMMARY STATISTICS (RURAL SAMPLES)

	Full		Sons		Daughters	
	Mean	SD	Mean	SD	Mean	SD
			CHINA			
CFPS 2016 (18-35)	N=8040		N=3955		N=4085	
Father's Sch.	5.9	4.27	5.93	4.29	5.88	4.26
Children's Sch.	8.96	4.08	9.2	3.91	8.74	4.23
CFPS 2016 (18-30)	N=5647		N=2833		N=2814	
Father's Sch.	6.01	4.16	6.11	4.17	5.91	4.15
Children's Sch.	9.4	3.93	9.53	3.75	9.26	4.1
CFPS 2010 (6-22)	N=4326		N=2224		N=2102	
Father's Sch.	6.44	3.88	6.45	3.9	6.42	3.87
Educ. Exp.	1301.35	2386.63	1328.64	2535.81	1272.48	2218.14
No. of Children	1.63	0.93	1.57	0.9	1.7	0.97
CFPS 2010 (8-23)	N=3632		N=1843		N=1789	
Father's Sch.	6.4	3.9	6.43	3.88	6.37	3.91
Educ. Exp.	1432.85	2593.57	1449.28	2710.91	1415.92	2467.5
No. of Children	1.62	0.96	1.52	0.9	1.72	1
			INDIA			
IHDS 2012 (18-35)	N=33979		N=16957		N=17022	
Father's Sch.	3.87	4.41	3.9	4.32	3.83	4.49
Children's Sch.	7.18	4.71	8.13	4.36	6.24	4.86
IHDS 2012 (18-30)	N=25903		N=12946		N=12957	
Father's Sch.	4.08	4.46	4.12	4.37	4.04	4.54
Children's Sch.	7.61	4.59	8.43	4.21	6.8	4.8
IHDS 2005 (6-22)	N=23058		N=12631		N=10427	
Father's Sch.	5.58	4.58	5.47	4.61	5.71	4.55
Educ. Exp.	1489.73	3110.61	1613.94	3440.39	1339.27	2649.23
No. of Children	2.87	1.53	2.79	1.51	2.97	1.55
IHDS 2005 (8-23)	N=19002		N=10514		N=8488	
Father's Sch.	5.59	4.56	5.47	4.6	5.74	4.52
Educ. Exp.	1667.11	3469.9	1802.6	3836.22	1499.27	2945.42
No. of Children	2.91	1.55	2.8	1.53	3.03	1.55
NSS 1995 (6-13)	N=26668		N=15819		N=10849	
Father's Sch.	3.31	2.08	3.18	2.06	3.50	2.10
Educ. Exp.	386.44	477.52	398.38	484.29	369.03	466.95
No. of Children	2.47	1.06	2.37	1.04	2.61	1.07
NSS 1995 (6-18)	N=37155		N=23172		N=13983	
Father's Sch.	3.36	2.10	3.21	2.08	3.59	2.12
Educ. Exp.	543.89	655.29	568.55	677.05	503.02	615.41
No. of Children	2.45	1.10	2.35	1.08	2.63	1.11

Notes: CFPS stands for China Family Panel Survey, IHDS stands for Indian Human Development Survey, and NSS stands for National Sample Survey.

Table T2.IU: Intergenerational Persistence in Schooling in Urban India

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	**0.46*** **	**0.52*** **	**0.066*** **	**0.55*** **	**0.65*** **	**0.094*** **
	(0.0074)	(0.0080)	(0.011)	(0.023)	(0.025)	(0.034)
Quadratic Coefft.				**-0.0070*** **	**-0.0093*** **	**-0.0022**
				(0.0014)	(0.0016)	(0.0022)
Intercept	**6.96*** **	**5.97*** **	**-0.99*** **	**6.81*** **	**5.80*** **	**-1.00*** **
	(0.071)	(0.075)	(0.10)	(0.085)	(0.086)	(0.12)
No. Observations	9449	9070	18519	9449	9070	18519

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	6.81	5.80	$IGME_0$	0.55	0.65
ES_5	9.39	8.82	$IGME_5$	0.485	0.556
ES_{10}	11.61	11.37	$IGME_{10}$	0.414	0.464
ES_{16}	13.82	13.82	$IGME_{16}$	0.330	0.353

Notes: (1) The data used are IHDS 2012 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T3.IU: Father's Education and Educational Expenditure on Children

	URBAN INDIA			
	IHDS 2005			
	(6-22) Years Children		**(8-23) Years Children**	
Father's Sch.	384.4***	338.7***	403.9***	348.0***
	(14.9)	(14.40)	(17.4)	(16.9)
Father's Sch. * Daughter Dummy	**-34.00***	**-37.50***	**-36.5**	**-40.2***
	(20.5)	**(20.3)**	**(23.9)**	**(23.5)**
Daughter Dummy	**-290.2*****	**-189.9**	**-325.1****	**-174.3**
	(136.9)	(138.7)	(164.4)	(162.9)
Intercept	784.8***	2763.50***	917.3***	3220.7***
	(105.1)	(148)	(124.9)	(175.6)
No. of Children		-673.1***		-777.7***
		(36.0)		(41.9)
No. Observations	13086	13086	11051	11051
	NSS 1995			
	(6-18) Years Children		**(8-18) Years Children**	
Father's Sch.	108.4***	108.4***	110.4***	110.9***
	(2.817)	(2.817)	(3.070)	(3.039)
Father's Sch. * Daughter Dummy	**-11.3*****	**-11.3*****	**-11.2*****	**-11.2*****
	(3.906)	(3.906)	(4.295)	(4.238)
Daughter Dummy	**-39.4**	**-39.4**	**-41.6**	**-11.1**
	(26.12)	(26.12)	(29.00)	(29.03)
Intercept	505.9***	505.9***	543.6***	1004.0***
	(17.95)	(17.95)	(19.75)	(26.13)
No. of Children				-178.0***
				(7.963)
No. Observations	27810	27810	24443	24443

Notes: (1) The data used are IHDS 2005 and NSS 1995 respectively. (2) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T2.IR: Intergenerational Persistence in Schooling in Rural India

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft	**0.45*** **	**0.52*** **	**0.075*** **	**0.52*** **	**0.64*** **	**0.12*** **
	(0.0064)	(0.0071)	(0.0095)	(0.019)	(0.021)	(0.028)
Quadratic Coefft.				**-0.0070*** **	**-0.011*** **	**-0.0070*** **
				(0.0014)	(0.0018)	(0.0014)
Intercept	**6.39*** **	**4.24*** **	**-2.14*** **	**6.32*** **	**4.16*** **	**-2.16*** **
	(0.044)	(0.043)	(0.062)	(0.048)	(0.046)	(0.066)
No. Observations	16957	17022	33979	16957	17022	33979

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	6.32	4.16	$IGME_0$	0.52	0.64
ES_5	8.75	7.09	$IGME_5$	0.454	0.533
ES_{10}	10.82	9.46	$IGME_{10}$	0.384	0.426
ES_{16}	12.85	11.58	$IGME_{16}$	0.300	0.298

Notes: (1) The data used are IHDS 2012 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T3.IR: Father's Education and Educational Expenditure on Children

	RURAL INDIA			
	IHDS 2005			
	(6-22) Years Children		**(8-23) Years Children**	
Father's Sch.	153.9***	145.4***	169.2***	158.7***
	(9.08)	(8.77)	(11.0)	(10.6)
Father's Sch. * Daughter	**-22.8****	**-21.9***	**-24.0***	**-22.4**
Dummy	**(11.4)**	**(11.3)**	**(13.9)**	**(13.7)**
Daughter Dummy	**-182.5*****	**-137.1*****	**-211.0*****	**-134.0****
	(43.5)	(43.7)	(52.3)	(52.7)
Intercept	772.3***	1585.4***	877.6***	1949.3***
	(33.3)	(54.7)	(39.8)	(67.9)
No. of Children		-274.4***		-361.9***
		(17.2)		(21.8)
No. Observations	23058	23058	19002	19002
	NSS 1995			
	(6-18) Years Children		**(8-18) Years Children**	
Father's Sch.	35.2***	35.2***	36.5***	37.5***
	(1.425)	(1.425)	(1.535)	(1.567)
Father's Sch. * Daughter	**-3.7***	**-3.7***	**-3.4**	**-3.5**
Dummy	(2.083)	(2.083)	(2.285)	(2.281)
Daughter Dummy	**-74.1*****	**-74.1*****	**-65.2*****	**-58.5*****
	(8.694)	(8.694)	(9.700)	(9.729)
Intercept	426.9***	426.9***	461.0***	507.7***
	(5.420)	(5.420)	(5.882)	(9.728)
No. of Children				-21.6***
				(3.749)
No. Observations	37144	37144	32499	32499

Notes: (1) The data used are IHDS 2005 and NSS 1995 respectively. (2) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T2.CU: Intergenerational Persistence in Schooling in Urban China

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	**0.29*** **	**0.35*** **	**0.061*** **	**0.093** **	**0.32*** **	**0.22*** **
	(0.016)	(0.016)	(0.023)	(0.045)	(0.045)	(0.063)
Quadratic Coefft.				**0.015*** **	**0.0023**	**-0.012*** **
				(0.0029)	(0.0029)	(0.0041)
Intercept	**8.97*** **	**8.51*** **	**-0.46** **	**9.33*** **	**8.57*** **	**-0.76*** **
	(0.15)	(0.15)	(0.21)	(0.18)	(0.18)	(0.25)
No. Observations	3192	3241	6433	3192	3241	6433

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	9.33	8.51	$IGME_0$	0.093	0.35
ES_6	10.43	10.61	$IGME_6$	0.268	0.35
ES_9	11.38	11.66	$IGME_9$	0.354	0.35
ES_{16}	14.66	14.11	$IGME_{16}$	0.558	0.35

Notes: (1) The data used are CFPS 2016 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T3.CU: Father's Education and Educational Expenditure on Children

	URBAN CHINA			
	CFPS 2010			
	(6-22) Years Children		(8-23) Years Children	
Father's Sch.	236.9***	162.8***	225.4***	138.3***
	(35.0)	(34.1)	(32.9)	(30.5)
Father's Sch. * Daughter	**36.8**	**18.6**	**27.5**	**13.5**
Dummy	(48.2)	(46.9)	(49.2)	(47.4)
Daughter Dummy	**-71.2**	**181.1**	**22.4**	**267.5**
	(400.2)	(386.8)	(413.7)	(397.5)
Intercept	827.4***	4137.0***	1034.3***	4592.9***
	(278.8)	(337.8)	(264.5)	(330.1)
No. of Children		-2222.0***		-2401.2***
		(132.7)		(154.4)
No. Observations	2784	2784	2435	2435

Notes: (1) The data used are CFPS 2010. (2) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T2.CR: Intergenerational Persistence in Schooling in Rural China

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft	**0.27*** **	**0.33*** **	**0.062*** **	**0.27*** **	**0.38*** **	**0.11** **
	(0.015)	(0.015)	(0.021)	(0.042)	(0.045)	(0.061)
Quadratic Coefft.				**-0.00025**	**-0.0047**	**-0.0045**
				(0.0035)	(0.0037)	(0.0051)
Intercept	**7.59*** **	**6.78*** **	**-0.81*** **	**7.59*** **	**6.73*** **	**-0.86*** **
	(0.11)	(0.12)	(0.17)	(0.12)	(0.13)	(0.18)
No. Observations	3955	4085	8040	3955	4085	8040

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	7.59	6.78	***IGRC***	0.27	0.33
ES_5	9.21	8.76			
ES_{10}	10.02	9.75			
ES_{16}	11.91	12.06			

Notes: (1) The data used are CFPS 2016 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table T3.CR: Father's Education and Educational Expenditure on Children

	RURAL CHINA			
	CFPS 2010			
	6-22 Year Children		8-23 Year Children	
Father's Sch.	105.5***	79.6***	115.7***	85.6***
	(12.8)	(12.1)	(15.0)	(14.0)
Father's Sch. * Daughter Dummy	**-31.8***	**-31.2***	**-21.7**	**-21.7**
	(17.3)	**(16.6)**	**(20.9)**	**(20.0)**
Daughter Dummy	**151.6**	**240.3****	**111.2**	**275.2****
	(103.1)	(100.6)	(120.7)	(117.1)
Intercept	648.0***	1939.7***	705.7***	2173.6***
	(71.0)	(117.9)	(83.3)	(132.7)
No. of Children		-716.8***		-838.0***
		(49.7)		(56.8)
No. Observations	4326	4326	3632	3632

Notes: (1) The data used are CFPS 2010. (2) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4.I: Returns to Education Estimates for India

	URBAN (U)		RURAL (R)		ALL INDIA (R + U)		
	Men	Women	Men	Women	Men	Women	Year
				SECONDARY			
Duraisamy (2002)	14.7	32.4	17.9	34.1			1993/94
Kingdon (1998)	4.9	13.4					1995
Kanjilal et al. (2017)	74.1	91.9					2011/12
Bargain et al. (2009)					24	64	1987/88
Bargain et al. (2009)					28	64	1993/95
Bargain et al. (2009)					25	41	2002/04
				HIGHER SECONDARY			
Duraisamy (2002)	10.1	12.9	8.4	11			1993/94
Kanjilal et al. (2017)	108	123	101.4	124.3			2011/12
Kingdon (1998)	17.6	20.8					
Bargain et al. (2009)					64	124	1987/88
Bargain et al. (2009)					60	136	1993/95
Bargain et al. (2009)					55	109	2002/04
				COLLEGE			
Duraisamy (2002)	13.2	9.3	11.6	10.1			1993/94
Kanjilal et al. (2017)	150.9	153.6	141	146.9			2011/12
Kingdon (1998)	18	8.9					
Bargain et al. (2009)					111	174	1987/88
Bargain et al. (2009)					108	175	1993/95
Bargain et al. (2009)					121	170	2002/04

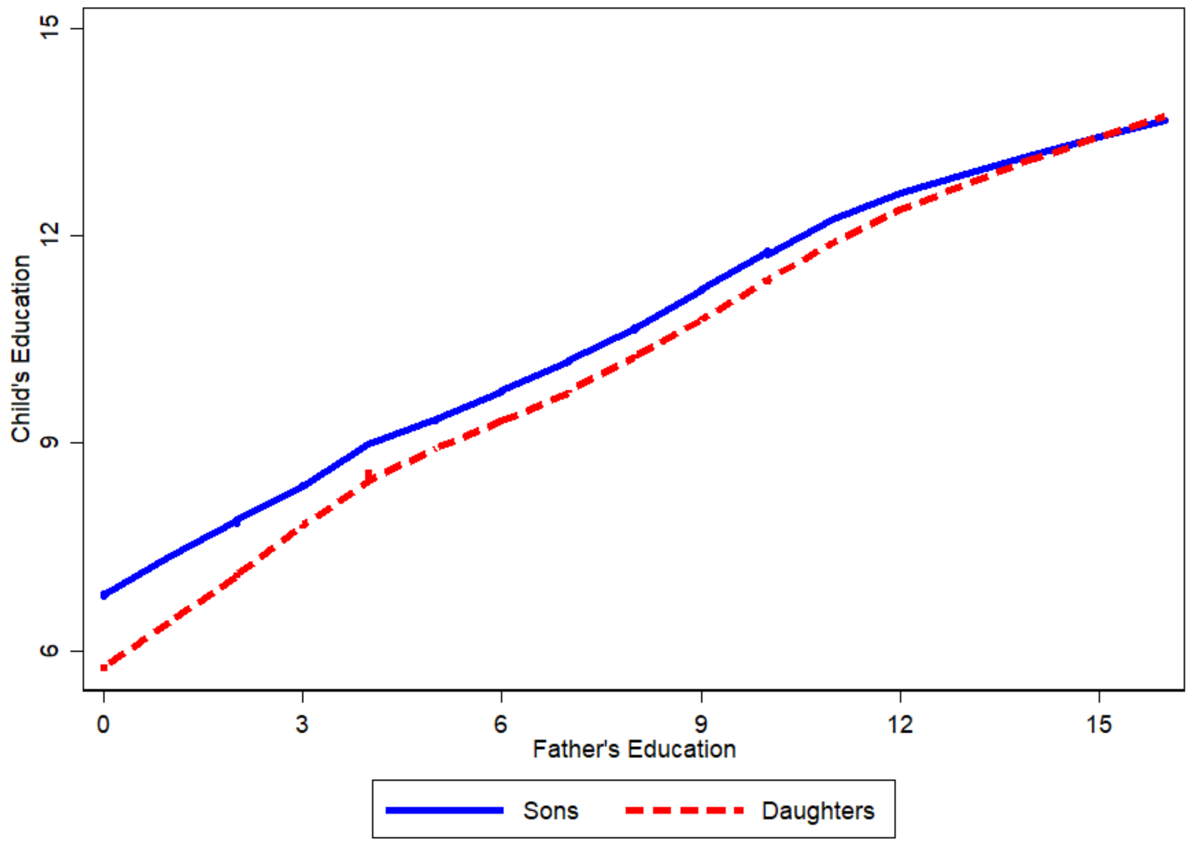
Note: The complete references for the studies cited are in the online appendix.

Table 4.C: Returns to Education Estimates for China

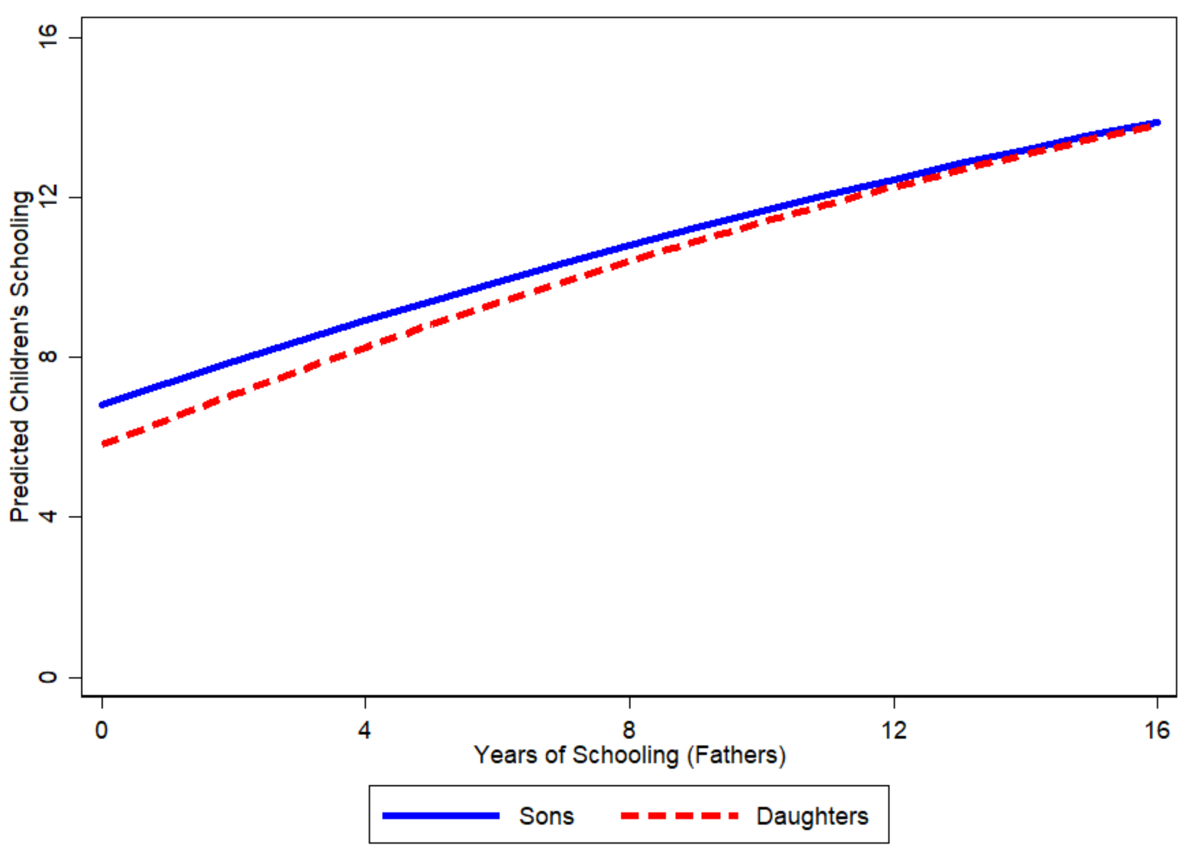
	URBAN (U)		RURAL (R)		
Mincerian Returns to Years of Schooling					
	Men	**Women**	**Men**	**Women**	**Year**
Jamison, D., & Van der Gaag, J. (1987)	4.5	5.5			1985
Xie, Y., & Hannum, E. (1996)	2.2	4.4			1988/1989
Johnson, E. N., & Chow, G. C. (1997)	2.78	4.46	2.95	4.82	1988/1989
Liu, Z. (1998)	2.39	3.31			1988/1989
Meng, X. (1998)			1.1	2.2	1986/1987
Maurer-Fazio, M. (1999)	3.74	4.94			1991/1992
Li, H. (2003)	4.3	6.9			1995/196
Bishop, J.., Luo, F., Wang, F. (2005)	3.56	4.43			1995/1996
Zhang, J., Zhao, Y., Park, A., Song, X. (2005)	2.9	5.2			1988
Zhang, J., Zhao, Y., Park, A., Song, X. (2005)	8.4	13.2			2001
Hauser, S. M., & Xie, Y. (2005)	3.6	7.4			1995/1996
Ren, W., & Miller, P. W. (2012)			3.81	7.18	2006
Chen, Q., Xu, J., Zhao, J., & Zhang, B. (2017)			6.8		2004
Xiao, S., & Asadullah, M. N (2018)	7.1	9			2010
SECONDARY (Estimates for All China (R+U))					
	Men		**Women**		
Bargain et al. (2009)	3		15		1987/88
Bargain et al. (2009)	11		25		2002/04
HIGHER SECONDARY (Estimates are for All China (R+U))					
	Men		**Women**		
Bargain et al. (2009)	9		26		1987/88
Bargain et al. (2009)	26		51		2002/04
COLLEGE					
	Rural		**All China (R+U)**		
	Men	**Women**	**Men**	**Women**	
Gustafsson, B and Li, S (2000)	8.9	10.2			1988/1989
Gustafsson, B and Li, S (2000)	15.5	20.8			1995/1996
Bargain et al. (2009)			24	42	1987/88
Bargain et al. (2009)			54	84	2002/04
Wang, L. (2012)	21.1	27			1995/1996
Wang, L. (2012)	48.2	56.6			2002/2003

Note: Full citations are provided in the online appendix.

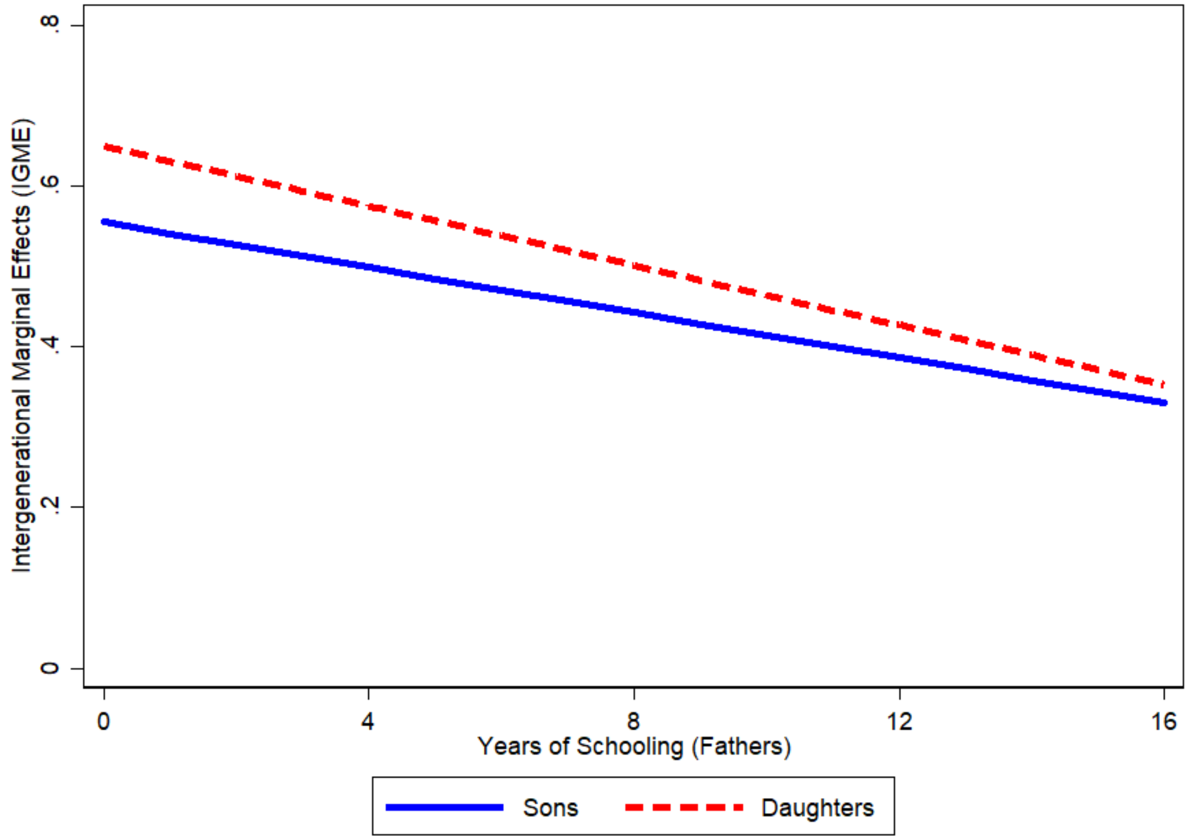
F2.IU: LOWESS Graph (Urban India)



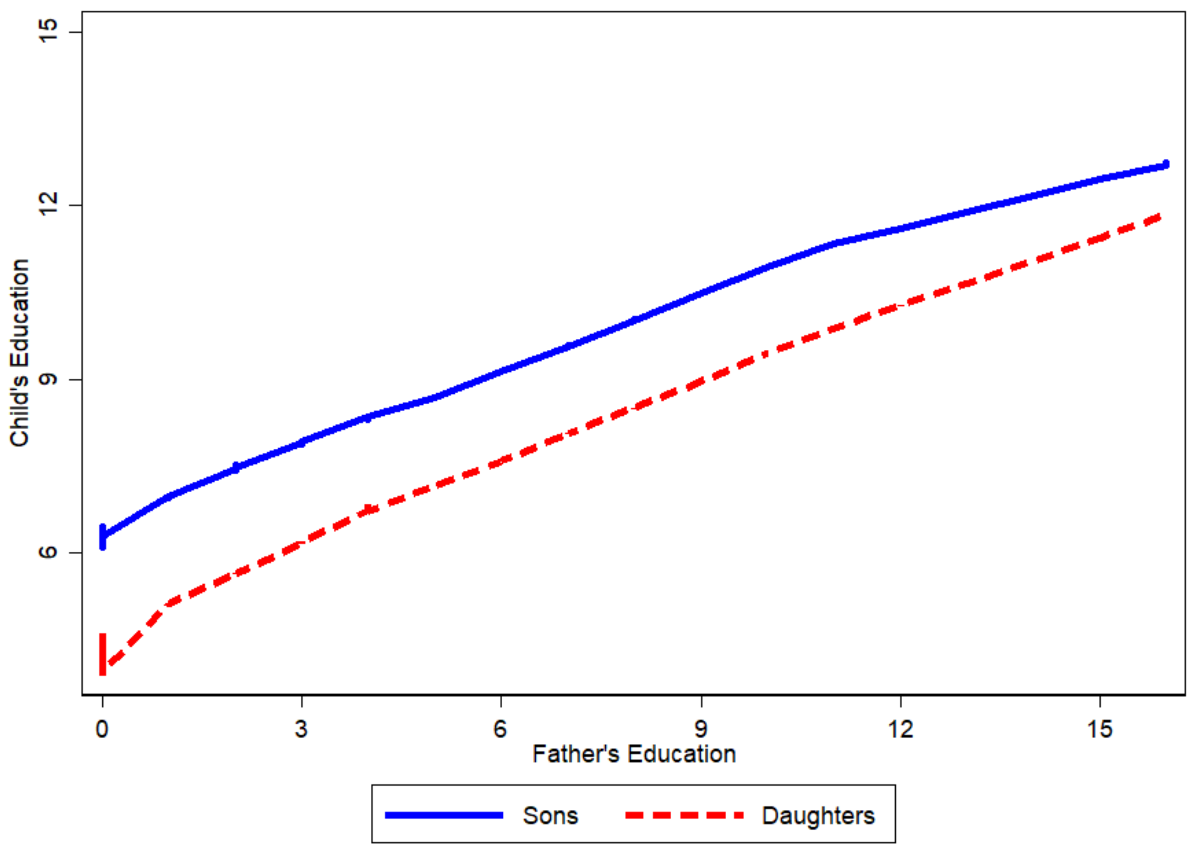
F3.IU: Estimated CEF (Urban India)



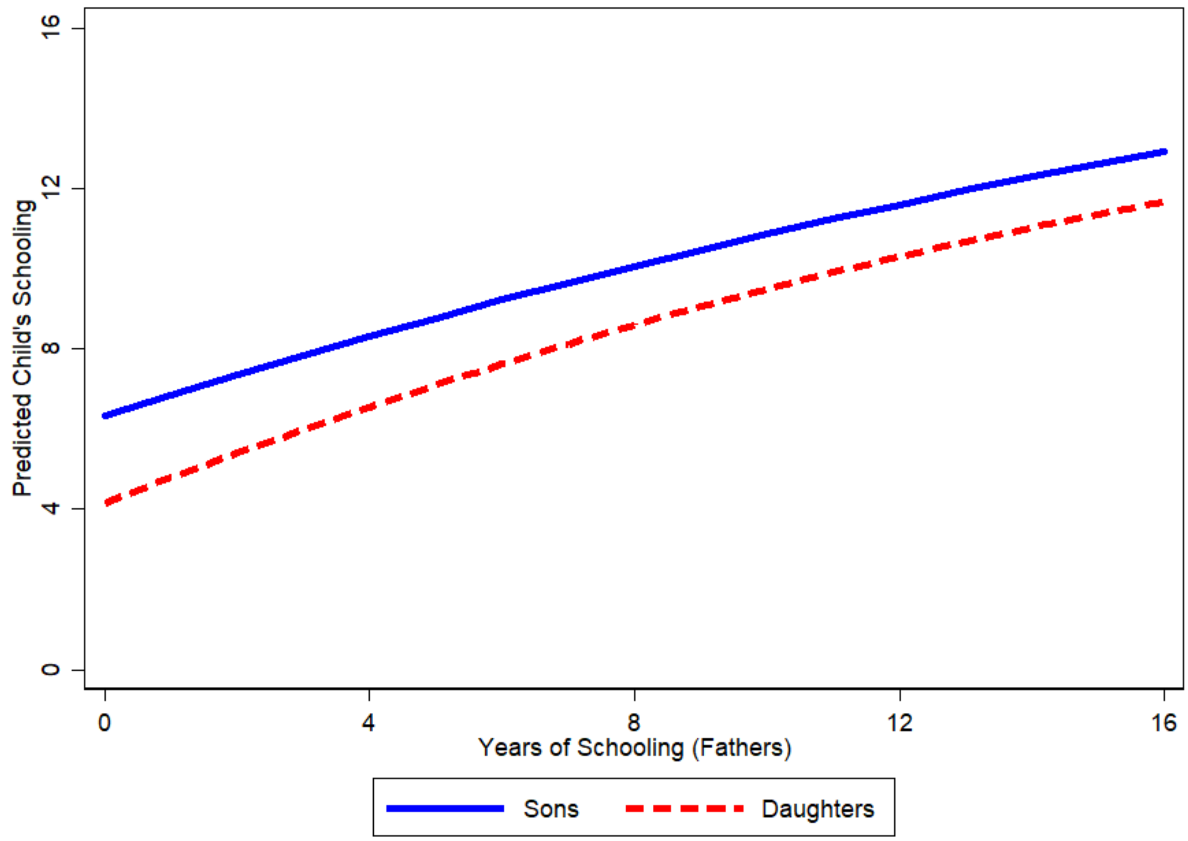
F4.IU: Relative Mobility (Urban India)



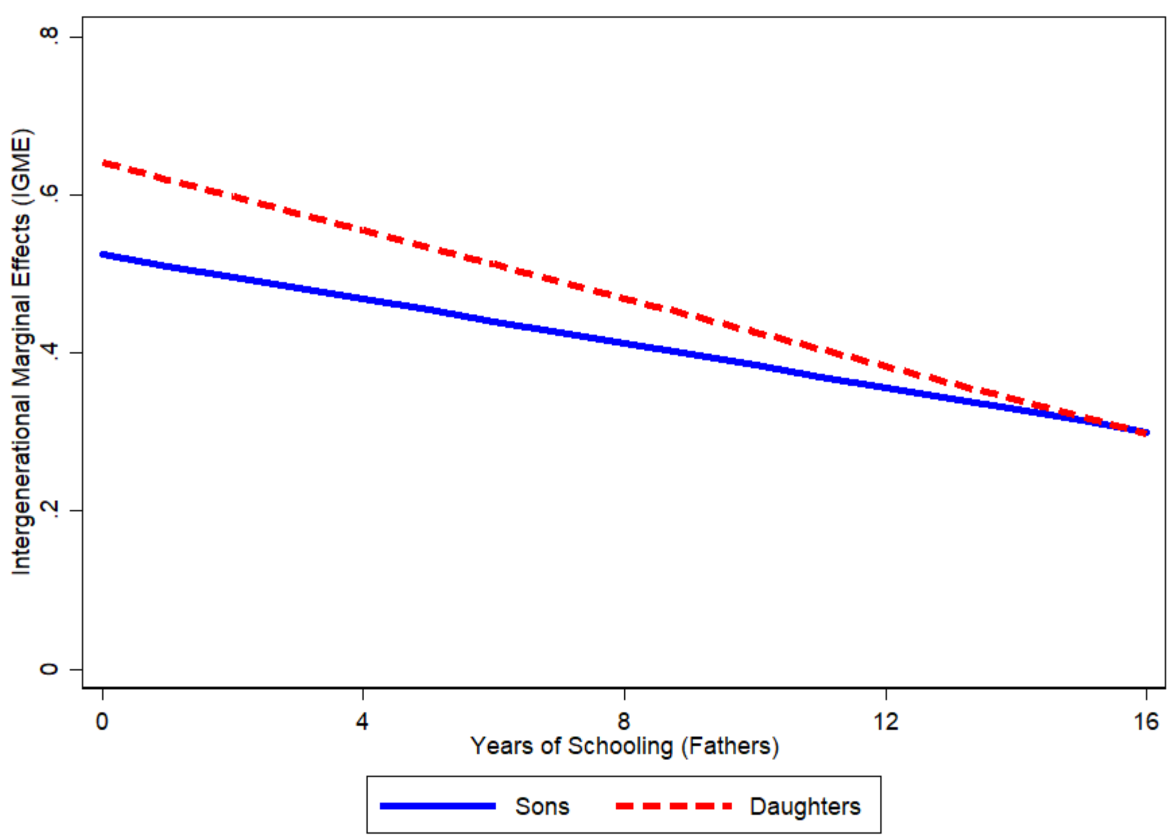
F2.IR: LOWESS Graph (Rural India)



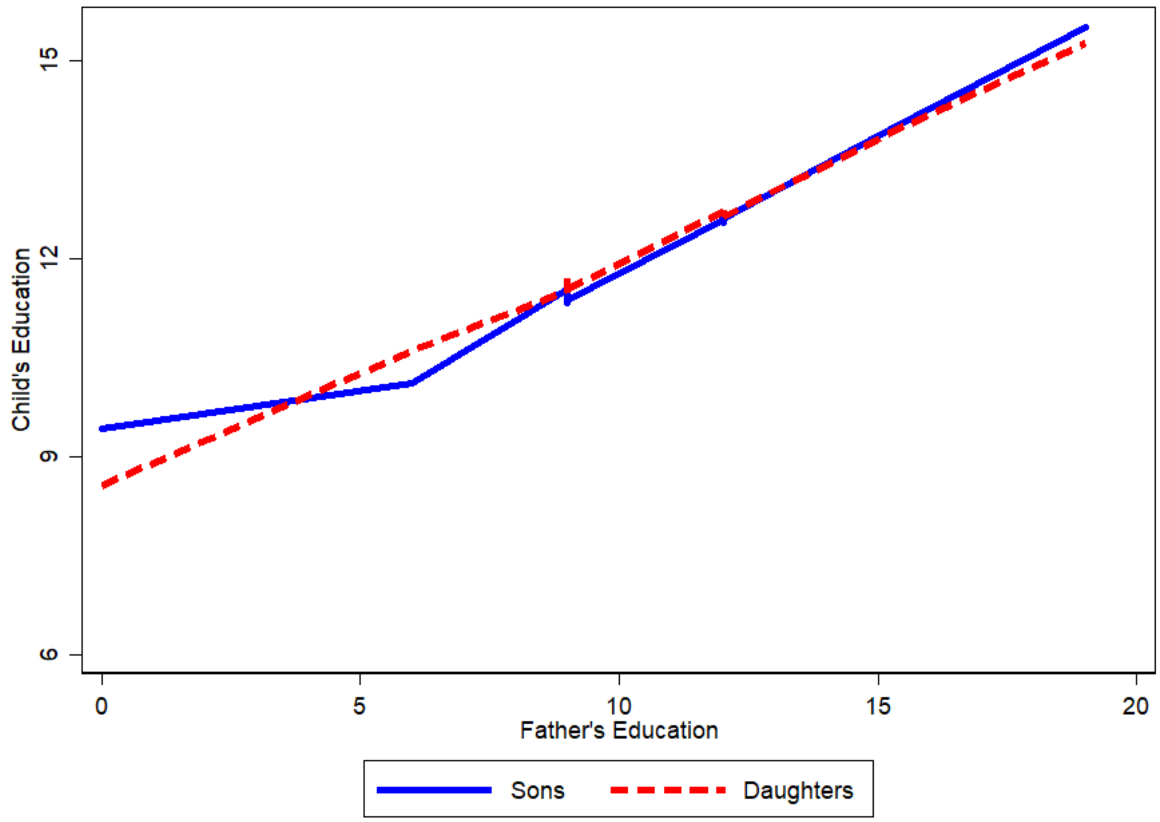
F3.IR: Estimated CEF (Rural India)



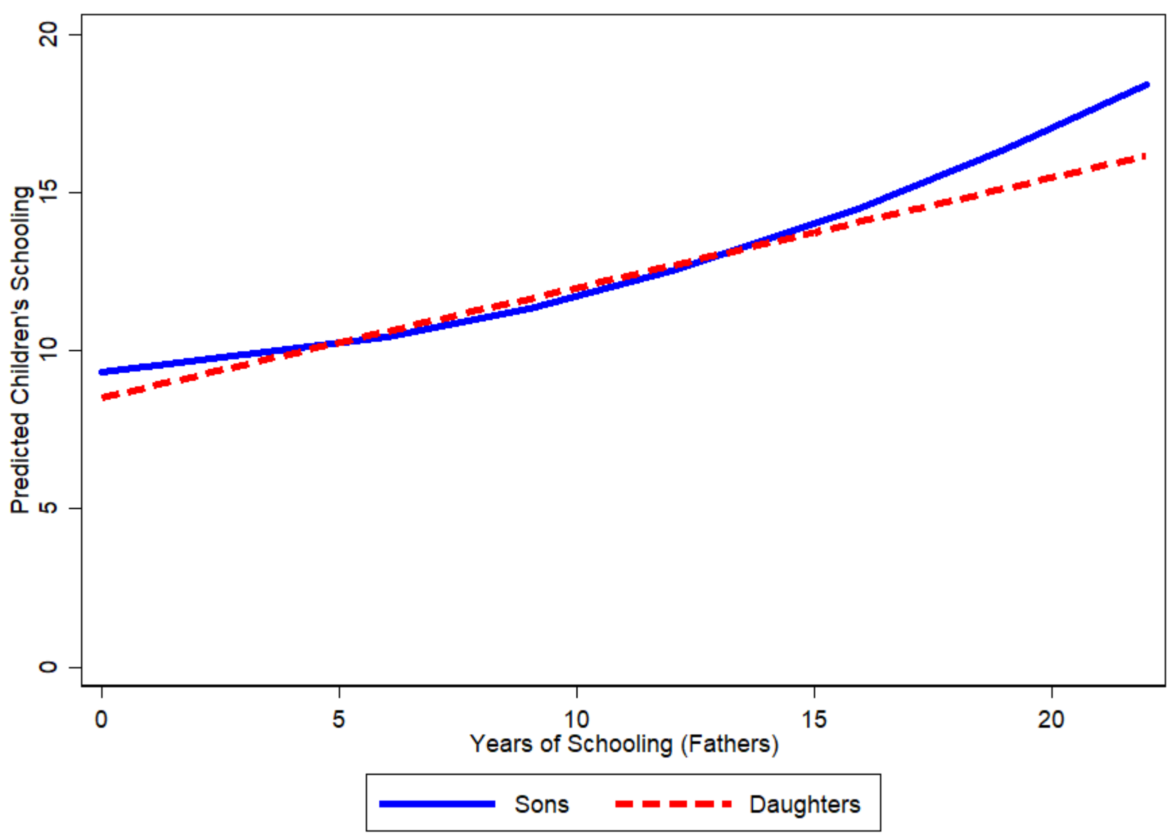
F4.IR: Relative Mobility (Rural India)



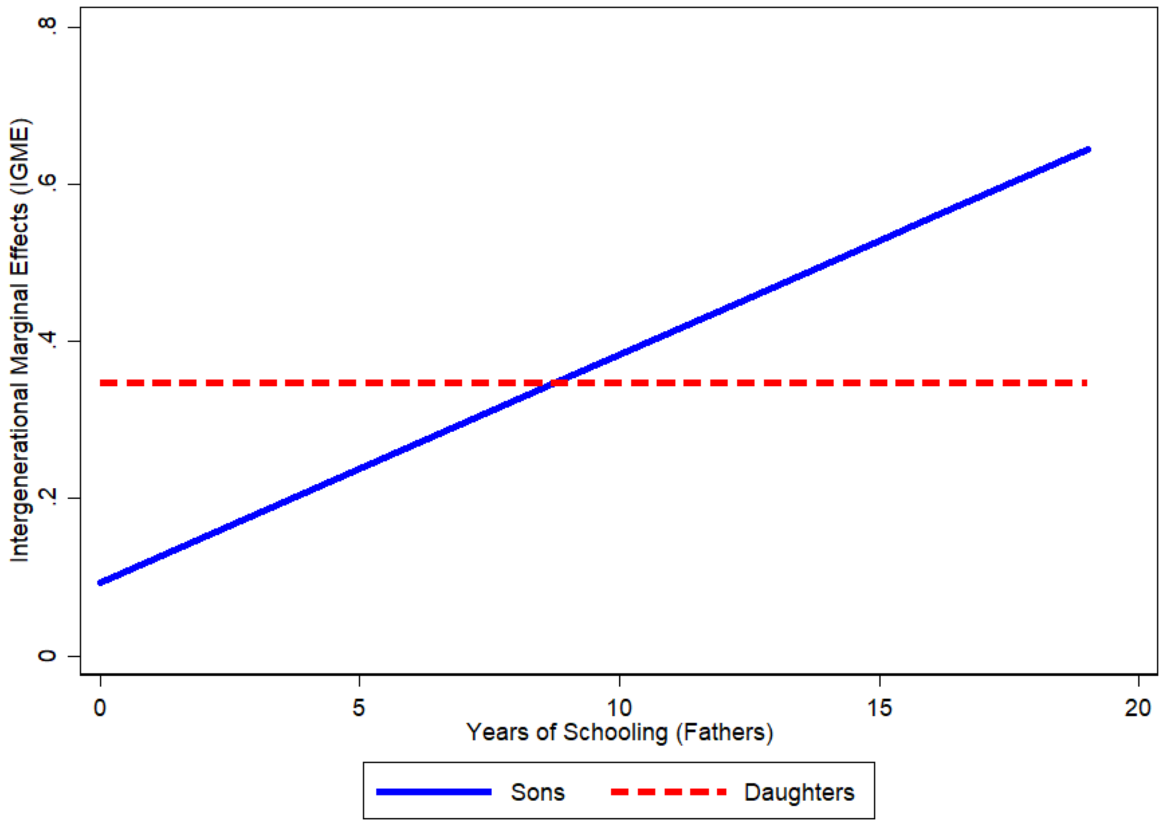
F2.CU: LOWESS Graph (Urban China)



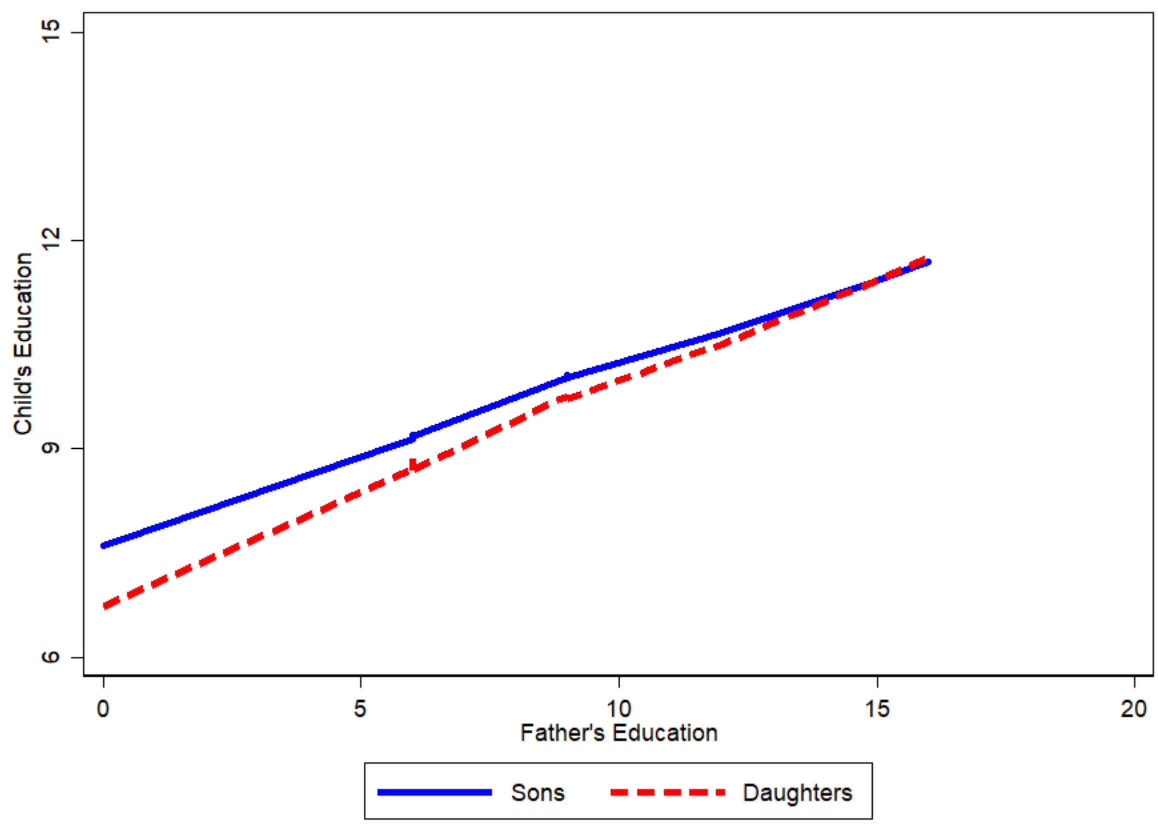
F3.CU: Estimated CEF (Urban China)



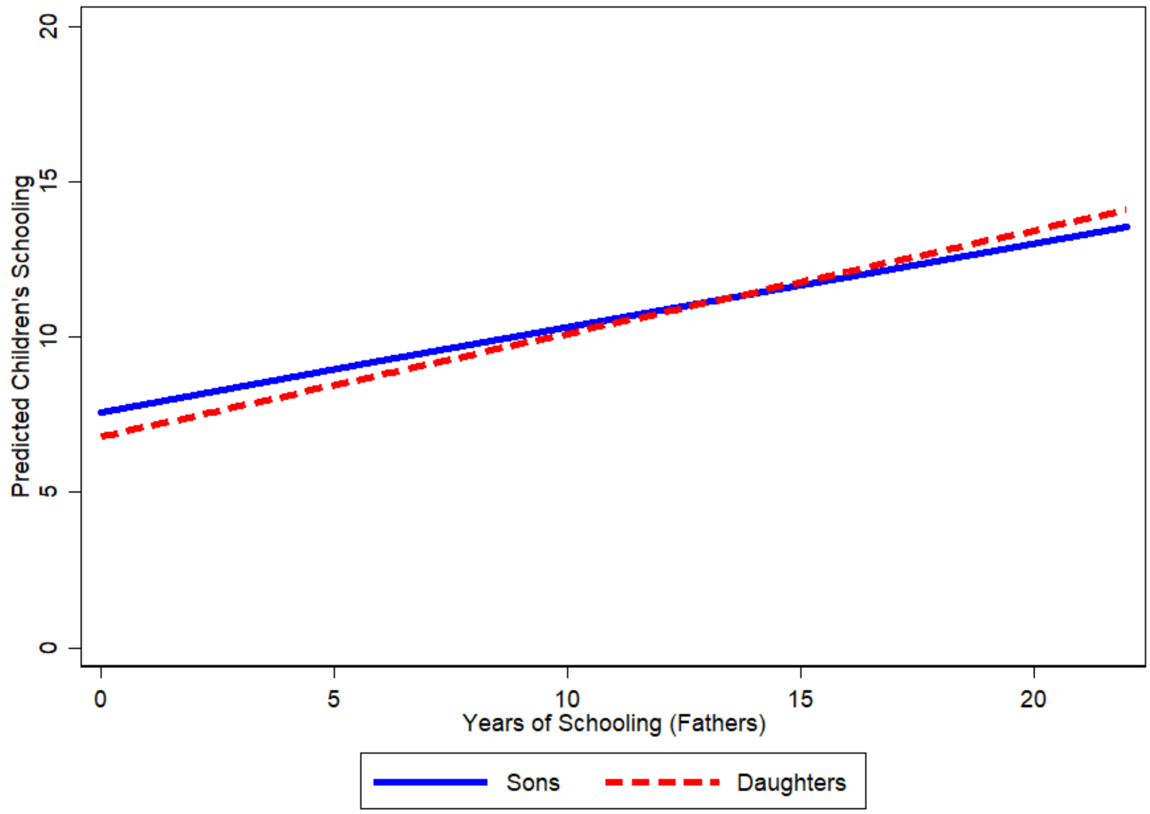
F4.CU: Relative Mobility (Urban China)



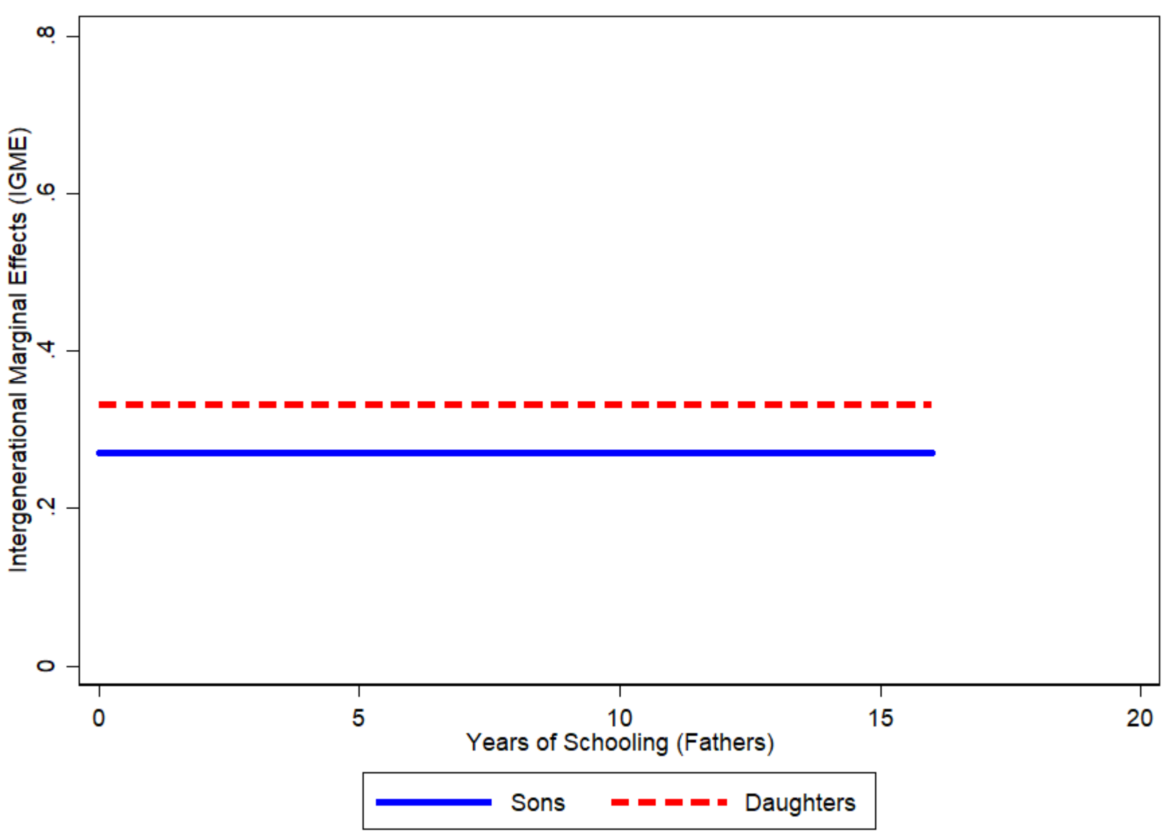
F2.CR: LOWESS Graph (Rural China)



F3.CR: Estimated CEF (Rural China)



F4.CR: Relative Mobility (Rural China)



Online Appendix to:
Gender Bias and Intergenerational Educational Mobility: Theory and Evidence from China and India

M. Shahe Emran
IPD, Columbia University

Hanchen Jiang
Johns Hopkins University

Forhad Shilpi
World Bank

NOT FOR PUBLICATION

Omitted Proofs for the Results on Urban India in Section (2.3)

(1) Using equation (11) in the text, we have the following:

$$\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial \tilde{\phi}^j} = \frac{\sigma^j}{\left(\chi_0^j\right)^3} \left\{ \alpha_2 \gamma_2 \chi_0^j + \omega_2 \alpha_2 \left(2\alpha_2 Y_0^p + 2\tilde{\delta}_1^j \sigma^j R^{cj} - \alpha_1 \right) + \omega_2 \sigma^j R^{cj} \tilde{\delta}_2^j \left(\alpha_1 - 2\alpha_2 Y_0^p \right) \right\} > 0$$

where $\chi_0^j = \alpha_2 + \tilde{\delta}_2^j \sigma^j R^{cj}$ and the last inequality above follows from the observation that $\left(2\alpha_2 Y_0^p + 2\tilde{\delta}_1^j \sigma^j R^{cj} - \alpha_1 \right) > 0$ when $\theta_0^j > 0$ which is in fact the case for both $j = s, d$ according to the empirical evidence reported in the text. Thus, a higher estimate of ability by parents would result in a higher slope of the curve at each point.

Since at $R^{cj} = 0$, the value of θ_0^j does not depend on the ability of a child, the curve for a higher ability estimate, ceteris paribus, lies above the curve for a lower ability estimate at all positive values of returns to schooling for children.

(2) For a higher school quality, we have the following (again, using equation (11) in the main text):

$$\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial q^j} = \frac{\sigma^j}{\left(\chi_0^j\right)^3} \left\{ \alpha_2 \gamma_1 \chi_0^j + \omega_1 \alpha_2 \left(2\alpha_2 Y_0^p + 2\tilde{\delta}_1^j \sigma^j R^{cj} - \alpha_1 \right) + \omega_1 \sigma^j R^{cj} \tilde{\delta}_2^j \left(\alpha_1 - 2\alpha_2 Y_0^p \right) \right\} > 0$$

(3) The claim that the effects of pure son preference on the slope is not unambiguous follows from the result below:

$$\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial \sigma^j} = \frac{1}{\left(\chi_0^j\right)^3} \left\{ \alpha_2 \tilde{\delta}_1^j + \tilde{\delta}_2^j \left(\alpha_1 - 2\alpha_2 Y_0^p \right) \right\} \left(\alpha_2 - \tilde{\delta}_2^j \sigma^j R^{cj} \right)$$

The above expression cannot be signed because we do not know the sign of $\left(\alpha_2 - \tilde{\delta}_2^j \sigma^j R^{cj} \right)$.

Papers Cited on Returns to Education in India and China in Tables T4.I and T4.C in the main Text

Papers Cited on Returns to Education in China

Jamison and Van der Gaag (1987), Xie and Hannum (1996), Johnson and Chow (1997), Liu (1998), Meng and Kidd (1997), Maurer-Fazio (1999), Li (2003), Bishop et al. (2005), Zhang et al. (2005), Asadullah and Xiao (2020), Hauser and Xie (2005), Ren and Miller (2012), Bargain et al. (2009), Wang (2012), Gustafsson and Li (2000).

Papers Cited on Returns to Education in India

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Zhang, J., Zhao, Y., Park, A., Song, X., et al. (2005). Economic returns to schooling in urban china, 1988 to 2001. *Journal of Comparative Economics*, 33(4):730–752.

Table A1.S: Construction of Matched Sons-Fathers in India

		IHDS Wave 1 Azam (2015)	IHDS Wave 2
Total Num of Individuals Surveyed in IHDS		215,784	204,569
Total Num of Men in 20-65 Age Group		58,194	56,883
Education Information Missing (dropped)		325	232
Identification through coresidence only	Father identified if coresidence is used	19,556	19,629
	percentage of male aged 20-65 who can be potentially matched using coresidence	33.60%	34.508%
Panel A. Total Number of Men (20-65 age group) with Education Information	Identification of Father		
	a) Individual is head of household	34,069	31,780
	b) Individual who are not household heads, however, whose father is living in the household	18,056	18,325
	c) Individual is neither head of the household, nor his father is living in the household (no father identification is provided)	4,029	1,905
	d1) Individual is head's father (dropped, father cannot be identified)	591	
	d2) Individual's father cannot be identified (dropped)	1,124	
Total number of men (20-65 age group) whose father is identified: a) + b) + c)		56,154	52,010
Percentage of men (20-65 age group, panel A) whose fathers are identified		96.494%	91.433%

Notes: Column 1-3 are directly obtained from Table 8 in Azam (2015) using IHDS 2005 while column 4 is based on authors' own calculation using IHDS 2012.

Table A1.D. Construction of Matched Daughters-Fathers in India

	IHDS Wave 2 Azam (2016)	IHDS Wave 2
Total Surveyed women in age 20-49	45,319	45,319
Total Surveyed women in age 20-49, with non-missing education information	45,276	45,276
Father's Edu from household co-resident	4,416	4,957
Father's edu from Women's Module	34,290	34,290
Total Women whose father's Edu is available	38,706	39,247
% of surveyed women for whom father's Edu is available	85.49%	86.68%

Notes: Column 1-2 are directly obtained from Table 1 in Azam (2016) using IHDS 2012 while column 3 is based on authors' own calculation using IHDS 2012.

Table A2.IU.A: Intergenerational Persistence in Schooling in Urban India (18-35 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	D-S	**Sons (S)**	**Daughters (D)**	D-S
Linear Coefft.	0.46	0.52	0.066	0.55	0.65	0.094
	(0.0074)***	(0.0080)***	(0.011)***	(0.023)***	(0.025)***	(0.034)***
	[0.012]***	[0.013]***	[0.013]***	[0.035]***	[0.036]***	[0.039]***
	{0.024}***	{0.022}***	{0.017}***	{0.046}***	{0.037}***	{0.043}***
Quadratic Coefft.				-0.0070	-0.0093	-0.0022
				(0.0014)***	(0.0016)***	(0.0022)
				[0.0022]***	[0.0022]***	[0.0025]
				{0.0022}***	{0.0025}***	{0.0025}
Intercept	6.96	5.97	-0.99	6.81	5.80	-1.00
	(0.071)***	(0.075)***	(0.10)***	(0.085)***	(0.086)***	(0.12)***
	[0.14]***	[0.17]***	[0.13]***	[0.15]***	[0.17]***	[0.13]***
	{0.34}***	{0.37}***	{0.17}***	{0.35}***	{0.35}***	{0.17}***
No. Observation	9449	9070	18519	9449	9070	18519

Mobility Estimates from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	6.81	5.80	***$IGME_0$***	0.55	0.65
ES_5	9.39	8.82	***$IGME_5$***	0.485	0.556
ES_{10}	11.61	11.37	***$IGME_{10}$***	0.414	0.464
ES_{16}	13.82	13.82	***$IGME_{16}$***	0.330	0.353

Notes: (1) The data used are IHDS 2012 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.IU.B: Intergenerational Persistence in Schooling in Urban India (18-30 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	D-S	**Sons (S)**	**Daughters (D)**	D-S
Linear Coefft.	0.44	0.50	0.06	0.53	0.62	0.084
	(0.0085)***	(0.0091)***	(0.012)***	(0.027)***	(0.029)***	(0.039)**
	[0.014]***	[0.014]***	[0.016]***	[0.040]***	[0.038]***	[0.041]**
	{0.029}***	{0.026}***	{0.016}***	{0.059}***	{0.038}***	{0.039}**
Quadratic Coefft.				-0.0069	-0.0088	-0.0019
				(0.0016)***	(0.0018)***	(0.0024)
				[0.0025]***	[0.0023]***	[0.0026]
				{0.0027}**	{0.0025}***	{0.0024}
Intercept	7.18	6.45	-0.74	7.02	6.27	-0.75
	(0.082)***	(0.089)***	(0.12)***	(0.10)***	(0.10)***	(0.14)***
	[0.17]***	[0.19]***	[0.14]***	[0.18]***	[0.19]***	[0.15]***
	{0.40}***	{0.42}***	{0.16}***	{0.43}***	{0.40}***	{0.16}***
No. Observation	7314	6826	14140	7314	6826	14140

Mobility Estimates from Quadratic CEF

	Absolute Mobility				Relative Mobility	
	Sons	**Daughters**			**Sons**	**Daughters**
ES_0	7.02	6.27		$IGME_0$	0.53	0.62
ES_5	9.50	9.15		$IGME_5$	0.463	0.528
ES_{10}	11.63	11.59		$IGME_{10}$	0.394	0.441
ES_{16}	13.73	13.94		$IGME_{16}$	0.312	0.335

Notes: (1) The data used are IHDS 2012 with children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CU.A: Intergenerational Persistence in Schooling in Urban China
(18-35 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.29	0.35	0.061	0.093	0.32	0.22
	(0.016)***	(0.016)***	(0.023)***	(0.045)**	(0.045)***	(0.063)***
	[0.027]***	[0.020]***	[0.025]**	[0.063]	[0.060]***	[0.074]***
Quadratic Coefft.				0.015	0.0023	-0.012
				(0.0029)***	(0.0029)	(0.0041)***
				[0.0034]***	[0.0037]	[0.0049]**
Intercept	8.97	8.51	-0.46	9.33	8.57	-0.76
	(0.15)***	(0.15)***	(0.21)**	(0.18)***	(0.18)***	(0.25)***
	[0.20]***	[0.27]***	[0.274]*	[0.25]***	[0.30]***	[0.31]**
No. Observations	3192	3241	6433	3192	3241	6433

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
$\boldsymbol{ES_0}$	9.33	8.51	$\boldsymbol{IGME_0}$	0.093	0.35
$\boldsymbol{ES_6}$	10.43	10.61	$\boldsymbol{IGME_6}$	0.268	0.35
$\boldsymbol{ES_9}$	11.38	11.66	$\boldsymbol{IGME_9}$	0.354	0.35
$\boldsymbol{ES_{16}}$	14.66	14.11	$\boldsymbol{IGME_{16}}$	0.558	0.35

Notes: (1) The data used are CFPS 2016 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling, (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CU.B: Intergenerational Persistence in Schooling in Urban China (18-30 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.26	0.35	0.089	0.067	0.34	0.28
	(0.019)***	(0.020)***	(0.027)***	(0.052)	(0.055)***	(0.076)***
	[0.025]***	[0.024]***	[0.028]***	[0.052]	[0.077]***	[0.075]***
Quadratic Coefft.				0.014	0.00048	-0.014
				(0.0034)***	(0.0034)	(0.0048)***
				[0.0030]***	[0.0045]	[0.0049]***
Intercept	9.19	8.58	-0.61	9.59	8.6	-0.99
	(0.17)***	(0.18)***	(0.25)**	(0.21)***	(0.23)***	(0.31)***
	[0.20]***	[0.28]***	[0.33]*	[0.23]***	[0.36]***	[0.38]**
No. Observations	2230	2205	4435	2230	2205	4435

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	9.59	8.58	$IGME_0$	0.067	0.35
ES_6	10.50	10.68	$IGME_6$	0.237	0.35
ES_9	11.33	11.73	$IGME_9$	0.322	0.35
ES_{16}	14.25	14.18	$IGME_{16}$	0.521	0.35

Notes: (1) The data used are CFPS 2016 with children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling, (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.IR.A: Intergenerational Persistence in Schooling in Rural India (18-35 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.45	0.52	0.075	0.52	0.64	0.12
	(0.0064)***	(0.0071)***	(0.0095)***	(0.019)***	(0.021)***	(0.028)***
	[0.011]***	[0.012]***	[0.012]***	[0.027]***	[0.030]***	[0.033]***
	{0.017}***	{0.025}***	{0.024}***	{0.031}***	{0.053}***	{0.044}***
Quadratic Coefft.				-0.007	-0.011	-0.007
				(0.0014)***	(0.0018)***	(0.0014)***
				[0.0019]***	[0.0022]***	[0.0019]***
				{0.0020}***	{0.0034}***	{0.0020}***
Intercept	6.38	4.24	-2.14	6.32	4.16	-2.14
	(0.044)***	(0.043)***	(0.062)***	(0.048)***	(0.046)***	(0.062)***
	[0.12]***	[0.14]***	[0.097]***	[0.12]***	[0.14]***	[0.0097]***
	{0.25}***	{0.38}***	{0.21}***	{0.25}***	{0.37}***	{0.21}***
No. Observations	16957	17022	33979	16957	17022	33979

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	6.32	4.16	$IGME_0$	0.52	0.64
ES_5	8.75	7.09	$IGME_5$	0.454	0.533
ES_{10}	10.82	9.46	$IGME_{10}$	0.384	0.426
ES_{16}	12.85	11.58	$IGME_{16}$	0.300	0.298

Notes: (1) The data used are IHDS 2012 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.IR.B: Intergenerational Persistence in Schooling in Rural India (18-30 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.42	0.51	0.083	0.49	0.63	0.14
	(0.0071)***	(0.0079)***	(0.011)***	(0.021)***	(0.023)***	(0.031)***
	[0.011]***	[0.013]***	[0.012]***	[0.028]***	[0.032]***	[0.034]***
	{0.017}***	{0.027}***	{0.023}***	{0.033}***	{0.054}***	{0.0020}***
Quadratic Coefft.				-0.0061	-0.011	-0.0051
				(0.0016)***	(0.0019)***	(0.0025)**
				[0.0019]***	[0.0023]***	[0.0025]**
				{0.0020}***	{0.0033}***	{0.0025}*
Intercept	6.69	4.76	-1.93	6.63	4.67	-1.96
	(0.050)***	(0.051)***	(0.072)***	(0.055)***	(0.054)***	(0.077)***
	[0.12]***	[0.15]***	[0.11]***	[0.13]***	[0.16]***	[0.11]***
	{0.26}***	{0.42}***	{0.23}***	{0.27}***	{0.41}***	{0.23}***
No. Observations	12946	12959	25903	12946	12959	25903

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	**Daughters**		**Sons**	**Daughters**
ES_0	6.63	4.67	***$IGME_0$***	0.49	0.63
ES_5	8.93	7.55	***$IGME_5$***	0.429	0.518
ES_{10}	10.92	9.87	***$IGME_{10}$***	0.369	0.407
ES_{16}	12.91	11.93	***$IGME_{16}$***	0.296	0.272

Notes: (1) The data used are IHDS 2012 with children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,5,10,16. (4) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CR.A: Intergenerational Persistence in Schooling in Rural China (18-35 Years Age Cohorts)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.27	0.33	0.062	0.27	0.38	0.11
	(0.015)***	(0.015)***	(0.021)***	(0.042)***	(0.045)***	(0.061)*
	[0.040]***	[0.045]***	[0.025]**	[0.096]***	[0.11]***	[0.062]*
Quadratic Coefft.				-0.00025	-0.0047	-0.0045
				(0.0035)	(0.0037)	(0.0051)
				[0.0058]	[0.0075]	[0.0050]
Intercept	7.59	6.78	-0.81	7.59	6.73	-0.86
	(0.11)***	(0.12)***	(0.17)***	(0.12)***	(0.13)***	(0.18)***
	[0.36]***	[0.42]***	[0.32]**	[0.40]***	[0.48]***	[0.33]**
No. Observations	3955	4085	8040	3955	4085	8040

Estimates of Mobility from Quadratic CEF

	Absolute Mobility				Relative Mobility	
	Sons	**Daughters**			**Sons**	**Daughters**
ES_0	7.59	6.78		***IGRC***	0.27	0.33
ES_6	9.21	8.76				
ES_9	10.02	9.75				
ES_{16}	11.91	12.06				

Notes: (1) The data used are CFPS 2016 with children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CR.B: Intergenerational Persistence in Schooling in Rural China
(18-30 Years Age Cohorts)

	LINEAR CEF			**QUADRATIC CEF**		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.27	0.32	0.054	0.27	0.38	0.11
	(0.017)***	(0.019)***	(0.025)**	(0.048)***	(0.053)***	(0.071)
	[0.039]***	[0.049]***	[0.028]*	[0.10]**	[0.12]***	[0.051]**
Quadratic Coefft.				-0.00047	-0.0056	-0.0052
				(0.0039)	(0.0043)	(0.0058)
				[0.0067]	[0.0075]	[0.0037]
Intercept	7.91	7.37	-0.54	7.90	7.31	-0.60***
	(0.13)***	(0.15)***	(0.20)***	(0.14)***	(0.16)***	(0.22)
	[0.34]***	[0.41]***	[0.27]*	[0.38]***	[0.47]***	[0.26]*
No. Observations	2833	2814	5647	2833	2814	5647

Estimates of Mobility from Quadratic CEF

	Absolute Mobility				**Relative Mobility**	
	Sons	**Daughters**			**Sons**	**Daughters**
ES_0	7.91	7.37		***IGRC***	0.27	0.32
ES_6	9.53	9.29				
ES_9	10.34	10.25				
ES_{16}	12.23	12.49				

Notes: (1) The data used are CFPS 2016 with children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CU.C: Intergenerational Persistence in Schooling in Urban China (18-35 Years Age Cohorts. First-born Sample)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	Daughters (D)	D-S	Sons (S)	Daughters (D)	D-S
Linear Coefft.	0.28	0.36	0.083	0.11	0.34	0.24
	(0.019)***	(0.018)***	(0.026)***	(0.053)**	(0.051)***	(0.074)***
	[0.024]***	(0.021)***	[0.027]***	[0.067]	[0.066]***	[0.079]***
Quadratic Coefft.				0.013	0.0015	-0.011
				(0.0033)***	(0.0032)	(0.0046)**
				[0.0037]***	[0.0040]	[0.0053]**
Intercept	9.26	8.47	-0.79	9.62	8.51	-1.11
	(0.18)***	(0.17)***	(0.25)***	(0.22)***	(0.21)***	(0.30)***
	[0.21]***	[0.30]***	[0.29]***	[0.28]***	[0.34]***	[0.33]***
No. Observations	2428	2617	5045	2428	2617	5045

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			Relative Mobility	
	Sons	Daughters		Sons	Daughters
ES_0	9.62	8.47	***$IGME_0$***	0.12	0.36
ES_6	10.75	10.63	***$IGME_6$***	0.257	0.36
ES_9	11.66	11.71	***$IGME_9$***	0.333	0.36
ES_{16}	14.71	14.23	***$IGME_{16}$***	0.51	0.36

Notes: (1) The data used are CFPS 2016 with first-born children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CU.D: Intergenerational Persistence in Schooling in Urban China
(18-30 Years Age Cohorts. First-born Sample)

	LINEAR CEF			**QUADRATIC CEF**		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft.	0.25	0.37	0.12	0.072	0.4	0.33
	(0.022)***	(0.023)***	(0.032)***	(0.062)	(0.065)***	(0.090)***
	[0.025]***	(0.026)***	[0.030]***	[0.066]	[0.089]***	[0.088]***
Quadratic Coefft.				0.013	-0.0018	-0.014
				(0.0038)***	(0.0039)	(0.0054)**
				[0.0039]***	[0.0053]	[0.0059]**
Intercept	9.53	8.45	-1.07	9.93	8.4	-1.53
	(0.21)***	(0.22)***	(0.30)***	(0.26)***	(0.28)***	(0.38)***
	[0.22]***	[0.30]***	[0.34]***	[0.30]***	[0.41]***	[0.40]***
No. Observations	1668	1748	3416	1668	1748	3416

Estimates of Mobility from Quadratic CEF

	Absolute Mobility			**Relative Mobility**	
	Sons	**Daughters**		**Sons**	**Daughters**
$\boldsymbol{ES_0}$	9.93	8.45	$\boldsymbol{IGME_0}$	0.12	0.37
$\boldsymbol{ES_6}$	10.83	10.67	$\boldsymbol{IGME_6}$	0.222	0.37
$\boldsymbol{ES_9}$	11.63	11.78	$\boldsymbol{IGME_9}$	0.298	0.37
$\boldsymbol{ES_{16}}$	14.41	14.37	$\boldsymbol{IGME_{16}}$	0.474	0.37

Notes: (1) The data used are CFPS 2016 with first-born children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CR.C: Intergenerational Persistence in Schooling in Rural China
(18-35 Years Age Cohorts. First-born Sample)

	LINEAR CEF			**QUADRATIC CEF**		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft	0.26	0.33	0.069	0.25	0.33	0.08
	(0.019)***	(0.019)***	(0.027)**	(0.055)***	(0.019)***	(0.078)
	[0.036]***	[0.046]***	[0.023]***	[0.097]**	[0.046]***	[0.074]
Quadratic Coefft.				0.00031	-0.00071	-0.001
				(0.0044)	(0.0047)	(0.0064)
				[0.0060]	[0.0073]	[0.0067]
Intercept	7.72	6.85	-0.86	7.72	6.84	-0.88
	(0.15)***	(0.15)***	(0.21)***	(0.17)***	(0.17)***	(0.24)***
	[0.31]***	[0.41]***	[0.27]***	[0.36]***	[0.47]***	[0.29]***
No. Observations	2444	2772	5216	2444	2772	5216

Estimates of Mobility from Quadratic CEF

	Absolute Mobility				**Relative Mobility**	
	Sons	**Daughters**			**Sons**	**Daughters**
ES_0	7.72	6.85		***IGRC***	0.26	0.33
ES_6	9.28	8.83				
ES_9	10.06	9.82				
ES_{16}	11.88	12.13				

Notes: (1) The data used are CFPS 2016 with first-born children aged 18-35. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling. (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.CR.D: Intergenerational Persistence in Schooling in Rural China
(18-30 Years Age Cohorts. First-born Sample)

	LINEAR CEF			QUADRATIC CEF		
	Sons (S)	**Daughters (D)**	**D-S**	**Sons (S)**	**Daughters (D)**	**D-S**
Linear Coefft	0.25	0.32	0.073	0.2	0.32	0.12
	(0.022)***	(0.024)***	(0.032)**	(0.062)***	(0.065)***	(0.090)
	[0.030]***	[0.044]***	[0.031]***	[0.091]**	[0.098]***	[0.055]
Quadratic Coefft.				0.0043	0.00048	-0.0039
				(0.0050)	(0.0052)	(0.0072)
				[0.0063]	[0.0060]	[0.0042]
Intercept	8.11	7.43	-0.68	8.16	7.43	-0.73
	(0.17)***	(0.18)***	(0.25)***	(0.19)***	(0.20)***	(0.28)***
	[0.25]***	[0.34]***	[0.24]***	[0.30]***	[0.40]***	[0.24]***
No. Observations	1732	1888	3620	1732	1888	3620

Estimates of Mobility from Quadratic CEF

	Absolute Mobility				Relative Mobility	
	Sons	**Daughters**			**Sons**	**Daughters**
ES_0	8.11	7.43		***IGRC***	0.25	0.32
ES_6	9.61	9.35				
ES_9	10.36	10.31				
ES_{16}	12.11	12.55				

Notes: (1) The data used are CFPS 2016 with first-born children aged 18-30. (2) $IGME_K$ is Intergenerational Marginal effect when father has K years of schooling, (3) ES_K is expected schooling when father has K years of schooling. K=0,6,9,16. (4) Robust standard errors in parentheses; standard errors clustered at province-level in square brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A3.IU: Father's Education and Educational Expenditure on Children

	URBAN INDIA			
	IHDS 2005			
	(6-22) Years Children		(8-23) Years Children	
Father's Sch.	384.4	338.7	403.9	348
	(14.9)***	(14.40)***	(17.4)***	(16.9)***
	[22.2]***	[20.4]***	[24.1]***	[22.6]***
	{28.2}***	{26.4}***	{30.9}***	{28.8}***
Father's Sch. * Daughter	-34.0	-37.5	-36.5	-40.2
Dummy	(20.5)*	(20.3)*	(23.9)	(23.5)*
	[19.0]*	[18.4]**	[21.9]*	[21.1]*
	{18.7}*	{16.7}**	{23.9}	{19.6}**
Daughter Dummy	-290.2	-189.9	-325.1	-174.3
	(136.9)***	(138.7)	(164.4)**	(162.9)
	[125.0]**	[118.9]	[144.0]**	[138.6]
	{142.2}*	{123.9}	{171.0}*	{148.0}
Intercept	784.8	2763.5	917.3	3220.7
	(105.1)***	(148)***	(124.9)***	(175.6)***
	[157.5]***	[271.2]***	[185.7]***	[332.3]***
	{223.2}***	{279.4}***	{255.2}***	{338.3}***
No. of Children		-673.1		-777.7
		(36.0)***		(41.9)***
		[75.9]***		[88.8]***
		{83.1}***		{99.8}***
No. Observations	13086	13086	11051	11051
	NSS 1995			
	(6-18) Years Children		(8-18) Years Children	
Father's Sch.	108.4	108.6	110.4	110.9
	(2.817)***	(2.789)***	(3.070)***	(3.039)***
	[7.819]***	[7.467]***	[7.436]***	[7.021]***
	{7.898}***	{7.735}***	{7.781}***	{7.644}***
Father's Sch. * Daughter	-11.3	-11.5	-11.2	-11.2
Dummy	(3.906)***	(3.860)***	(4.295)***	(4.238)***
	[2.766]***	[2.788]***	[3.114]***	[3.121]***
	{4.559}**	{4.497}**	{4.682}**	{4.616}**
Daughter Dummy	-39.4	-14.3	-41.55	-11.14
	(26.12)	(26.15)	(29.00)	(29.03)
	[16.95]***	[17.48]	[21.47]	[22.19]
	{26.77}	{29.61}	{30.19}	{33.90}
Intercept	505.9	923.0	543.6	1004.0

	(17.95)***	(23.74)***	(19.75)***	(26.13)***
	[22.78]***	[54.14]***	[23.99]***	[57.27]***
	{43.75}***	{79.43}***	{44.32}***	{85.89}***
No. of Children		-161.1		-178.0
		(7.164)***		(7.963)***
		[19.38]***		[19.83]***
		{22.93}***		{24.72}***
No. Observations	27810	27810	24443	24443

Notes: (1) The data used are IHDS 2005 and NSS 1995 respectively. (2) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A3.CU: Father's Education and Educational Expenditure on Children

	URBAN CHINA			
	CFPS 2010			
	(6-22) Years Children		(8-23) Years Children	
Father's Sch.	236.9	162.8	225.4	138.3
	(35.0)***	(34.1)***	(32.9)***	(30.5)***
	[38.7]***	[36.0]***	[39.1]***	[33.9]***
	{63.9}***	{47.5}***	{72.6}***	{56.4}**
Father's Sch. * Daughter Dummy	36.8	18.6	27.5	13.5
	(48.2)	(46.9)	(49.2)	(47.4)
	[39.2]	[39.6]	[38.6]	[38.9]
	{31.9}	{31.5}	{24.4}	{27.9}
Daughter Dummy	-71.2	181.1	22.4	267.5
	(400.2)	(386.8)	(413.7)	(397.5)
	[327.1]	[348.5]	[334.6]	[364.5]
	{275.1}	{305.8}	{252.7}	{318.8}
Intercept	827.4	4137.0	1034.3	4592.9
	(278.8)***	(337.8)***	(264.5)***	(330.1)***
	[300.0]***	[397.1]***	[295.5]***	[401.7]***
	{316.8}**	{436.8}***	{292.6}***	{488.9}***
No. of Children		-2222.0		-2401.2
		(132.7)***		(154.4)***
		[211.3]***		[233.4]***
		{366.3}***		{412.4}***
No. Observations	2784	2784	2435	2435

Notes: (1) The data used are CFPS 2010. (2) Robust standard errors in parentheses; standard errors clustered at county-level in square brackets; standard errors clustered at province-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A3.IR: Father's Education and Educational Expenditure on Children

	RURAL INDIA			
	IHDS 2005			
	(6-22) Years Children		(8-23) Years Children	
Father's Sch.	153.9	145.4	169.2	158.7
	(9.08)***	(8.77)***	(11.0)***	(10.6)***
	[16.3]***	[15.5]***	[19.8]***	[18.5]***
	{23.5}***	{21.5}***	{262.4}***	{23.8}***
Father's Sch. * Daughter	-22.8	-21.9	-24.0	-22.4
Dummy	(11.4)**	(11.3)*	(13.9)*	(13.7)
	[13.0]*	[12.8]*	[15.4]	[15.1]
	{8.69}**	{9.11}**	{9.63}**	{10.3}**
Daughter Dummy	-182.5	-137.1	-211.0	-134.0
	(43.5)***	(43.7)***	(52.3)***	(52.7)**
	[47.7]***	[49.1]***	[58.6]***	[60.9]**
	{38.1}***	{42.5}***	{48.5}***	{56.7}**
Intercept	772.3	1585.4	877.6	1949.3
	(33.3)***	(54.7)***	(39.8)***	(67.9)***
	[60.9]***	[101.5]***	[69.7]***	[125.9]***
	{106.3}***	{214.7}***	{118.4}***	{256.0}***
No. of Children		-274.4		-361.9
		(17.2)***		(21.8)***
		[32.4]***		[42.4]***
		{52.7}***		{65.7}***
No. Observations	23058	23058	19002	19002
	NSS 1995			
	(6-18) Years Children		(8-18) Years Children	
Father's Sch.	35.2	36.0	36.5	37.5
	(1.425)***	(1.453)***	(1.535)***	(1.567)***
	[2.444]***	[2.408]***	[2.501]***	[2.477]***
	{4.779}***	{4.739}***	{4.678}***	{4.647}***
Father's Sch. * Daughter	-3.7	-3.8	-3.4	-3.5
Dummy	(2.083)*	(2.081)*	(2.285)	(2.281)
	[2.115]*	[2.094]*	[2.236]	[2.210]
	{2.097}*	{2.068}*	{2.100}	{2.053}*
Daughter Dummy	-74.1	-69.2	-65.2	-58.5
	(8.694)***	(8.719)***	(9.700)***	(9.729)***
	[9.920]***	[9.122]***	[9.454]***	[8.760]***
	{13.59}***	{13.40}***	{15.46}***	{15.11}***
Intercept	426.9	463.7	461.0	507.7

	(5.420)***	(8.892)***	(5.882)***	(9.728)***
	[13.84]***	[14.70]***	[14.66]***	[16.35]***
	{31.18}***	{43.40}***	{32.70}***	{45.84}***
No. of Children		-17.0		-21.6
		(3.393)***		(3.749)***
		[7.615]		[7.554]***
		{16.69}		{17.29}
No. Observations	37144	37144	32499	32499

Notes: (1) The data used are IHDS 2005 and NSS 1995 respectively. (2) Robust standard errors in parentheses; standard errors clustered at district-level in square brackets; standard errors clustered at state-level in braces; *** p<0.01, ** p<0.05, * p<0.1.

Table A3.CR: Father's Education and Educational Expenditure on Children

	RURAL CHINA			
	CFPS 2010			
	(6-22) Years Children		(8-23) Years Children	
Father's Sch.	105.5	79.6	115.7	85.6
	(12.8)***	(12.1)***	(15.0)***	(14.0)***
	[15.3]***	[14.1]***	[17.5]***	[15.6]***
	{18.7}***	{15.3}***	{20.7}***	{14.8}***
Father's Sch. * Daughter	-31.8	-31.2	-21.7	-21.7
Dummy	(17.3)*	(16.6)*	(20.9)	(20.0)
	[18.9]*	[17.8]*	[21.6]	[19.8]
	{21.0}	{16.9}*	{23.2}	{16.5}
Daughter Dummy	151.6	240.3	111.2	275.2
	(103.1)	(100.6)**	(120.7)	(117.1)**
	[116.9]	[110.3]**	[132.5]	[121.1]**
	{147.9}	{126.6}*	{168.4}	{135.9}*
Intercept	648.0	1939.7	705.7	2173.6
	(71.0)***	(117.9)***	(83.3)***	(132.7)***
	[88.1]***	[171.4]***	[100.0]***	[186.5]***
	{86.4}***	{229.6}***	{87.9}***	{246.5}***
No. of Children		-716.8		-838.0
		(49.7)***		(56.8)***
		[87.2]***		[100.1]***
		{123.2}***		{141.5}***
No. Observations	4326	4326	3632	3632

Notes: (1) The data used are CFPS 2010. (2) Robust standard errors in parentheses; standard errors clustered at county-level in square brackets; standard errors clustered at province-level in braces; *** p<0.01, ** p<0.05, * p<0.1.