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**Is Gender Destiny?**
**Gender Bias and Intergenerational Educational Mobility in India**[1]

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ABSTRACT

We develop a model of intergenerational educational mobility incorporating gender bias against girls in the family, school, and labor market. Mobility and investment equations from the model are estimated for India using data not truncated by coresidency. The standard linear model misses important heterogeneity and yields misleading conclusions. Daughters of uneducated fathers face lower relative and absolute mobility (rural and urban). We find gender equality in absolute mobility for children of urban college educated fathers, but not in rural areas. Theoretical insights help understand the mechanisms. Parental nonfinancial inputs, unwanted girls, and patrilineal states are important for explaining the findings.

**Key Words:** Gender Bias, Intergenerational Mobility, Education, Becker-Tomes Model, Heterogeneity, Son Preference, Unwanted Girls, India, Patrilineal, Matrilineal, Coresidency Bias

**JEL Codes:** I24, J62, J16, O20

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**(1) Introduction**

Gender bias against girls in developing countries has been the focus of a large economic literature (for excellent surveys, see World Bank (2012), Duflo (2012)). India has been under the microscope in many of these studies reporting evidence of gender bias against girls, for example, in health (Jayachandran and Pande (2017)), education expenditure (Azam and Kingdon (2013)), breast feeding (Jayachandran and Kuziemko (2011)), and a skewed sex ratio because of sex selection (Sen (1990)).[2] In contrast, the gender gap (boys-girls) in schooling in India has gone down substantially over the decades. The gender gap in gross enrollment ratios for the grades 1-8 was 30.1 percent in 1981, but India achieved near gender parity in 2011 with a gap of only 1.2 percent.[3] Estimates based on the India Human Development Survey (IHDS) 2012 data show a gender gap of 3 years of schooling for the 1950s birth cohort, which declined to a gap of 0.60 years of schooling for the 1990s and later birth cohorts.[4] The gains toward gender parity in schooling seem incompatible with the extensive evidence of gender bias noted above. Does gender convergence in schooling attainment imply that the girls in the younger generation in India enjoy *equal educational opportunities* as the boys?

To analyze this question, we study intergenerational educational persistence in India with a focus on the implications of gender bias in the family, school and labor market. A burgeoning literature in economics and sociology analyzes inequality in economic opportunities of children by estimating intergenerational persistence in indicators of economic status. The focus of this literature is on understanding the role of family background in shaping the life chances of a child. A vast literature on developed countries primarily focuses on intergenerational persistence in permanent income. In contrast, the literature on developing countries largely focuses on education because the required panel data on income are not available. Although both intergenerational mobility and gender bias have been active research areas in economics, there is little work at the intersection of these two. Most of the available studies of intergenerational mobility focus on the father-son linkage, and research on women in general, and gender bias in particular, remains scarce.[5]

[2] Estimates for the 1990s suggest 39.1 million women were missing in India (Klasen and Wink (2003)).

[3] Estimates from Statistics of School Education 2011-2012, Government of India.

[4] In most developing countries, girls have historically lagged behind boys in educational attainment. However, the gender gap is narrowing over time and a reverse gender gap has emerged in Latin America in educational attainment (Grant and Behrman (2010)).

[5] Among the available contributions on intergenerational mobility of daughters, see Chadwick and Solon (2002) on the USA, Azam (2016) on India. Azomahou and Yitbarek (2021) find that relative educational

We need to address two major challenges to understand whether the girls in the younger generation in India face unequal educational opportunities despite the recent gains in schooling attainment. First, most of the household surveys use coresidency to define household membership and the resulting sample truncation from the missing nonresident members causes upward bias in the estimates of relative mobility.[6] More importantly, the gender gap is likely to be severely underestimated because the upward bias is significantly higher for girls (Emran et al. (2018)). To overcome this, we use data from India Human Development Survey (IHDS, 2012) which do not suffer from any significant sample truncation. The second challenge is that it is difficult to interpret the evidence when the estimating equations are not derived from a theoretical model (Mogstad (2017)).[7] To address this, we develop a model of intergenerational educational mobility in the tradition of Becker and Tomes (1986) incorporating gender bias against girls in the family, school, and labor market. We show that the workhorse linear mobility equation implies no gender gap in relative mobility even when the parents have son preference and systematically underestimate the academic ability of a daughter. Without the guidance of the theory, a researcher relying on the standard linear model would (incorrectly) conclude that there is no gender bias when relative mobility is not significantly different between sons and daughters. This paper provides the first theoretically grounded empirical analysis of the extent, sources, and consequences of gender bias for intergenerational educational mobility in a developing country. Our focus is on the younger generation in India who went to school during the 1990s to 2010s.

The model of intergenerational educational persistence in this paper captures different sources of gender bias against girls. The most common sources of gender bias in the family are: (i) biased parental estimates of academic ability, (ii) lower weight to the welfare of a daughter compared to that of a son ("pure son preference"), and (iii) lower expected returns

mobility is lower for girls in 7 out of 9 African countries in their sample, and Alesina et al. (2019) provide estimates of absolute educational mobility for both men and women in 27 African countries. But these papers do not study the sources of gender gap. For evidence on intergenerational transmission of gender attitudes in India, see Dhar et al. (2019).

[6] For education, relative mobility is measured by persistence in schooling attainment across generations, usually estimated as the slope parameter of a regression of children's schooling on parent's schooling. Relative mobility = 1- slope; thus, higher persistence implies lower relative mobility. In a perfectly mobile society, there is no persistence (a zero slope), implying that father's education is immaterial for educational opportunities of children.

[7] Most of the recent studies on intergenerational educational mobility do not derive the estimating equations from theory. The only exception we are aware of is Card et al. (2018) on the USA, but their focus is not gender bias.

to a daughter's education. The expected returns may in part reflect gender bias in the labor market.[8] These factors affect financial investment in education of daughters, but gender differences can also be important in nonfinancial impacts of parents' education such as role model effect and home tutoring. Another important concern is unfavorable school environment faced by the girls; for example, the absence of toilets for girls can result in dropouts when a girl reaches puberty.

The conditional expectation function (CEF) of children's education (years of schooling) given parental education is assumed to be linear in the existing studies on intergenerational educational mobility we are aware of. In a Becker-Tomes model with self-financing constraint, the intergenerational educational mobility equation is linear when the education production function has constant returns. This "linear model" of intergenerational educational mobility, however, yields strong predictions: parental bias against girls in financial investment arising from pure son preference and biased estimates of ability does not affect relative mobility; the effects of parental biases are captured by the intercept of the regression function.[9] When education production function exhibits diminishing returns, the estimating equation for intergenerational educational mobility is concave in parental schooling.[10] In contrast to the linear model, parental gender bias in financial investment affects both relative and absolute educational mobility when diminishing returns are important.[11] In the absence of biases against girls, we expect no significant gender gaps in both relative and absolute mobility, and girls enjoy equal educational opportunities.

The main conclusions from our empirical analysis are as follows.[12] Evidence rejects the

[8]However, a substantial body of evidence on India shows that returns to education are *higher for girls*, even though there is substantial gender wage gap in the labor market. The wage gap reflects a lower base for the girls.

[9]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.

[10]To our knowledge, the quadratic intergenerational educational persistence equation was first derived by Becker et al. (2015). Our set-up is different from theirs in three ways. First, the complementarity and convexity emphasized by Becker et al. (2015) is unlikely to be important in a country such as India. Evidence below shows that the mobility function is concave in both rural and urban India. Second, our modeling of the credit constraint is different (section 3 below). Third, Becker et al. (2015) do not explore gender bias in intergenerational mobility.

[11]For education, absolute mobility is measured by the expected years of schooling of a child conditional on parent's education which depends on both the intercept and the slope of the mobility equation. Even when there is no significant gender gap in relative mobility (slope measure), we can have substantial gender gap in absolute mobility because of differences in the intercepts.

[12]An advantage of the approach developed in this paper is that the conclusions regarding the nature of gender bias and its implications for intergenerational educational mobility pertain to the whole population of

widely used linear model of intergenerational educational persistence in both rural and urban India. The mobility CEF is concave irrespective of gender and location, implying heterogeneous relative mobility across the distribution of father's schooling. Girls face lower relative mobility when the father has low education but there is no significant gender gap for the children of fathers with college education, both in urban and rural areas. If one relies on the standard linear model, the estimates lead to the incorrect conclusion that girls face substantially lower relative mobility even when the fathers are college educated. Evidence suggests that absolute mobility is also lower for girls born to fathers with low education irrespective of location, but the gender gap closes only in the urban areas when the father is college educated. The girls born into low educated households are thus doubly disadvantaged: they face lower relative and absolute mobility, and this is true in both rural and urban areas.

The evidence, interpreted in terms of the theory, helps uncover some of the underlying mechanisms: (i) girls face unfavorable school environments in both rural and urban India; (ii) there is pure son preference in rural India, but the estimates are not informative in urban India; and (iii) parent's direct (nonfinancial) impact is stronger for girls in urban households. The analysis of the mechanisms based on a linear model leads us astray, implying no son preference in rural India. Evidence from the first child sample suggests that the phenomenon of "unwanted girls" is important in accounting for gender gap in educational opportunities in India.[13] A lower incidence of unwanted girls and a higher impact of parental nonfinancial inputs on girls provide plausible explanations for the gender parity in absolute mobility in college educated households in urban India. Strikingly, the evidence indicates no statistically significant gender bias in intergenerational educational persistence in the matrilineal states in India, suggesting a central role of the patrilineal and patrilocal Hindu kinship system in the observed gender differences at the national level. The approach developed in this paper is of wider interest as it can be fruitfully used in other developing countries.

The rest of this paper is organized as follows. In section 2, we discuss the related literature with a focus on India, and put the contributions of this paper in perspective. The next section develops a theoretical model that incorporates gender bias in both financial investment and

interest.

[13] "Unwanted girls" are the girls who would have been aborted as foetus if ultrasonography technology was available and affordable to the parents. In India, the use of ultrasonography was limited during our study period, and as a consequence many parents had unwanted girls. See section (10) below.

nonfinancial inputs by parents, and also in the labor market (returns to education) and school. Section 4 discusses the measures of relative and absolute mobility in a concave mobility model. Section 5 is devoted to a discussion of the data, sample construction, and summary statistics. Section 6 reports and discusses the estimates of the investment and mobility equations for urban India, along with an analysis of how the estimated parameters can help sort out the underlying mechanisms. Section 7 is devoted to a similar analysis for rural India. Robustness checks for alternative age ranges are contained in section 8. Section 9 offers a discussion on the pitfalls of the maintained assumption of linearity. The following section provides an analysis of the role played by unwanted girls. Section 11 reports the estimates for patrilineal vs. matrilineal states. The last section (section 12) 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 extensive, 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 (see, for example, Solon (1992), Mazumder (2005)).[14] However, most studies deal with father-son linkages, and research on women, and in particular on gender bias is lacking.

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, with a relatively small strand devoted to occupational persistence.[15] For an excellent survey of this literature, see Iversen et al. (2019). For cross-country evidence, please see Hertz et al. (2008) and Neidhofer et al. (2018). The recent studies on India include Azam and Bhatt (2015), Azam (2016), Emran and Shilpi (2015), Asher et al. (2018). For recent analysis of

[14]The recent papers on developed countries include Chetty et al. (2014), Card et al. (2018), Chetty et al. (2020), Black et al. (2020).

[15]For a discussion on the methodological challenges and data constraints in research on intergenerational mobility in developing countries, see Emran and Shilpi (2019).

intergenerational educational mobility in Africa, see Azomahou and Yitbarek (2021), and Alesina et al. (2019). While Azomahou and Yitbarek (2021) and Alesina et al. (2019) provide estimates of intergenerational educational mobility for both men and women, their focus is not on the sources and implications of gender bias.[16] We are not aware of any study that analyzes gender bias in intergenerational mobility using estimating equations derived from an explicit theoretical model. The close connection between theory and empirical work in this paper sets it apart from the existing literature on intergenerational educational mobility in developing countries. Among the studies on intergenerational occupational persistence, see Azam (2015) on India, Emran and Shilpi (2011) on Nepal and Vietnam. For evidence on intergenerational persistence in health in developing countries, see Bhalotra and Rawlings (2013).

**(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 $s$, and 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 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, we couch the discussion in terms of father as the parent. The income determination equation assumes that fathers with zero years of schooling earn $Y_0^p > 0$, and the return to education is $R^p$ in the parental generation. The assumption that $Y_0^p > 0$ reflects our empirical context where 40-50 percent of fathers have zero years of schooling, but most of them report positive income.[17]

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

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

[16] Alesina et al. (2019) provide estimates of absolute mobility, but relative mobility is not studied. Azomahou and Yitbarek (2021) focus on relative mobility, but do not study absolute mobility. We study both relative and absolute mobility.

[17] In our main estimation sample of 18-35 years aged children, 39.83 percent fathers have zero schooling.

The budget constraint assumes that there is no credit market where the father can borrow to finance children's education. This is a plausible assumption in the context of developing countries where the student loan market (public or private) is underdeveloped or nonexistent.

We assume that the education production function exhibits two features: (i) diminishing returns to investment, and (ii) parent's education has a direct (nonfinancial) impact on children's education:

$$H_i^{cj} = \delta_0 + \delta_1^j I_i - \delta_2^j I_i^2 + \delta_3^j H_i^p - \delta_4^j \left(H_i^p\right)^2, \tag{3}$$

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 $\delta_2^j, \delta_4^j \geq 0$.[18] 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 captures nonfinancial aspects including home tutoring and role model effects. The intercept term ($\delta^0$) 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 in the production function are specified as below:

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

where $L^j$ denotes the learning environment faced by a child of gender $j$ in the school, and $\phi$ is the ability of a child.[19] The specifications in (4) imply that higher ability and better learning environment increase the marginal returns to parental investment by both increasing the linear coefficient $\delta_1^j$ and by reducing the degree of diminishing returns through a lower $\delta_2^j$. The girls may face a relatively unfavorable learning environment ($L^d < L^s$) when going to the same school as the boys because of factors such as a lack of female teachers as role models, and the unavailability of appropriate infrastructure such as separate restrooms for girls. They may also face harassment on the road to school and in school by boys.

It is important to appreciate the distinction between the true ability of a child $\phi$ and a parent's estimate of a child's ability denoted as $\tilde{\phi}^j$. Investment choices of parents ($I_i$) are

[18] Equation (3) is different from the Becker et al. (2018) specification in that it does not admit possible convexity in the mobility CEF arising from complementarity between parental education and financial investment. The evidence below shows that the mobility CEF in India is concave, consistent with the assumption of no significant complementarity.

[19] 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, *ceteris paribus* (Hyde et al. (2008)).

determined by the estimated ability $\tilde{\phi}^j$, and given an investment level, the actual educational attainment ($H^{cj}$) is determined by the true ability of a child $\phi$. 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 $\tilde{\phi}^s > \phi > \tilde{\phi}^d$.[20] The schooling production function used by the father (denoted as $\tilde{H}^c$) for a given level of financial investment can be written as:

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

where $\tilde{\delta}_1^j = \delta_1^0 + \gamma_1 L^j + \gamma_2 \tilde{\phi}^j$ and $\tilde{\delta}_2^j = \delta_2^0 - \omega_1 L^j - \omega_2 \tilde{\phi}^j$. 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:

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

The returns to education $R^{cj}$ are gender specific. There is substantial evidence that returns to education in the labor market may be higher for women. In an 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 during the 1980s and 1990s (see, for example, Bargain et al. (2009)). Pitt et al. (2012) suggest that the higher returns to education for girls reflect two factors: (i) structural change in favor of skill-intensive occupations, and (ii) women's comparative advantage in skill-intensive occupations as opposed to brawn-intensive occupations. However, the evidence also consistently shows that there is a substantial gender wage-gap against women due to the fact that $Y_0^{cd} < Y_0^{cs}$ in most of the cases. It is well-known that returns to education play a prominent role in intergenerational educational persistence (Solon (2004)). As we will see below, in contrast, the intercept $Y_0^{cj}$ matters much less.

For the 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, even though they might hold incorrect expectations about the *levels* of the returns.[21]

[20]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. In this case, the inequality above will also reflect the actual differences in cognitive ability generated by gender bias.

[21]In a widely-cited study, Jensen (2010) shows that parents in the Dominican Republic underestimate the

We also show that the empirical evidence from the mobility and investment equations leads to highly implausible conclusions if we assume that the parents are not aware of higher returns to education for girls, and incorrectly believe the returns to be lower for them. To the best of our knowledge, there are no studies on eliciting parental belief about returns to education for sons vs. daughters in India.[22]

**(3.1) Optimal Educational Investment**

Following Becker et al. (2015), the consumption sub-utility of the parent is a concave quadratic function:

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

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

$$Max_{C_{i}^{p},I_{i}}V_{i}^{p}=U\left(C_{i}^{p}\right)+\sigma^{j}E\left(Y_{i}^{cj}\right)+\lambda\left[Y_{i}^{p}-C_{i}^{p}-I_{i}\right] \tag{8}$$

where $\sigma^{j}$ is the degree of parental altruism, and "pure son preference" implies that $\sigma^{s}>\sigma^{d}$, and parents use production function (5) to estimate the expected income of children $E\left(Y_{i}^{cj}\right)$.[23]

The first order conditions are (ignoring the $i$ subscript for notational simplicity):

$$\begin{gathered}\alpha_{1}-2\alpha_{2}C^{p}-\lambda=0\\ \sigma^{j}R^{cj}\left(\tilde{\delta}_{1}^{j}-2\tilde{\delta}_{2}^{j}I\right)-\lambda=0\end{gathered} \tag{9}$$

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:

$$I^{*j}=\theta_{0}^{j}+\theta_{1}^{j}H^{P} \tag{10}$$

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, suggesting labor market returns are important for parental decisions regarding women's education in India.

[22]Some readers might argue that casual observations suggest that many parents believe it is not "worth" investing in a girl's education. However, parents' beliefs primarily reflect the gender wage gap against girls (reflecting a lower intercept for girls) which is likely to be salient in their information set. To elicit their belief about Mincerian returns (wage gradient) one needs a well-designed study.

[23]Pure son preference reflects cultural norms in a patrilineal and patrilocal society. The parents may also value the income of a son more for economic reasons such as old age support.

where

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

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

It is important to note some of the implications of equations (11) and (12) which are not well appreciated in the current literature on intergenerational educational mobility. The intergenerational mobility equation is linear when the education production function is linear ($\delta_2^j = \delta_4^j = 0$) (see the next sub-section).[24] 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.,* $R^{cd} < R^{cs}$*)*, a lower estimate of academic ability of girls *(i.e.,* $\tilde{\phi}^d < \tilde{\phi}^s$*)*, and unfavorable school environment faced by girls in schools *(i.e.,* $L^d < L^s$*)* implies that $\theta_0^d < \theta_0^s$, but $\theta_1^d = \theta_1^s = R^p$. This suggests that we should be careful in interpreting the estimates of the investment equation (10) above. Without the benefit of the theory, many 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.

**(3.2) Intergenerational Persistence in Education**

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

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

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

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

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

[24]We assume that the parents know the true functional form of the education production function, and thus $\delta_2^j = 0$ implies that $\tilde{\delta}_2^j = 0$. It seems highly implausible that parents would mistakenly think the production function to be quadratic when it is linear. One can argue that when the true production function is quadratic, parents might use a rule-of-thumb linear production function for their optimization because of bounded rationality and imperfect information. However, a testable implication of a linear rule of thumb production function is that the slope of the investment function does not vary by gender which we test in the empirical section.

where

$$\psi_0^j = \delta_0 + \theta_0^j \left[\delta_1^j - \delta_2^j \theta_0^j\right] \tag{15}$$

$$\psi_1^j = \theta_1^j \left(\delta_1^j - 2\delta_2^j \theta_0^j\right) + \delta_3^j \tag{16}$$

$$\psi_2^j = -\delta_2^j \left(\theta_1^j\right)^2 - \delta_4^j \tag{17}$$

The theoretical analysis above clarifies the assumptions implicit in the linear CEF used almost universally in the existing empirical literature on intergenerational educational mobility. A linear intergenerational persistence equation implies that $\psi_2^j = 0$ which requires $\delta_2^j = \delta_4^j = 0$, implying constant returns in the education production function. In the linear model, parental bias against girls in financial investment does not affect relative mobility, as measured by the slope parameter $\psi_1^j$. In this case, relative mobility can be affected by parental bias only through nonfinancial inputs as captured by the parameter $\delta_3^j$ or unfavorable school environment $L^j$ in the production function because $\psi_1^j = \delta_1^j R^p + \delta_3^j = \left(\delta_1^0 + \gamma_1 L^j + \gamma_2 \phi\right) R^p + \delta_3^j$. The effects of parental bias in financial investment are captured by the intercept of the linear CEF (i.e., $\hat{\psi}_0^j$) alone, and affects absolute mobility. In a linear model, the mobility intercept is $\psi_0^j = \delta_0 + \theta_0^j \delta_1^j = \delta_0 + \left[(2\alpha)^{-1}\left(2\alpha_2 Y_0^p + \tilde{\delta}_1^j \sigma^j R^{cj} - \alpha_1\right)\right]\delta_1^j$. The mobility intercept thus depends on parental bias in altruism ($\sigma^j$), and the estimate of ability ($\tilde{\phi}^j$) working through $\tilde{\delta}_1^j = \delta_1^0 + \gamma_1 L^j + \gamma_2 \tilde{\phi}^j$.

### (3.3) Sources of Gender Bias: 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 especially useful in understanding the role played by the direct (non-financial) impact of parents' education on children's schooling.[25]

From the investment equation (10) and mobility equation (14), we estimate 5 parameters for each gender, and the estimated parameters provide us 5 binary relations for girls vs. boys. These binary relations impose restrictions on the potential explanations, and help sort out the existence and mechanisms of gender bias.[26] We combine the evidence from a

[25]The existing work on intergenerational educational mobility we are aware of exclusively focuses on the mobility equation and does not estimate the investment equation.

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

substantial literature on the gender differences in returns to education with the estimates of the investment and mobility parameters for sons vs. daughters. Once we have the estimates of the parameters of the investment equation, the linear and quadratic coefficients of the mobility equation help us understand gender bias in parental nonfinancial inputs. Although the potential importance of parental nonfinancial inputs in intergenerational mobility has been emphasized in the literature including by Becker and Tomes (1979, 1986), we are not aware of any analysis of intergenerational educational mobility in developing countries that provides evidence on this issue.[27]

However, it is also important to recognize a limitation of the approach developed in this paper: in some cases, evidence on the binary relations and returns to education may not be able to discriminate between alternative hypotheses about a particular source of gender bias. Thus, we cannot say whether this specific mechanism is operative in the data, and in such cases, we call the evidence "uninformative" or "not informative".

**(4) Measures of Relative and Absolute Mobility**

In a linear model of mobility (i.e., with $\psi_2 = 0$), the slope parameter $\psi_1$ is known as intergenerational regression coefficient (IGRC) in the literature. IGRC is the most widely used measure of relative mobility (Hertz et al. (2008)). 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 distribution, and we call it "intergenerational marginal effect" or IGME for short:

$$IGME_k^j = \hat{\psi}_1^j + 2\hat{\psi}_2^j H_k^p, \tag{18}$$

where $IGME_k$ stands for intergenerational marginal effect for the children of fathers with $H_k^p$ years of schooling. In the empirical analysis, we will provide estimates of $IGME_k$ at focal points of father's education distribution such as no schooling, primary (5 years), secondary (10 years), college (15 years), and Masters (17 years).[28]

As a measure of absolute mobility, we provide estimates of expected years of schooling for the children conditional on father's schooling, denoted as $EH_k^c$ when the father has $H_k^p$ years

[27] Lefgren et al. (2012) provide evidence that father's financial resources explain only a minority of intergenerational income elasticity in Sweden.

[28] In India, Masters programs are usually 2 years after a 3 year Bachelors degree.

of schooling:

$$EH_k^{cj} = \hat{\psi}_0^j + \hat{\psi}_1^j H_k^p + \hat{\psi}_2^j (H_k^p)^2 \tag{19}$$

Absolute mobility thus depends on both the slope and the intercept estimates of the intergenerational persistence equation (14) above. This definition of absolute mobility is similar to that of Chetty et al. (2014).[29]

An important subgroup in our analysis consists of the children of the parents with zero schooling (i.e., $H_k^p = 0$), as the proportion of fathers with no schooling is substantial in our data. For example, in rural areas, 47 percent of fathers have no schooling (based on the 18-35 age sample). These children come from the most disadvantaged socioeconomic background. For this subgroup, absolute mobility is defined solely by the intercept term $\hat{\psi}_0^j$. Thus, the potential biases in the estimated intercept is of especial interest in our analysis, even though the focus of the current literature is on the biases in the estimated slope. Recent evidence shows that sample truncation due to coresidency results in an upward biased estimate of $\hat{\psi}_0^j$ (see Emran and Shilpi (2019)); consequently, the estimates based on coresident samples are likely to *overestimate* the absolute mobility of the children from the most disadvantaged background.[30] There are also important conceptual implications: $\hat{\psi}_0^j$ does not depend on $\delta_3$ and $\delta_4$, implying that the absolute mobility of the children of fathers with no education is unaffected by the nonfinancial influences of fathers such as home tutoring. The fact that only educated parents can provide nonfinancial inputs such as home tutoring is an important source of heterogeneity in absolute mobility between the children of educated and uneducated parents. In contrast, relative mobility of the children of fathers with zero schooling is given by the parameter $\hat{\psi}_1^j$ which depends on the nonfinancial inputs of parents through $\delta_3$. This reflects the fact that relative mobility captures the marginal effect of one year of more schooling for a father.

[29]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. This is a weak concept of upward mobility in a context where a substantial proportion of fathers has zero schooling (47 percent in our rural India sample). In this case, even one year of schooling would be counted as upward mobility for the children from almost 50 percent of the households in rural India, even though they are still at the bottom of the schooling distribution in their own generation.

[30]Sample truncation at the tails of the distribution rotates a positively sloped regression function clockwise inflating the intercept estimate while lowering the slope.

### (5) Data

The data for estimating the intergenerational educational mobility come from the second round of India Human Development Survey (IHDS)-2012. The IHDS is a high quality nationally representative household panel survey of 41554 households with two rounds in 2005 and 2012.[31] The survey covers both rural and urban areas. Compared to other data sets commonly used to study intergenerational mobility in India (e.g., National Sample Survey (NSS), and National Family Health Survey (NFHS)), IHDS-2012 has three important advantages. First, it includes a nonresident module to collect information on the children not in the household at the time of the survey including those who are away attending college. This module also includes the noresident husbands of the female headed households. Second, it collected information on the nonresident father of household head. Third, it includes an "eligible women" module that collected information on the father of two ever married women of age 15-49, including household head's spouse (irrespective of father's residency status).

To generate matched son-father pairs for our mobility analysis, we implement a two-step procedure. First, we follow Azam and Bhatt (2015) closely (see the Table 8 in Azam and Bhatt (2015)) and gather household head's father's education information directly from the household module, irrespective of a father's residency status at the time of the survey.[32] In the second step (not implemented by Azam and Bhatt (2015)), we include children from the nonresident module.[33] There are 9877 father-son pairs in our urban sample and 17761 in our rural sample for the 18-35 age group. To generate matched daughter-father pairs, we follow Azam (2016) closely, and include women from the "eligible women" module (see the Table 1 in Azam (2016)).[34] Again, we add the daughters from the nonresident module, unlike Azam (2016). However, note that our estimation samples differ from that in Azam and Bhatt (2015) and Azam (2016) in another respect. Unlike Azam and Bhatt (2015) and Azam (2016), our sample does not include the children from the female headed households where household

[31]The survey is a collaborative project between University of Maryland and National Council for Applied Economic Research (NCAER) in India.

[32]The only difference is that we use wave 2 (2012) while Azam and Bhatt (2015) use wave 1 (2005) of IHDS panel data. IHDS 2005 cannot be used for our mobility analysis as it does not include the "eligible women" module discussed above.

[33]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.

[34]Since Azam (2016) also uses IHDS-2012 data, we can compare our sample precisely, as shown in the online appendix Table A1.D.

head is a widow, because their father's education information is not available.[35] In our main estimation sample of 18-35 age group of children, there are 9326 daughter-father pairs in urban areas, and 17387 in rural areas.[36] To check whether the conclusions are driven by the older children in our sample, we progressively exclude older children from the sample and use 18-30 and 18-28 age ranges for the estimation of the mobility equation. For rural India, we also use 16-35 age group because the average level of education is low. For urban India, we use 20-35 age group to ensure that the conclusions are not affected by censoring of years of schooling for those children who attend 3-year college. For details, see section (8) below.

For estimation of the investment equation, we take advantage of the first round of the IHDS survey in 2005 that provides education expenditure data at the child level. Education expenditure includes school fees, books, uniform, transportation and other materials, and private tuition for the last year. We report investment estimates for two age groups: 8-28 and 11-28 in 2005. We set 28 years as the upper age cutoff as it corresponds to 35 years in 2012. However, many children in the age group 18-28 in 2005 have already completed their schooling, and are not captured in the investment sample. This constitutes part of the motivation to check the robustness of the mobility results using samples that exclude older children (18-30, 18-28) as noted in the preceding paragraph. To ensure that the conclusions are not driven by a few outliers, we winsorize and trim the expenditure data at 99.9 percentile. In the 11-28 age group, this affects only 16 observations out of 15285 observations in rural sample, and 10 observations out of 9360 observations in urban sample.

The summary statistics for our main estimation samples are reported in Table 1, the upper panel for the urban sample and the lower panel for the rural sample. The mean education of fathers in urban areas is 6.70 years in the sons sub-sample, and 6.51 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 9.43 for daughters in urban sample. In the rural sample, the average education of fathers is much lower; 4.01 years (sons sub-sample) and 3.87 (daughters sub-sample). The gender gap in average schooling is also much

[35] We are grateful to Sonalde Desai, principal investigator for the IHDS survey, for clarifying the questionnaire in this regard which was apparently misinterpreted by Azam and Bhatt (2015) because of confusing wording. Please see the discussion in online appendix section OA.5.

[36] If one relies on only the coresident sub-sample, 54 percent of our estimation sample in urban areas and 46 percent in the rural areas would be included. Sample truncation is especially severe for girls: the coresident sub-sample is only 32 percent of our estimation sample in urban areas and 22 percent in rural.

more pronounced in the rural areas; 8.31 years (sons) vs. 6.35 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: 8-28 year old and 11-28 year old.

### (6) Gender and Intergenerational Educational Mobility in Urban India: Evidence and Interpretations

The discussion focuses on the results from the sample of 18-35 year old children (reported in the main paper) with reference to the estimates from the 18-30, 18-28, and 20-35 age ranges where necessary. All the regressions (investment and mobility) control for the number of children in a family. The standard errors are clustered at the primary sampling unit which is district in the IHDS survey.

#### (6.1) Estimates of the Mobility Equation

The estimates of intergenerational schooling persistence in urban India are reported in the upper panel of Table 2. The first two columns contain the evidence from a linear CEF comparable to the existing literature. The estimate of the slope parameter $\psi_1$ in urban India for daughters (0.523) is higher than that for sons (0.450), suggesting a higher intergenerational persistence in schooling (lower relative mobility) for the daughters irrespective of father's education (the gender difference is significant at the 1 percent level). The intercept for the daughters is also lower.

The estimates from a linear CEF are consistent with the common perception of strong gender bias against girls in India. However, evidence rejects the assumption of linearity; the estimates of the quadratic coefficient in columns (4) (for sons) and (5) (for daughters) in Table 2 are negative and statistically significant at the 1 percent level. The quadratic coefficient is numerically or statistically not significantly different (at the 10 percent level) across gender.

As a measure of absolute mobility, we report estimated expected years of schooling conditional on a father having 0, 5, 10, 15, and 17 years of schooling in the bottom panel of Table 2.[37] The daughters born to low educated fathers face substantial disadvantage in term of expected schooling attainment (the $EH_0^c$ estimates are: 5.85 (daughters) vs. 6.92 (sons)), and the gender difference is significant at the 1 percent level.[38] But the gender difference

[37]We chose 15 years as a focal point (instead of 16 years) because of 3 years Bachelors degree in Indian education system after the higher secondary schooling (12 years). 17 years of schooling refer to the two-year Master's degree.

[38]The $EH_0^c$ estimates refer to the children of fathers with zero years of schooling. The proportion of fathers

is numerically small and not significant at the 10 percent level when the father has college education (the $EH^c_{15}$ estimate is 13.48 for daughters and 13.52 for sons).

For relative mobility, the estimated $IGMEs$[39] in the bottom panel of Table 2 show that the persistence is much stronger for the girls born to fathers with low education ($IGME_0$ estimates are: 0.65 (daughters) vs. 0.56 (sons)), but the gender difference becomes negligible and statistically insignificant when the father has college or more education: ($IGME_{15}$ estimates are: 0.32 (sons) vs. 0.37 (daughters)).

Evidence on absolute and relative mobility thus favors the idea that the gender differences in educational mobility of children may primarily be a product of low education of parents. This also brings into focus the incorrect conclusions from the standard linear mobility CEF that the daughters face substantially lower relative mobility throughout the parental schooling distribution. Section (9) below provides a detailed discussion of the misleading conclusions one might get when linearity is a maintained assumption.

**(6.2) Estimates of the Investment Equation**

The estimates of the parameters of the investment equation $\theta_0$ and $\theta_1$ for urban India are reported in the upper panel of Table 4, using the first round of IHDS (2005) data. The evidence from alternative age groups suggests that $\hat{\theta}^d_1 < \hat{\theta}^s_1$; the interaction of father's education with the daughter dummy is negative and statistically significant at the 5 percent level in 3 cases, and at the 10 percent level in 1 case.[40] The estimates of the intercept show a different picture: the daughter dummy is *not* statistically significant at the 10 percent level across the board, suggesting $\hat{\theta}^d_0 = \hat{\theta}^s_0$.[41]

For ease of reference, we summarize the binary relations across gender for the estimated investment and mobility parameters in Table 5. To help a reader keep track of the different parameters we present a summary of the notation and interpretation of the key parameters in Table N at the beginning of the online appendix.

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with zero schooling in urban India is 26.44 percent in our sample.

[39]Recall that IGME is defined as the slope of the mobility CEF. $IGME^j_k = \hat{\psi}^j_1 + 2\hat{\psi}^j_2 H^p_k$.

[40]This is consistent with the existing evidence on gender bias against girls in educational expenditure in India (see Kingdon (2007), Azam and Kingdon (2013)). 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.

[41]The magnitude of the coefficient on girl dummy is small compared to the estimated constant in the 11-28 sample. This sample includes only those age cohorts that overlap with our mobility sample.

**(6.3) Sources of Gender Bias in Urban India**

The evidence that $\hat{\theta}_0^d = \hat{\theta}_0^s$ implies the following relation from theory:

$$\frac{2\alpha_2 Y_0^p + \tilde{\delta}_1^d \sigma^d R^{cd} - \alpha_1}{2\left\{\alpha_2 + \tilde{\delta}_2^d \sigma^d R^{cd}\right\}} = \frac{2\alpha_2 Y_0^p + \tilde{\delta}_1^s \sigma^s R^{cs} - \alpha_1}{2\left\{\alpha_2 + \tilde{\delta}_2^s \sigma^s R^{cs}\right\}}. \tag{20}$$

A substantial body of evidence on urban India suggests that the returns to education in the labor market are *higher for daughters*, especially at the secondary and higher secondary levels (see, for example, Duraisamy (2002), Aslam et al. (2010)).[42] For a summary of the available estimates of returns to education in urban India, please see Table A0 in online appendix section OA.4.[43] Given that $R^{cd} > R^{cs}$ in urban India, an immediate observation is that it is not possible to satisfy equation (20) if there are no gender biases, i.e, if $\tilde{\phi}^s = \tilde{\phi}^d$, $L^s = L^d$, and $\sigma^d = \sigma^s$. This follows from the fact that $\tilde{\phi}^s = \tilde{\phi}^d$, $L^s = L^d$ imply $\tilde{\delta}_1^d = \tilde{\delta}_1^s$ , $\tilde{\delta}_2^d = \tilde{\delta}_2^s$.

*School Environment and Parental Estimate of Ability*

Starting with $\tilde{\phi}^s = \tilde{\phi}^d$, $L^s = L^d$, and $\sigma^d = \sigma^s$, we consider whether bias against girls in school $\left(L^d < L^s\right)$ and/or lower ability estimate by parents $\left(\tilde{\phi}^d < \tilde{\phi}^s\right)$ are consistent with the evidence: $R^{cd} > R^{cs}$ and $\hat{\theta}_0^d = \hat{\theta}_0^s$, keeping $\sigma^d = \sigma^s$. For this, it is useful to look at the intercept of the investment equation as a function of returns to education (i.e., $\theta_0\left(R^c\right)$) and how it changes with school environment $(L^j)$ and parental ability estimate $\left(\tilde{\phi}^j\right)$ because $\tilde{\delta}_1^j = \delta_1^0 + \gamma_1 L^j + \gamma_2 \tilde{\phi}^j$ and $\tilde{\delta}_2^j = \delta_2^0 - \omega_1 L^j - \omega_2 \tilde{\phi}^j$. Note that $\tilde{\phi}^d < \tilde{\phi}^s$ and/or $L^d < L^s$ make $\tilde{\delta}_1^d < \tilde{\delta}_1^s$ , $\tilde{\delta}_2^d > \tilde{\delta}_2^s$. As discussed in detail in the online appendix OA.1, $\theta_0\left(R^c\right)$ is a positively sloped concave function. A higher $\tilde{\delta}_1$ and/or a lower $\tilde{\delta}_2$ rotates up the $\theta_0\left(R^c\right)$ curve without changing its vertical intercept (please see Figure F1). We impose a horizontal line representing $\hat{\theta}_0^d = \hat{\theta}_0^s > 0$ in Figure F1. An inspection of Figure F1 shows that the returns to education must be smaller for the upper curve with higher ability estimate and/or better learning environment. Since the evidence suggests $R^{cd} > R^{cs}$, the upper curve must refer

[42] There is 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 in the income equation. 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.

[43] 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.

to the sons, implying that the parents hold systematically lower estimates of the ability of daughters and/or the girls face substantial hurdles in school. The evidence thus is consistent with the joint hypothesis that $\tilde{\phi}^s > \tilde{\phi}^d$ and/or $L^s > L^d$, and $\sigma^d = \sigma^s$.[44]

For unfavorable school environment, the evidence is in fact much stronger. This can be seen from the estimates of the intercepts of the investment equation and the mobility equation together. The estimates in Table 2 suggest $\hat{\psi}_0^d < \hat{\psi}_0^s$, implying the following (denote the common investment intercept by $\hat{\theta}_0^c$):

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

Note that $\delta_1^j$ and $\delta_2^j$ in inequality (21) are the parameters of true production function not affected by parental bias in estimating a girl's ability. Any gender differences in these parameters must be due to differences in learning environment in school as captured by $L^j$. It is easy to check that bias in the school against girls, i.e., $L^d < L^s$, is necessary and sufficient for inequality (21) to hold. To check that $L^d < L^s$ is necessary, assume that $L^d \geq L^s$ which implies $\delta_1^d - \delta_1^s = \gamma_1 \left(L^d - L^s\right) \geq 0$ and $\delta_2^d - \delta_2^s = \omega_1 \left(L^s - L^d\right) \leq 0$. Thus, we have $\hat{\theta}_0^c \left[\delta_1^d - \delta_1^s\right] \geq \left(\hat{\theta}_0^c\right)^2 \left[\delta_2^d - \delta_2^s\right]$ contradicting inequality (21). $L^d < L^s$ is sufficient because $\delta_1^d - \delta_1^s = \gamma_1 \left(L^d - L^s\right) < 0$ and $\delta_2^d - \delta_2^s = \omega_1 \left(L^s - L^d\right) > 0$ in this case and inequality (21) is satisfied. The evidence thus is strong that the girls in urban India face unfavorable learning environment in school.

*Pure Son Preference*

The evidence in urban India is, however, not informative about whether the parents exhibit significant "pure son preference". The two pieces of evidence discussed above, i.e., $R^{cd} > R^{cs}$ and $\hat{\theta}_0^d = \hat{\theta}_0^s$, are not helpful because, without additional information on the curvatures of the utility and the education production function, we cannot determine whether a higher value of $\sigma^j$ shifts the $\theta_0 \left(R^c\right)$ curve up or down (please see online appendix section OA.1). As it turns out, the evidence on the slope of the investment equation also does not help: $\hat{\theta}_1^d < \hat{\theta}_1^s$ implies

[44] As discussed before we assume that the parents are aware of the fact that the returns to education is higher for girls. If one assumes that the parents incorrectly believe lower returns for daughters, i.e., $R^{cd} < R^{cs}$, then retracing of the preceding argument implies gender bias against boys: the girls enjoy more favorable school environment and/or parents estimate the academic ability of daughters to be higher. These conclusions are inconsistent with the extensive evidence on gender bias against girls discussed earlier. In a patrilineal society, one can strive for equality for girls; and gender bias against boys seems highly implausible, if not impossible, in Indian context.

$\tilde{\delta}_2^d \sigma^d R^{cd} > \tilde{\delta}_2^s \sigma^s R^{cs}$. Since $R^{cd} > R^{cs}$ and $\tilde{\delta}_2^d > \tilde{\delta}_2^s$, $\hat{\theta}_1^d < \hat{\theta}_1^s$ does not impose any restrictions on the binary relation between $\sigma^d$ and $\sigma^s$.[45]

<u>*Parental Direct (nonfinancial) Inputs*</u>

The direct (nonfinancial) influences of parents are represented by the parameters $\delta_3^j$ and $\delta_4^j$ in the education production function, and the evidence is informative for both. The focus here is on whether the marginal direct effect of father's schooling $\left(\delta_3^j - 2\delta_4^j H^p\right)$ depends on the gender of a child.

As noted in section (3.3), the parameters of the investment equation are not affected by direct (nonfinancial) inputs of parents, but parameters of the mobility equation are. We first analyze whether the evidence is informative about possible gender differences in $\delta_3^j$ which shows the marginal direct effect for the children of fathers with zero schooling ($H^p = 0$).[46] $\hat{\psi}_1^d > \hat{\psi}_1^s$ implies the following:

$$\delta_3^d - \delta_3^s > \hat{\theta}_1^s \left(\delta_1^s - 2\delta_2^s \hat{\theta}_0^s\right) - \hat{\theta}_1^d \left(\delta_1^d - 2\delta_2^d \hat{\theta}_0^d\right) \tag{22}$$

According to the educational investment estimates discussed above, $\hat{\theta}_1^d < \hat{\theta}_1^s$ and $\hat{\theta}_0^d = \hat{\theta}_0^s$. The evidence discussed earlier suggests unfavorable school environment, i.e., $L^d < L^s$, implying that $\delta_1^d < \delta_1^s$ and $\delta_2^d > \delta_2^s$.[47] This implies that $\hat{\theta}_1^s \left(\delta_1^s - 2\delta_2^s \hat{\theta}_0^s\right) - \hat{\theta}_1^d \left(\delta_1^d - 2\delta_2^d \hat{\theta}_0^d\right) > 0$. It is thus necessary to have $\delta_3^d > \delta_3^s$ for inequality (22) to hold. The evidence thus suggests that parental direct inputs are important for relative mobility of the daughters born into the most disadvantaged family background.

To understand gender differences in the degree of diminishing returns to the direct parental inputs ($\delta_4^j$), the relevant mobility parameter of interest is the quadratic coefficient. The evidence that $\hat{\psi}_2^d = \hat{\psi}_2^s$ implies the following:

$$\delta_2^d \left(\hat{\theta}_1^d\right)^2 + \delta_4^d = \delta_2^s \left(\hat{\theta}_1^s\right)^2 + \delta_4^s \tag{23}$$

From the estimates of the investment equation, we know that $\hat{\theta}_1^d < \hat{\theta}_1^s$, which implies that

[45] We emphasize that this does not imply an absence of son preference in urban India, just that we cannot say anything about it.

[46] In urban India, 26.44 percent of children have fathers with zero schooling in our sample.

[47] Once again, it is important to keep in mind that $\delta_1^j$ and $\delta_2^j$ are not affected by parental biases. The parameters affected by parent bias are $\tilde{\delta}_1^j$ and $\tilde{\delta}_2^j$.

equation (23) cannot be satisfied without some form of gender bias that works through $\delta_2$ and/or $\delta_4$.[48] However, unfavorable school environment for girls working through $\delta_2$ does not help satisfy equation (23). This follows from the observation that, starting at no gender penalty against girls at school, i.e., $L^d = L^s = L$, an unfavorable school environment for the girls $\left(L^d < L\right)$ reduces the value of $\delta_2^d\left(\theta_1^d\right)^2$, while a better learning environment for the boys $(L^s > L)$ increases $\delta_2^s(\theta_1^s)^2$.[49] The upshot of the above discussion is that, to satisfy equation (23), we need gender bias in the form of $\delta_4^d > \delta_4^s$, implying that the diminishing returns to the direct impact of father's education are stronger for daughters. As noted earlier, the evidence that $L^d < L^s$ implies $\delta_2^d > \delta_2^s$ which suggests that girls face stronger diminishing returns to financial investment because of the constraints in school. The daughters in urban India thus seem to face stronger diminishing returns at double margins: both at home and school.

When taken together, $\delta_3^d > \delta_3^s$ and $\delta_4^d > \delta_4^s$ suggest 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, assuming that father's education is not too high. Given the evidence of bias in educational expenditure, the higher nonfinancial impacts of educated parents on girls seem to play an important role in gender parity in absolute mobility in the college-educated households in urban India.

### (7) Gender and Intergenerational Educational Mobility in Rural India: Evidence and Interpretations

#### (7.1) Estimates of Intergenerational Mobility

The estimates of intergenerational persistence in schooling in rural India for the 18-35 age cohorts are reported in Table 3. The estimates from the linear CEF are similar to those in urban India; the IGRC (i.e., $\hat{\psi}_1^j$) estimate is larger for the daughters implying a lower relative mobility, while the intercept is smaller.

Evidence in columns (4) and (5) in Table 3 rejects the null hypothesis of a linear CEF at the 1 percent level in favor of a concave CEF, for both sons and daughters. Similar to the urban case, gender equality is rejected at the 1 percent level for the intercepts and the linear coefficients of the concave CEF. But the evidence on the quadratic coefficients suggests that $\left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|$, in contrast to the urban areas where $\left|\hat{\psi}_2^d\right| = \left|\hat{\psi}_2^s\right|$. The estimate for girls $\left(\left|\hat{\psi}_2^d\right|\right)$ is 57 percent higher in rural India. Although the gender difference is significant only at the

[48]Again, it is important to recognize that $\delta_2$ and $\delta_4$ are the parameters of the "true" production function not affected by parental bias.

[49]Note that such a change also keeps the $\hat{\theta}_1^d < \hat{\theta}_1^s$ satisfied.

10 percent level in Table 3, it is significant at the 5 percent level for the 18-30 age range (see Table A3 in online appendix) and at the 1 percent level for the 16-35 age range (see Table A5 in online appendix) and 18-28 years age range (available from the authors). Taken together, the evidence thus is strong for $\left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|$ in rural India.

The estimates of intergenerational mobility in the bottom panel of Table 3 show that the girls face substantially lower mobility, both in absolute and relative measures, when they are born to low educated parents (primary schooling or lower). The girls face lower absolute mobility across the distribution of father's education, and the gender difference is significant at the 1 percent level across the board. For the fathers with no schooling, the gender gap in absolute mobility of the children is large in villages: 2.19 years of less expected schooling for girls (1.07 years in urban India). Even when her father is college educated, a girl growing up in rural India expects 1.4 year less schooling on average. This is in contrast to the evidence on urban India where the gender gap in absolute mobility becomes small and statistically insignificant for the children of college educated fathers.

The estimates show substantially lower relative mobility for the daughters born into rural households with low educated fathers (compare the $IGME_0$ estimates: of 0.52 (sons) and 0.65 (daughters)).[50] The gender difference in $IGME$, however, becomes negligible for the households with fathers having 10 years or more schooling. Again, the conclusion from the standard linear model that the daughters face lower relative mobility across the distribution turns out to be incorrect.

### (7.2) Estimates of the Investment Equation

The estimates of the parameters of the investment equation in lower panel of Table 4 show that the results are different from those in urban India. The daughter dummy is negative and statistically significant at the 1 percent level across the board, implying that $\hat{\theta}_0^d < \hat{\theta}_0^s$. This is consistent with the existing literature in the context of rural India (Azam and Kingdon (2013)).[51] The null hypothesis of no gender difference in the slopes $\hat{\theta}_1^d = \hat{\theta}_1^s$ cannot be rejected; the interaction of daughter dummy with father's schooling is not statistically significant in any of the four columns in the lower panel of Table 4 at the 5 percent level.[52]

[50] Recall that about 47 percent of fathers in rural India in our data have zero schooling.

[51] Azam and Kingdon (2013) show that the gender bias against girls in education expenditure is larger in rural areas in India.

[52] Only 1 out of 4 estimates is significant at the 10 percent level. The magnitudes of the gender difference in the estimated slopes are also small compared to the estimates for urban India in the upper panel of Table 4.

Again, for easy reference, the binary relations across sons and daughters in the estimated parameters of both the investment and mobility equations are summarized in Table 5. Table N at the beginning of the online appendix will be useful to keep track of the different parameters in the discussion on mechanisms below.

### (7.3) Sources of Gender Bias in Rural India

*School Environment and Parental Estimate of Ability*

The evidence reported in Table A0 (see online appendix section OA.4) suggests higher returns to education for girls, i.e., $R^{cd} > R^{cs}$ holds in the rural areas. We thus have the following: $\hat{\theta}_0^d < \hat{\theta}_0^s$ with $R^{cd} > R^{cs}$. Again, we consider the $\theta_0 (R^c)$ function for alternative values of parental estimate of children's ability and/or school environment. This case is depicted in Figure F2 where the upper curve refers to higher ability estimate and/or more favorable learning environment, similar to Figure F1 discussed earlier. However, unlike Figure F1 where a single horizonal line represents $\hat{\theta}_0^d = \hat{\theta}_0^s$ , here we impose two horizontal lines representing the evidence that $0 < \hat{\theta}_0^d < \hat{\theta}_0^s$. An inspection of the graph makes it clear that it is not possible to have $\hat{\theta}_0^d < \hat{\theta}_0^s$ with $R^{cd} > R^{cs}$ if the upper curve in Figure F2 refers to the daughters. The evidence depicted in Figure F2 is consistent only with the case where the upper curve refers to sons, suggesting gender bias against girls in the form of lower ability estimate by parents and/or unfavorable school environment (keeping $\sigma^d = \sigma^s$).

The evidence on the intercepts of the mobility and investment equations: $\hat{\theta}_0^d < \hat{\theta}_0^s$ and $\hat{\psi}_0^d < \hat{\psi}_0^s$, when considered together, is consistent with unfavorable school environment for girls. But, unlike urban India, they do not help strengthen the conclusions discussed in the preceding paragraph. Because $L^d < L^s$ is a sufficient condition for $\hat{\theta}_0^d < \hat{\theta}_0^s$ and $\hat{\psi}_0^d < \hat{\psi}_0^s$ to hold simultaneously, but it is not necessary (in urban India, it is necessary). For details, please see section OA.2 in online appendix.

*Pure Son Preference*

The evidence in urban India discussed above did not allow us to make any inferences regarding whether the parents exhibit pure son preference in the sense of $\sigma^d < \sigma^s$. However, the estimates of the slope of the investment function in rural areas are informative about this question, suggesting that the parents do exhibit pure son preference. We have $\hat{\theta}_1^d = \hat{\theta}_1^s$ which 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 $\tilde{\delta}_2^d \sigma^d < \tilde{\delta}_2^s \sigma^s$. Evidence discussed in the preceding section suggests that the girls face constraints in schools in rural

India, implying $\tilde{\delta}_2^d > \tilde{\delta}_2^s$. Thus, we can have $\tilde{\delta}_2^d \sigma^d < \tilde{\delta}_2^s \sigma^s$ only if $\sigma^d < \sigma^s$, suggesting pure son preference.

*Parental Direct Influence*

As before, to see if the evidence is informative about the direct impact of parents in rural India, we turn to the estimates of the linear and quadratic coefficients of the mobility equation.

Unlike urban India, $\hat{\psi}_1^d > \hat{\psi}_1^s$ does not allow us to sign the term $\delta_3^d - \delta_3^s$ in rural areas , given that $\hat{\theta}_1^d = \hat{\theta}_1^s$ and $\hat{\theta}_0^d < \hat{\theta}_0^s$ (please check inequality (22) above). Interestingly, the evidence that $\left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|$ suggests stronger diminishing returns to nonfinancial inputs faced by the rural sons, opposite of the conclusion reached earlier in urban India. To see this, note that the inequality $\left|\hat{\psi}_2^d\right| > \left|\hat{\psi}_2^s\right|$ implies the following: $\delta_2^d \left(\hat{\theta}_1^d\right)^2 + \delta_4^d > \delta_2^s \left(\hat{\theta}_1^s\right)^2 + \delta_4^s$. Given $\hat{\theta}_1^d = \hat{\theta}_1^s$, denote the common value by $\hat{\theta}_1^c$. Then we have $\delta_4^d - \delta_4^s = \left(\hat{\theta}_1^c\right)^2 \left(\delta_2^s - \delta_2^d\right) < 0$. The last inequality follows from the evidence discussed earlier that $\delta_2^d > \delta_2^s$ because of stronger diminishing returns to financial investment arising from the constraints girls face in school. The evidence thus suggests that $\delta_4^d < \delta_4^s$. However, unlike urban India, we cannot say whether the marginal direct effect of father's education is larger or smaller for girls in rural India, as we cannot sign $\delta_3^d - \delta_3^s$. This suggests that the impact of nonfinancial inputs may not be favorable to girls in villages, unlike the case of urban India. This provides part of the explanation for the lack of gender parity in absolute mobility in rural areas even when the father is college educated, in sharp contrast to the parity observed in the urban areas where the marginal direct impact of father's education on girls is larger (section (6.3) above).

**(8) Robustness Checks: Evidence from Alternative Age Ranges**

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. One might wonder whether the conclusions change when we exclude relatively older children from the sample, a relevant concern given our focus on the younger generation. To check the robustness of the findings, we estimated the mobility equation (14) for alternative age ranges. The estimates for the age cohorts 18-30 years are reported in the online appendix; please see Tables A2 (urban), A3 (rural) in section OA.6.[53] In the context of urban areas with higher average education, a concern is that a minimum age of 18 years might cause censoring of years of schooling

[53] The estimates for 18-28 age range are also similar and are not reported for the sake of brevity.

for a substantial proportion of children who go to college after 12 years of schooling.[54] We report estimates for the 20-35 age sample in the urban areas in the online appendix Table A4. However, note that the estimation sample with a higher minimum age cut-off will miss many children with low schooling attainment, especially in rural areas.[55] In fact, a 18 year age cutoff might be too high in rural areas because it misses the children who do not progress beyond the matriculation public examination administered at the end of 10th grade. We thus report estimates for 16-35 age cohorts in rural India (Table A5 in online appendix). The main conclusions remain intact across these different age groups.

**(9) Pitfalls of the Maintained Assumption of Linearity**

How do the conclusions about gender bias in mobility and the underlying mechanisms differ if we rely on a linear CEF for estimation, and appeal to the linear model without any significant diminishing returns to interpret the results? Such a comparison is useful because most of the studies on intergenerational educational mobility in the current literature we are aware of adopt the linear functional form, and many researchers would argue that it is an approximation to an underlying nonlinear relation.[56]

In urban India, the (incorrect) linear CEF estimates imply that the girls face significantly lower relative mobility even when the father has college or higher education, in sharp contrast to the finding in section 6 above that there is no significant gender bias for such highly educated households. The estimated investment equation leads to a contradiction: evidence suggests $\theta_1^d < \theta_1^s$, but the model implies $\theta_1^d = \theta_1^s = R^p$.

In rural India, the investment equation estimates do not reject the linear model because $\hat{\theta}_1^d = \hat{\theta}_1^s$, but the mobility equation is concave. The linear mobility model again misses the gender parity in relative mobility in the highly educated households. When interpreted in terms of the linear model, $\theta_0^d < \theta_0^s$ and $\psi_1^d > \psi_1^s$ together lead to incorrect conclusions about the mechanisms. For example, the evidence suggests no pure son preference in a linear model while the correct conclusion from the concave mobility model is that there is pure son preference in

[54] In our 18-35 age sample, 20 percent children have college or more education in urban areas, but only 7 percent in rural areas.

[55] In our data, 59 percent rural children in 18-19 year age group did not progress beyond 10 years of schooling, and the corresponding estimate for urban areas is 41 percent. These children are excluded when the minimum age is raised to 20.

[56] Following Chetty et al. (2014), some recent papers use a linear CEF for ranks rather than years of schooling. The rank-rank linear model can be consistent with an underlying nonlinear model in terms of years of schooling.

rural India (section 7 above). For details, please see online appendix section OA.3.

**(10) The Implications of Sex Selection and Unwanted Girls**

How does sex selective abortion affect the estimates of intergenerational educational mobility? An important insight here is that prevalence of sex selective abortion in fact implies that the degree of gender bias we observe in the data is lower compared to a benchmark without any such sex selection. When the parents do not have access to ultrasonography technology to know the sex of a foetus, they are likely to have unwanted girls. We expect parental bias against girls in educational choices to be especially strong for such unwanted girls. The availability of ultrasonography (especially in private clinics) is likely to be higher in urban areas. Since the average income level is also higher in the urban areas, more households can afford ultrasonography. Evidence from the first round of IHDS data (2005) shows that 19.97 percent of parents in rural areas had at least one ultrasonography during the two most recent pregnancies, while the corresponding estimate for the urban India is 41.68 percent. 8.79 percent of the medical facilities in the rural sample had ultrasound equipment that is in good condition, and 19.12 percent in the urban sample.

When ultrasonography is more accessible and affordable, the surviving girls are likely to be born to parents with little or no bias against girls. If this channel is important in our data, we should expect gender differences in intergenerational persistence in urban areas to be smaller in magnitude even though many people believe that gender bias is stronger because sex ratio is more skewed. A comparison of the estimates in Tables 2 and 3 in fact shows that the gender differences in the estimated coefficients of the mobility CEF are much smaller in magnitude in urban India. For example, the gender difference in the intercept is 1.61 in urban areas (see Table 2) and 2.62 in rural areas (see Table 3), and the rural-urban estimates are significantly different at the 5 percent level. This suggests that part of the explanation for the gender equality observed in urban households with college educated fathers is the fact that the higher educated (and thus higher income) urban households are less likely to have unwanted girls.

A related and perhaps more important question is what would be the gender gap in intergenerational educational mobility in India if the parents had no gender preference for a new born, and thus there were no unwanted girls; in other words, if the gender of a child was effectively random.[57] Anukriti et al. (2020) report evidence that the gender of the first child in India can be treated as quasi random. The evidence from the first child sample (18-35 age range) are reported in Table 6 (for the 18-30 age range estimates, see online appendix section OA.7).[58] The gender differences in both rural and urban India are less pronounced in the first child sample when compared to the full sample estimates reported earlier in Tables 2 and 3. For example, the gender difference in the linear coefficients observed for urban India in the full sample is no longer statistically significant at the 10 percent level when we use the first child sample.[59]

**(11) Patrilineal vs. Matrilineal States in India: The Importance of Patrilineal and Patrilocal Hindu Kinship System**

The final exercise we report follows the analysis of Jayachandran and Pande (2017). It takes advantage of the observation that bias against girls is likely to be much lower in matrilineal states. The intergenerational mobility estimates for 18-35 age cohorts in patrilineal and matrilineal states are reported in Tables 7 (urban) and 8 (rural) (18-30 age cohort results are in the online appendix section OA.8). While the pattern of the estimates in patrilineal sample is consistent with the conclusions discussed earlier in the paper, the results on matrilineal states are strikingly different: gender differences are not significant at the 10 percent level for any of the coefficients in the matrilineal sample, and this is true in both rural and urban areas. Using the first round IHDS (2005) data, we find that the matrilineal states provide better learning environment for girls in school: the share of women teachers in the school and the probability of having a separate restroom for girls are significantly higher in the matrilineal states. The share of female teachers is 54 percent in matrilineal states compared to 46 percent in patrilineal states, and the difference is significant at the 1 percent level. The evidence on toilets is more striking: 66 percent of schools have separate toilets for girls in matrilineal states compared to 53 percent in patrilineal states, again the difference is significant at the 1 percent level. This suggests that patrilineal and patrilocal Hindu kinship system plays an important role in the gender bias in intergenerational educational mobility observed at the

[57] It is important to appreciate that we can also have no unwanted girls in a very different case: when sex selection technology is available at no cost to all parents so that all the unwanted girls are aborted.

[58] In the IHDS survey, it is not possible to determine the birth order of the household head and spouse. We treat them as the oldest child for the analysis.

[59] It is easy to check this does not affect the conclusion that $\delta_3^d > \delta_3^s$ in urban India.

national level.

**(12) Concluding Comments**

This paper provides a theory-based empirical analysis of the sources and implications of gender bias against girls for intergenerational educational mobility in India. We develop an extension of the Becker-Tomes model where parents self-finance children's schooling because of credit market imperfections, and girls may face bias in the family, school, and labor market. The model yields a linear conditional expectation function (CEF) under the assumption of constant returns in education production function but delivers sharp predictions: parental bias against girls in financial investment arising from pure son preference and/or a biased estimate of a girls ability is irrelevant for relative mobility. 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 on intergenerational mobility relying on a linear estimating equation. When the education production function exhibits diminishing returns to financial investment, the mobility CEF is concave. With a concave CEF, parental gender bias in financial investment affects both relative and absolute mobility.

Using data free of truncation owing to coresidency, we test the above ideas in rural and urban India. Evidence rejects the linear model: the mobility CEF is concave for both sons and daughters in rural and urban India. The daughters of uneducated fathers face lower relative and absolute mobility. There is no significant gender gap in absolute mobility in the educated households in urban areas, but the gap remains substantial in rural areas. Differences in the incidence of unwanted girls and direct (nonfinancial) impact of father's education provide a plausible explanation for the rural-urban differences in gender gap in absolute mobility in the educated households. The theoretical insights when combined with the estimates of the parameters of investment and mobility equations help us pin down some of the sources of observed gender bias. School environment is unfavorable to girls in both rural and urban India. There is evidence of pure son preference in rural India, but the evidence is not informative in urban India. The widely used linear model yields misleading conclusions such as no pure son preference in rural India, and misses gender parity in relative mobility for the children of college educated fathers. We find that there are no statistically significant gender differences in the estimated parameters of the mobility equation in the matrilineal states, while gender gaps in patrilineal states are significant. This suggests that patrilineal and patrilocal Hindu kinship system plays a major role in the observed gender bias in intergenerational educational mobility at the national level. Evidence from the first child sample suggests that part of the gender bias is due to the unwanted girls, especially in the rural areas. The theory and empirical approach developed in this paper may be of wider interest as they are applicable to other developing countries.

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**Figure F1**

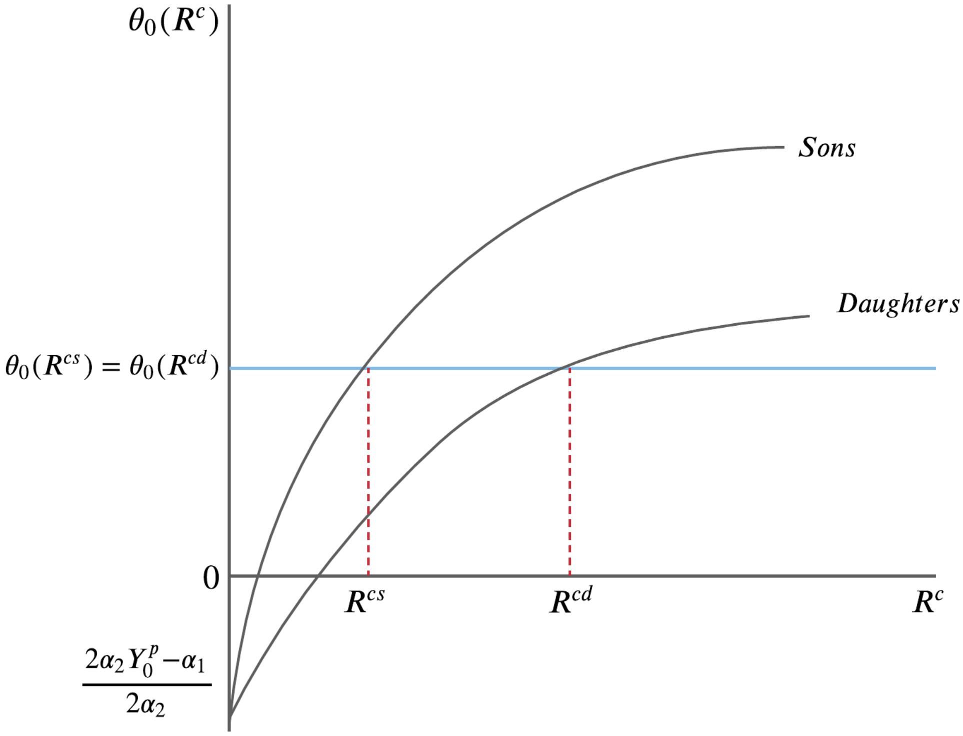


**Figure F2**

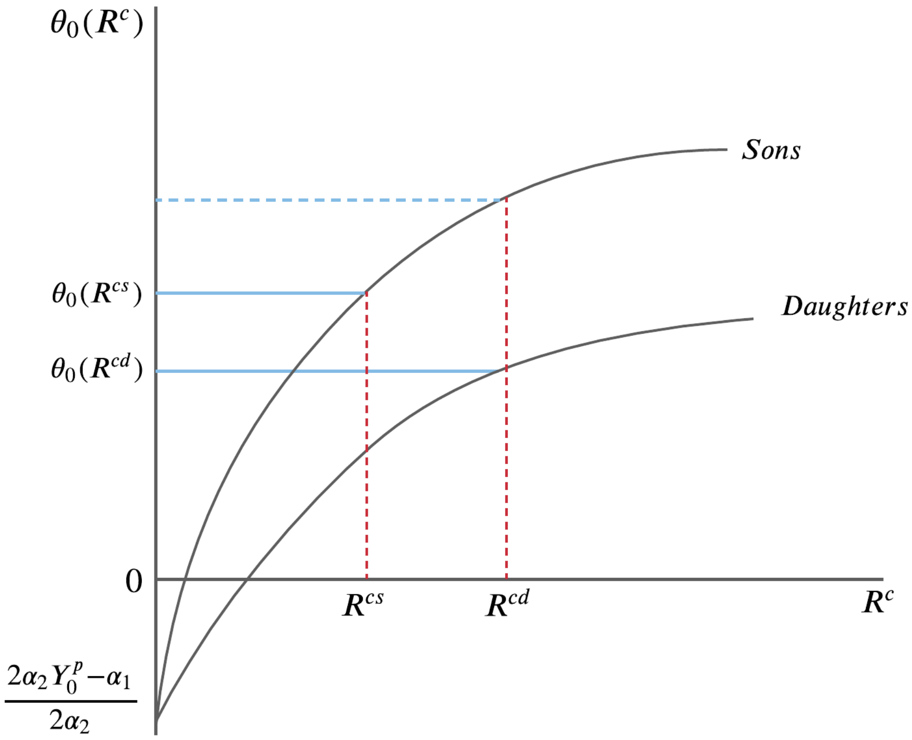

**Table 1: Summary Statistics**

| | Full | | Sons | | Daughters | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| | **Urban India** | | | | | |
| IHDS 2012 (18-35 age) | N=19203 | | N=9877 | | N=9326 | |
| Father's Sch. | 6.60 | 5.08 | 6.70 | 5.00 | 6.51 | 5.15 |
| Children's Sch. | 9.77 | 4.51 | 10.09 | 4.20 | 9.43 | 4.80 |
| IHDS 2005 (11-28 age) | N=9360 | | N=4964 | | N=4396 | |
| Father's Sch. | 8.86 | 4.59 | 8.82 | 4.61 | 8.90 | 4.57 |
| Educ. Exp. (Winsor) | 4519.07 | 6177.10 | 4822.22 | 6615.88 | 4176.75 | 5621.89 |
| | N=9350 | | N=4959 | | N=4391 | |
| Educ. Exp. (Trim) | 4454.38 | 5854.96 | 4761.54 | 6337.05 | 4107.49 | 5236.73 |
| IHDS 2005 (8-28 age) | N=12817 | | N=6785 | | N=6032 | |
| Father's Sch. | 8.63 | 4.67 | 8.58 | 4.69 | 8.67 | 4.66 |
| Educ. Exp. (Winsor) | 3998.07 | 5593.53 | 4283.93 | 5989.68 | 3676.51 | 5092.73 |
| | N=12803 | | N=6777 | | N=6026 | |
| Educ. Exp. (Trim) | 3936.83 | 5280.94 | 4218.16 | 5678.84 | 3620.43 | 4774.87 |
| | **Rural India** | | | | | |
| IHDS 2012 (18-35 age) | N=35148 | | N=17761 | | N=17387 | |
| Father's Sch. | 3.94 | 4.45 | 4.01 | 4.39 | 3.87 | 4.51 |
| Children's Sch. | 7.34 | 4.75 | 8.31 | 4.39 | 6.35 | 4.89 |
| IHDS 2005 (11-28 age) | N=15285 | | N=8595 | | N=6690 | |
| Father's Sch. | 5.76 | 4.59 | 5.58 | 4.62 | 5.99 | 4.53 |
| Educ. Exp. (Winsor) | 2006.78 | 3593.54 | 2163.89 | 3960.94 | 1804.93 | 3045.83 |
| | N=15269 | | N=8584 | | N=6685 | |
| Educ. Exp. (Trim) | 1951.25 | 3159.29 | 2096.18 | 3482.35 | 1765.14 | 2676.88 |
| IHDS 2005 (8-28 age) | N=22849 | | N=12632 | | N=10217 | |
| Father's Sch. | 5.62 | 4.58 | 5.48 | 4.61 | 5.78 | 4.55 |
| Educ. Exp. (Winsor) | 1623.89 | 3020.55 | 1766.77 | 3331.76 | 1447.23 | 2573.70 |
| | N=22826 | | N=12615 | | N=10211 | |
| Educ. Exp. (Trim) | 1577.16 | 2638.84 | 1704.46 | 2868.96 | 1419.88 | 2313.77 |

*Notes*: IHDS stands for Indian Human Development Survey. Education expenditure data are at the child level including school fees, books, uniform, transportation and other materials, and private tuition. Education expenditure are winsorized and trimmed at 99.9 percentile. N stands for number of observations.

**Table 2: Intergenerational Persistence in Schooling in Urban India**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | Sons (S) | Daughters (D) | D – S | Sons (S) | Daughters (D) | D – S |
| $\hat{\psi}_1$ | 0.450 | 0.523 | 0.073 | **0.559** | **0.649** | **0.089** |
| | (0.010) | (0.010) | (0.011) | **(0.029)** | **(0.028)** | **(0.033)** |
| $\hat{\psi}_2$ | | | | **-0.008** | **-0.009** | **-0.001** |
| | | | | **(0.002)** | **(0.002)** | **(0.002)** |
| $\hat{\psi}_0$ | 7.741 | 6.124 | -1.618 | **7.585** | **5.970** | **-1.614** |
| | (0.146) | (0.154) | (0.158) | **(0.155)** | **(0.158)** | **(0.167)** |
| $N$ | 9877 | 9326 | 19203 | **9877** | **9326** | **19203** |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | S | D | D – S | | S | D | D – S |
| $EH_0^c$ | 6.920 | 5.853 | -1.067 | $IGME_0^c$ | 0.559 | 0.649 | 0.090 |
| | (0.126) | (0.121) | (0.122) | | (0.029) | (0.028) | (0.033) |
| $EH_5^c$ | 9.518 | 8.863 | -0.655 | $IGME_5^c$ | 0.480 | 0.555 | 0.075 |
| | (0.073) | (0.085) | (0.080) | | (0.014) | (0.013) | (0.015) |
| $EH_{10}^c$ | 11.718 | 11.407 | -0.311 | $IGME_{10}^c$ | 0.400 | 0.462 | 0.062 |
| | (0.060) | (0.071) | (0.074) | | (0.012) | (0.013) | (0.014) |
| $EH_{15}^c$ | 13.522 | 13.484 | -0.038 | $IGME_{15}^c$ | 0.321 | 0.369 | 0.048 |
| | (0.076) | (0.087) | (0.102) | | (0.026) | (0.028) | (0.033) |
| $EH_{17}^c$ | 14.133 | 14.184 | 0.051 | $IGME_{17}^c$ | 0.289 | 0.331 | 0.042 |
| | (0.124) | (0.136) | (0.162) | | (0.033) | (0.034) | (0.041) |

*Notes*: (1) The data are from the IHDS 2012 round with children aged 18-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father of child *c* has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree.

**Table 3: Intergenerational Persistence in Schooling in Rural India**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | Sons (S) | Daughters (D) | D – S | Sons (S) | Daughters (D) | D – S |
| $\hat{\psi}_1$ | 0.447 | 0.521 | 0.074 | **0.523** | **0.648** | **0.125** |
| | (0.009) | (0.009) | (0.010) | **(0.023)** | **(0.026)** | **(0.030)** |
| $\hat{\psi}_2$ | | | | **-0.007** | **-0.011** | **-0.005*** |
| | | | | **(0.002)** | **(0.002)** | **(0.002)** |
| $\hat{\psi}_0$ | 6.548 | 3.955 | -2.593 | **6.484** | **3.868** | **-2.616** |
| | (0.106) | (0.113) | (0.118) | **(0.109)** | **(0.112)** | **(0.121)** |
| $N$ | 17761 | 17387 | 35148 | **17761** | **17387** | **35148** |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | S | D | D – S | | S | D | D – S |
| $EH_0^c$ | 6.451 | 4.262 | -2.189 | $IGME_0^c$ | 0.523 | 0.648 | 0.125 |
| | (0.080) | (0.080) | (0.077) | | (0.023) | (0.026) | (0.030) |
| $EH_5^c$ | 8.896 | 7.215 | -1.681 | $IGME_5^c$ | 0.455 | 0.534 | 0.079 |
| | (0.060) | (0.085) | (0.080) | | (0.009) | (0.010) | (0.011) |
| $EH_{10}^c$ | 11.003 | 9.598 | -1.405 | $IGME_{10}^c$ | 0.388 | 0.420 | 0.032 |
| | (0.054) | (0.087) | (0.082) | | (0.014) | (0.019) | (0.021) |
| $EH_{15}^c$ | 12.772 | 11.412 | -1.360 | $IGME_{15}^c$ | 0.320 | 0.306 | -0.014 |
| | (0.110) | (0.160) | (0.179) | | (0.029) | (0.037) | (0.044) |
| $EH_{17}^c$ | 13.384 | 11.978 | -1.406 | $IGME_{17}^c$ | 0.293 | 0.260 | -0.033 |
| | (0.169) | (0.232) | (0.266) | | (0.036) | (0.045) | (0.053) |

*Notes*: (1) The data come from the IHDS 2012 round with children aged 18-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree.

**Table 4: Father's Education and Investment on Children's Education in India**

| | Urban India | | | |
|---|---|---|---|---|
| | 11-28 Years Children | | 8-28 Years Children | |
| | Winsorized | Trimmed | Winsorized | Trimmed |
| Father's Sch. | 367.283 | 358.137 | 350.967 | 340.811 |
| | (24.588) | (23.839) | (19.815) | (18.952) |
| **Father's Sch. * Daughter Dummy** | **-54.251** | **-55.506** | **-47.108** | **-45.476** |
| | (27.887) | (25.772) | (21.175) | (19.284) |
| **Daughter Dummy** | **-30.029** | **-32.967** | **-104.807** | **-115.510** |
| | (199.178) | (188.131) | (146.257) | (137.216) |
| Intercept | -877.520 | -841.611 | 3148.633 | 3072.146 |
| | (86.050) | (80.543) | (239.654) | (224.719) |
| No. Observations | 9360 | 9350 | 12817 | 12803 |
| | **Rural India** | | | |
| Father's Sch. | 174.056 | 154.131 | 149.402 | 131.150 |
| | (15.440) | (12.635) | (11.150) | (8.732) |
| **Father's Sch. * Daughter Dummy** | **-24.947** | **-13.917** | **-20.855** | **-9.583** |
| | (16.152) | (13.093) | (10.807) | (8.340) |
| **Daughter Dummy** | **-182.634** | **-225.084** | **-183.298** | **-217.123** |
| | (64.533) | (58.570) | (43.546) | (39.522) |
| Intercept | -394.579 | -349.332 | 1801.340 | 1728.625 |
| | (34.429) | (27.823) | (84.267) | (75.720) |
| No. Observations | 15285 | 15269 | 22849 | 22826 |

*Notes*: (1) The data used come from IHDS 2005 round. (2) The dependent variable is educational expenditure at the child level which includes school tuition and fees, supplementary fees (such as books, uniforms, transportation, and others), and private tutor fees. The dependent variable is winsarized and trimmed at 99.9 percentile. (3) Number of children in a household is controlled for in each regression. (4) Standard errors in parentheses are clustered at primary sampling unit level; *** p<0.01, ** p<0.05, * p<0.1.

**Table 5: Summary of the Binary Relations across Gender for Mobility and Investment Equation Estimates**

| | | Urban India | Rural India |
|---|---|---|---|
| Mobility Equation | $\hat{\psi}_0$ | $\hat{\psi}_0^d < \hat{\psi}_0^s$ | $\hat{\psi}_0^d < \hat{\psi}_0^s$ |
| | $\hat{\psi}_1$ | $\hat{\psi}_1^d > \hat{\psi}_1^s$ | $\hat{\psi}_1^d > \hat{\psi}_1^s$ |
| | $\hat{\psi}_2$ | $\hat{\psi}_2^d, \hat{\psi}_2^s < 0$<br>$\hat{\psi}_2^d = \hat{\psi}_2^s$ | $\hat{\psi}_2^d, \hat{\psi}_2^s < 0$<br>$\lvert\hat{\psi}_2^d\rvert > \lvert\hat{\psi}_2^s\rvert$ |
| Investment Equation | $\hat{\theta}_0$ | $\hat{\theta}_0^d = \hat{\theta}_0^s$ | $\hat{\theta}_0^d < \hat{\theta}_0^s$ |
| | $\hat{\theta}_1$ | $\hat{\theta}_1^d < \hat{\theta}_1^s$ | $\hat{\theta}_1^d = \hat{\theta}_1^s$ |

**Table 6: Estimates of Intergenerational Mobility in India from the First-Born Child Sample**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | Sons (S) | Daughters (D) | D – S | Sons (S) | Daughters (D) | D – S |
| | | | **Urban India** | | | |
| $\hat{\psi}_1$ | 0.474 | 0.537 | 0.063 | 0.576 | 0.627 | 0.052 |
| | (0.011) | (0.010) | (0.013) | (0.031) | (0.030) | (0.038) |
| $\hat{\psi}_2$ | | | | -0.007 | -0.007 | 0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 7.409 | 6.017 | -1.392 | 7.271 | 5.910 | -1.360 |
| | (0.156) | (0.157) | (0.177) | (0.164) | (0.161) | (0.187) |
| $N$ | 6288 | 7627 | 13915 | 6288 | 7627 | 13915 |
| | | | **Rural India** | | | |
| $\hat{\psi}_1$ | 0.476 | 0.523 | 0.047 | 0.543 | 0.627 | 0.085 |
| | (0.009) | (0.010) | (0.011) | (0.025) | (0.027) | (0.033) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.010 | -0.003 |
| | | | | (0.002) | (0.002) | (0.003) |
| $\hat{\psi}_0$ | 6.231 | 4.015 | -2.183 | 6.148 | 3.946 | -2.202 |
| | (0.076) | (0.112) | (0.124) | (0.114) | (0.112) | (0.126) |
| $N$ | 12623 | 15424 | 28047 | 12623 | 15424 | 28047 |

*Notes*: (1) The data used are from the IHDS 2012 round with the first-born child aged 18-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.

**Table 7: Estimates of Intergenerational Mobility in Urban India**
**Patrilineal States vs. Matrilineal States**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D – S** | **Sons (S)** | **Daughters (D)** | **D – S** |
| | | | **Patrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.455 | 0.529 | 0.071 | 0.550 | 0.629 | 0.086 |
| | (0.010) | (0.010) | (0.011) | (0.031) | (0.029) | (0.035) |
| $\hat{\psi}_2$ | | | | -0.007 | -0.007 | -0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 7.615 | 5.887 | -1.124 | 7.489 | 5.776 | -1.123 |
| | (0.154) | (0.163) | (0.111) | (0.162) | (0.167) | (0.126) |
| $N$ | 9058 | 8488 | 17546 | 9058 | 8488 | 17546 |
| | | | **Matrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.335 | 0.395 | 0.058 | 0.434 | 0.497 | 0.058 |
| | (0.034) | (0.025) | (0.032) | (0.103) | (0.086) | (0.110) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.007 | -0.000 |
| | | | | (0.005) | (0.005) | (0.006) |
| $\hat{\psi}_0$ | 9.422 | 8.380 | -0.363 | 9.160 | 8.150 | -0.318 |
| | (0.370) | (0.292) | (0.284) | (0.490) | (0.362) | (0.434) |
| $N$ | 819 | 838 | 1657 | 819 | 838 | 1657 |

*Notes*: (1) The data used are from the IHDS 2012 round with children aged 18-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) The patrilineal and matrilineal classification follows that of Jayachandran and Pande (2017). (3) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.

**Table 8: Estimates of Intergenerational Mobility in Rural India**
**Patrilineal States vs. Matrilineal States**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D – S** | **Sons (S)** | **Daughters (D)** | **D – S** |
| | | | **Patrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.443 | 0.510 | 0.070 | 0.512 | 0.614 | 0.106 |
| | (0.009) | (0.010) | (0.011) | (0.024) | (0.026) | (0.031) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.009 | -0.003 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 6.498 | 3.739 | -2.271 | 6.441 | 3.670 | -2.285 |
| | (0.109) | (0.115) | (0.073) | (0.112) | (0.115) | (0.078) |
| *N* | 16573 | 16250 | 32823 | 16573 | 16250 | 32823 |
| | | | **Matrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.473 | 0.559 | 0.086 | 0.645 | 0.813 | 0.168 |
| | (0.031) | (0.034) | (0.032) | (0.096) | (0.089) | (0.102) |
| $\hat{\psi}_2$ | | | | -0.014 | -0.022 | -0.008 |
| | | | | (0.006) | (0.006) | (0.007) |
| $\hat{\psi}_0$ | 7.329 | 6.684 | -0.507 | 7.096 | 6.423 | -0.523 |
| | (0.418) | (0.392) | (0.281) | (0.444) | (0.411) | (0.316) |
| *N* | 1188 | 1137 | 2325 | 1188 | 1137 | 2325 |

*Notes*: (1) The data used are IHDS 2012 with children aged 18-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) The patrilineal and matrilineal classification follows that of Jayachandran and Pande (2017). (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.

**NOT FOR PUBLICATION**
**Online Appendix to:**

# Is Gender Destiny? Gender Bias and Intergenerational Educational Mobility in India

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**Table N: Summary of the Notations and Interpretations of Key Parameters**

| Notation | Interpretation |
|---|---|
| $Y_i^p$ | Parent's income |
| $Y_0^p$ | Intercept of parent's income equation |
| $R^p$ | Return to parent's education |
| $H_i^p$ | Parent's schooling |
| $Y_i^{cj}$ | Gender-specific child's education |
| $Y_0^{cj}$ | Gender-specific intercept of child's income equation |
| $R^{cj}$ | Gender-specific return to child's education |
| $H_i^{cj}$ | Gender-specific child's education |
| $C_i^p$ | Parent's own consumption |
| $I_i$ | Financial investment in child's education |
| $\delta_0$ | Intercept of the true education production function |
| $\delta_1^j$ | Gender-specific productivity of *linear* financial investment $I$ of the true education production function |
| $\delta_2^j$ | Gender-specific productivity of *quadratic* financial investment $I^2$ of the true education production function |
| $\delta_3^j$ | Gender-specific productivity of *linear* non-financial input (direct effect) $H^p$ of the true education production function |
| $\delta_4^j$ | Gender-specific productivity of *quadratic* non-financial input (direct effect) $H^p$ of the true education production function |
| $L^j$ | Gender-specific school learning environment faced by a child |
| $\phi$ | True ability of a child |
| $\tilde{\phi}^j$ | Gender-specific parental estimation of a child's ability |
| $\tilde{\delta}_1^j$ | Gender-specific productivity of *linear* financial investment $I$ of the *parental estimated* education production function |
| $\tilde{\delta}_2^j$ | Gender-specific productivity of *quadratic* financial investment $I^2$ of the *parental estimated* education production function |
| $\sigma^j$ | Gender-specific degree of parental altruism |
| $\theta_0^j$ | Gender-specific intercept of the optimal financial investment equation |
| $\theta_1^j$ | Gender-specific slope of the optimal financial investment equation |
| $\psi_0^j$ | Gender-specific intercept of the intergenerational educational persistence equation |
| $\psi_1^j$ | Gender-specific *linear* coefficient of the intergenerational educational persistence equation |
| $\psi_2^j$ | Gender-specific *quadratic* coefficient of the intergenerational educational persistence equation |

## OA.1: The Intercept of the Investment Equation as a Function of Returns to Education

Combining information about returns to education with the estimated *intercepts* of the investment equation can help understand better 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:

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

It is easy to check that $\theta_0^d = \theta_0^s < 0$ when $R^{cd} = R^{cs} = 0$. This follows from the observation that $(\alpha_1 - 2\alpha_2 Y_0^p)$ is the marginal utility of income for the father with zero schooling when he spends all his income on own consumption. Under the plausible assumption of non-satiation, $(\alpha_1 - 2\alpha_2 Y_0^p) > 0$. Thus, the intercept of the function $\theta_0^j\left(R^{cj}\right)$ is negative and does not depend on the gender of a child.

Next note that, $\theta_0^j\left(R^{cj}\right)$ is an increasing concave function of returns to schooling, with a horizontal asymptote equal to $\frac{\tilde{\delta}_1^j}{2\tilde{\delta}_2^j}$.

$$\frac{d\theta_0^j}{dR^{cj}} = \frac{\sigma^j}{\left(\chi_0^j\right)^2}\left[\alpha_2\tilde{\delta}_1^j + \tilde{\delta}_2^j\left(\alpha_1 - 2\alpha_2 Y_0^p\right)\right] > 0$$

where $\chi_0^j = \alpha_2 + \delta_2^j \sigma^j R^{cj}$.

Concavity follows from:

$$\frac{d^2\theta_0^j}{d\left(R^{cj}\right)^2} = -\frac{\left(\sigma^j\right)^2 \tilde{\delta}_2^j}{\left(\chi_0^j\right)}\left[\alpha_2\tilde{\delta}_1^j + \tilde{\delta}_2^j\left(\alpha_1 - 2\alpha_2 Y_0^p\right)\right] < 0$$

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 $\frac{\partial^2 \theta_0^j}{\partial R^{cj} \partial q^j} > 0$. In contrast, the effects of pure son preference on $(\frac{\partial \theta_0^j}{\partial R^{cj}})$, are not unambiguous without additional restrictions on the curvature of the consumption sub-utility function ($\alpha_2$). The condition that $\theta_0^j > 0$ is satisfied in all the cases we consider below in India.

(1) *The Effects of higher ability Estimate on the slope of $\theta_0^j(R^{cj})$ function*

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 $\chi_0^j = \alpha_2 + \delta_2^j \sigma^j R^{cj}$ 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 $\theta_0^j$ 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) *The effects of a higher school quality on the slope of $\theta_0^j(R^{cj})$ function*

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 effects of a stronger son preference on the slope of the $\theta_0^j(R^{cj})$ function*

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 $\left( \alpha_2 - \tilde{\delta}_2^j \sigma^j R^{cj} \right)$.

**OA.2: Proof that unfavorable school environment is sufficient but not Necessary in Rural India (refer to section 7.3 in the main text)**

To see this, define $\Delta > 0$ such that $\hat{\theta}_0^s = \hat{\theta}_0^d + \Delta$. Now, $\hat{\psi}_0^d < \hat{\psi}_0^s$ implies the following:

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

The LHS of the above inequality is negative when girls face unfavorable school environment, and the RHS is positive in the relevant range where marginal returns to financial investment is positive: $\left[\delta_1^s - \delta_2^s \hat{\theta}_0^s\right] > \delta_1^s - 2\delta_2^s \left(\theta_0^s + \theta_1^s H^P\right) = \delta_1^s - 2\delta_2^s I^* > 0$. However, clearly the inequality can be satisfied even when the LHS is positive if $\Delta > 0$ is large enough.

**OA.3: The Pitfalls of Linearity: Additional Discussion**

In section (9) of the manuscript, we provide a brief discussion on the conclusions one gets when the mobility estimates are based on the standard linear CEF, and the linear theoretical model without any significant diminishing returns is used for interpretation of the results. Here we provide additional discussions on the claims in section (8) of the manuscript.

Note that in a linear model, $\theta_0^s = R^p = \theta_0^d$, and we should not see any difference in the estimates of the slope of the investment equation across gender. However, the estimates in urban India show $\hat{\theta}_1^d < \hat{\theta}_1^s$, in contradiction to the theory. This suggests that the linear model is inappropriate in this case.

In rural India, the evidence is consistent with no son preference when linearity is a maintained assumption. To see this, assume that there is no son preference i.e., $\sigma^d = \sigma^s$, and we show that it is consistent with the evidence from both the investment and mobility equations.

First, $\hat{\theta}_0^d < \hat{\theta}_0^s$ implies that $\tilde{\delta}_1^d \sigma^d < \tilde{\delta}_1^s \sigma^s$. This inequality is satisfied with $\sigma^d = \sigma^s$, if the parents underestimate the ability of a girl and/or the girls face unfavorable school environment. Second, $\hat{\psi}_0^d < \hat{\psi}_0^s$ implies $\hat{\theta}_0^d \delta_1^d < \hat{\theta}_0^s \delta_1^s$. The investment estimates show that $\hat{\theta}_0^d < \hat{\theta}_0^s$, and $\hat{\psi}_0^d < \hat{\psi}_0^s$ does not impose any additional restrictions. Third, $\hat{\psi}_1^d > \hat{\psi}_1^s$ implies $\theta_1^d \delta_1^d + \delta_3^d > \theta_1^s \delta_1^s + \delta_3^s$. Since $\theta_1^d = \theta_1^s$ according to the investment estimates, this last inequality can be satisfied if $(i)\delta_1^d > \delta_1^s$, and/or $(ii)\delta_3^d > \delta_3^s$. If the girls face unfavorable school environment, then $(i)\delta_1^d < \delta_1^s$ implying that we need to have $(ii)\delta_3^d > \delta_3^s$.

The upshot of the above discussion is that the evidence from the investment and mobility equations is consistent with the following: (i) no pure son preference, (ii) girls face unfavorable environment school, and (iii) parent's direct inputs favor girls.

# OA 4: Table on the Available Estimates of Returns to Education and List of the Papers Cited

**Table A0: Returns to Education in 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 |

**Papers Cited on Returns to Education in India**

Duraisamy (2002), Bargain et al. (2009), Kingdon (1998), Kanjilal-Bhaduri and Pastore (2018).

# References


Bargain, O., Bhaumik, S. K., Chakrabarty, M., and Zhao, Z. (2009). Earnings Differences Between Chinese And Indian Wage Earners, 19872004. *Review of Income and Wealth*, 55:562–587.

Duraisamy, P. (2002). Changes in returns to education in India, 1983-94: by gender, age-cohort and location. *Economics of Education Review*, 21(6):609–622.

Kanjilal-Bhaduri, S. and Pastore, F. (2018). Returns to Education and Female Participation Nexus: Evidence from India. *The Indian Journal of Labour Economics*, 61(3):515–536.

Kingdon, G. G. (1998). Does the labour market explain lower female schooling in India? *Journal of Development Studies*, 35(1):39–65.

# OA.5: Supplementary Discussions on the India Human Development Survey (IHDS)

## OA.5.1 The Education of Household Head's Father

The India Human Development Survey (IHDS) is unique for intergenerational educational and occupational mobility studies in India because it collected information on the parents of the household head. The following two questions are relevant:

- IHDS 2005 – 1.19 *What was the occupation of the household head's father/husband (for most of his life)*?
- IHDS 2005 – 1.20 *And how many standards/years of education had he completed*?

These two questions provide information on a household head's father's education and occupation, irrespective of the head's father's co-residence status. Such questions are not available in other Indian household surveys such as NSS or NFHS.

In IHDS 2012, there are similar questions:

- IHDS 2012 – 1.18 *What was the primary occupation of the household head's father / husband's father (for most of his life)*?
- IHDS 2012 – 1.18c *And how many standards/years of education had he completed*?

For *male headed households*, these two questions (1.20 in IHDS 2005 and 1.18c in IHDS 2012) are consistent, which provide unambiguous information about male household head's father's years of education.

However, when it comes to *female headed households*, the interpretation of these two questions (1.20 in IHDS 2005 and 1.18c in IHDS 2012) becomes ambiguous. In IHDS 2005, does question 1.20 refer to the female household head's husband's education, since the question includes *"/husband"*? In IHDS 2012, does question 1.18c refer to the female household head's husband's father's education, since the question includes *"/husband's father"*? Are these two questions essentially measuring different household members' years of education? Are these two questions supposed to measure the same thing, but were phrased differently with typos in the questionnaires? Answers to these questions matters and have important implications for coresidence bias and intergenerational mobility analysis.

For example, in the analytic sample of Azam & Bhatt (2015), there are 2425 sons in female headed households whose fathers (i.e., husbands of female household heads) were deceased and thus years of education are not directly available. On the one hand, if question 1.20 refers to years of education of the female head's husband, this question then provides information on education of those 2425 sons' deceased fathers. On the other hand, if question 1.20 has the same meaning as question 1.18c in IHDS 2012, then question 1.20 provides information on those 2425 sons' grandfather's years of education instead of father's years of education.

After communicating with the IHDS team, Dr. Sonalde Desai, one of the Principal Primary Investigators, offered clarification and confirmation by replying that "***Both questions are the same across the two waves as clarified in interviewer training as well as in local language translations. In both cases it is head's father if male and heads's husband's father if female.***" on June 24th, 2020.

Therefore, the correct interpretations of question 1.20 in IHDS 2005 and question 1.18c in IHDS 2012 are:

- For a male headed household, this question provides information on the male household head's father's education.
- For a female headed household, this question provides information on the female household head's husband's father's education.

### OA.5.2 The Non-Resident Family Members Module

There are two types of non-residence in the intergenerational mobility literature (for a discussion, please see Emran and Shilpi (2019) cited in the main text). The first type is related to the older generation, such as the non-parents of a household head. The second type is related to the younger generation, such as the non-resident children of a household head. While the education of household head's father variable provides useful information to deal with the first type of non-residence issue, as discussed in section OA.5.1, there are two data issues to be solved: (i) the non-resident children of household heads, (ii) the non-resident father of female household heads. We tackle these two issues by taking advantage of the non-resident family members module, which has been largely ignored in the studies using IHDS data such as Azam and Bhatt (2015) and Azam (2016) cited in the main text.

The non-resident family members module provides information on both demographics and education of non-resident family members. In particular, this module includes children studying outside the household, and spouse who lives outside the household. Therefore, we are able to match non-resident children of a household head with his/her father, and match children with his/her non-resident father of female household heads. The only limitation of this module is the lack of information on the female household head's spouse who has passed away.

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

| | | IHDS 1 Azam (2015) | IHDS 2 |
|---|---|---|---|
| Total Num of Individuals Surveyed in IHDS | | 215,784 | 204,568 |
| 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 |
| Total number of men (20-65 age group) whose father is identified: a) + b) + c) | | 56,154 | 52,010 |
| New: Non-resident Household Member Sample | Non-resident Father | N/A | 287 |
| | Non-resident Son | N/A | 534 |
| Percentage of men (20-65 age group, panel A) whose fathers are identified | | 96.494% | 92.097% |

*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 2 Azam (2016) | IHDS 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 | 4,416 |
| Father's Edu from Women's Module | 34,290 | 34,290 |
| Total Women whose father's Edu is available | 38,706 | 38,706 |
| New: Individual is head of household, who is not in Eligible Women's Module | N/A | 194 |
| New: Individual is neither head of the household, nor his father is living in the household (no father identification is provided) | N/A | 335 |
| New: Non-resident Father | N/A | 113 |
| New: Non-resident Daughter | N/A | 179 |
| % of surveyed women for whom father's Edu is available | 85.49% | 86.91% |

*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.

## OA.6: Intergenerational Mobility Estimates for Alternative Age Ranges

**Table A2: Intergenerational Persistence in Schooling in Urban India (Age 18-30)**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D – S** | **Sons (S)** | **Daughters (D)** | **D – S** |
| $\hat{\psi}_1$ | 0.422 | 0.495 | 0.073 | 0.524 | 0.614 | 0.089 |
| | (0.011) | (0.011) | (0.012) | (0.034) | (0.033) | (0.038) |
| $\hat{\psi}_2$ | | | | -0.007 | -0.009 | -0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 8.246 | 6.468 | -1.779 | 8.074 | 6.306 | -1.768 |
| | (0.165) | (0.168) | (0.184) | (0.180) | (0.174) | (0.198) |
| $N$ | 7728 | 7068 | 14796 | 7728 | 7068 | 14796 |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | **S** | **D** | **D – S** | | **S** | **D** | **D – S** |
| $EH_0^c$ | 7.202 | 6.337 | -0.865 | $IGME_0^c$ | 0.524 | 0.614 | 0.090 |
| | (0.143) | (0.143) | (0.143) | | (0.034) | (0.033) | (0.038) |
| $EH_5^c$ | 9.641 | 9.188 | -0.453 | $IGME_5^c$ | 0.451 | 0.527 | 0.076 |
| | (0.078) | (0.093) | (0.087) | | (0.016) | (0.015) | (0.017) |
| $EH_{10}^c$ | 11.713 | 11.603 | -0.110 | $IGME_{10}^c$ | 0.378 | 0.440 | 0.062 |
| | (0.065) | (0.076) | (0.079) | | (0.013) | (0.014) | (0.015) |
| $EH_{15}^c$ | 13.419 | 13.584 | 0.165 | $IGME_{15}^c$ | 0.305 | 0.353 | 0.048 |
| | (0.085) | (0.089) | (0.107) | | (0.029) | (0.030) | (0.035) |
| $EH_{17}^c$ | 13.999 | 14.254 | 0.255 | $IGME_{17}^c$ | 0.275 | 0.318 | 0.043 |
| | (0.138) | (0.144) | (0.172) | | (0.036) | (0.038) | (0.044) |

*Notes*: (1) The data are from the IHDS 2012 round with children aged 18-30. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father of child *c* has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree.

**Table A3: Intergenerational Persistence in Schooling in Rural India (Age 18-30)**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D – S** | **Sons (S)** | **Daughters (D)** | **D – S** |
| $\hat{\psi}_1$ | 0.421 | 0.502 | 0.081 | 0.486 | 0.636 | 0.149 |
| | (0.009) | (0.010) | (0.011) | (0.024) | (0.028) | (0.032) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.012 | -0.006 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 7.248 | 4.479 | -2.769 | 7.189 | 4.379 | -2.810 |
| | (0.115) | (0.125) | (0.133) | (0.119) | (0.125) | (0.135) |
| $N$ | 13724 | 13308 | 27032 | 13724 | 13308 | 27032 |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | **S** | **D** | **D – S** | | **S** | **D** | **D – S** |
| $EH_0^c$ | 6.809 | 4.796 | -2.013 | $IGME_0^c$ | 0.486 | 0.636 | 0.150 |
| | (0.086) | (0.094) | (0.087) | | (0.024) | (0.028) | (0.032) |
| $EH_5^c$ | 9.097 | 7.677 | -1.420 | $IGME_5^c$ | 0.429 | 0.517 | 0.088 |
| | (0.062) | (0.088) | (0.083) | | (0.010) | (0.011) | (0.012) |
| $EH_{10}^c$ | 11.097 | 9.964 | -1.133 | $IGME_{10}^c$ | 0.371 | 0.398 | 0.027 |
| | (0.055) | (0.087) | (0.084) | | (0.015) | (0.019) | (0.022) |
| $EH_{15}^c$ | 12.808 | 11.656 | -1.152 | $IGME_{15}^c$ | 0.313 | 0.279 | -0.034 |
| | (0.118) | (0.160) | (0.181) | | (0.031) | (0.038) | (0.045) |
| $EH_{17}^c$ | 13.411 | 12.166 | -1.245 | $IGME_{17}^c$ | 0.290 | 0.231 | -0.059 |
| | (0.179) | (0.233) | (0.271) | | (0.038) | (0.046) | (0.055) |

*Notes*: (1) The data come from the IHDS 2012 round with children aged 18-30. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree.

**Table A4: Intergenerational Persistence in Schooling in Urban India (Age 20-35)**

| | LINEAR CEF | | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D – S** | | **Sons (S)** | **Daughters (D)** | **D – S** |
| $\hat{\psi}_1$ | 0.475 | 0.545 | 0.071 | | 0.567 | 0.649 | 0.082 |
| | (0.011) | (0.010) | (0.012) | | (0.031) | (0.030) | (0.036) |
| $\hat{\psi}_2$ | | | | | -0.007 | -0.008 | -0.001 |
| | | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 7.528 | 5.597 | -1.931 | | 7.402 | 5.475 | -1.927 |
| | (0.156) | (0.158) | (0.168) | | (0.164) | (0.163) | (0.177) |
| $N$ | 8553 | 8185 | 16738 | | 8553 | 8185 | 16738 |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | **S** | **D** | **D – S** | | **S** | **D** | **D – S** |
| $EH_0^c$ | 6.841 | 5.711 | -1.130 | $IGME_0^c$ | 0.567 | 0.649 | 0.082 |
| | (0.131) | (0.126) | (0.129) | | (0.031) | (0.030) | (0.036) |
| $EH_5^c$ | 9.508 | 8.761 | -0.747 | $IGME_5^c$ | 0.500 | 0.571 | 0.071 |
| | (0.078) | (0.092) | (0.090) | | (0.015) | (0.014) | (0.016) |
| $EH_{10}^c$ | 11.839 | 11.424 | -0.415 | $IGME_{10}^c$ | 0.433 | 0.494 | 0.061 |
| | (0.065) | (0.077) | (0.081) | | (0.013) | (0.014) | (0.017) |
| $EH_{15}^c$ | 13.834 | 13.700 | -0.134 | $IGME_{15}^c$ | 0.365 | 0.416 | 0.051 |
| | (0.086) | (0.099) | (0.120) | | (0.028) | (0.031) | (0.037) |
| $EH_{17}^c$ | 14.538 | 14.502 | -0.036 | $IGME_{17}^c$ | 0.339 | 0.386 | 0.047 |
| | (0.138) | (0.154) | (0.190) | | (0.035) | (0.038) | (0.046) |

*Notes*: (1) The data are from the IHDS 2012 round with children aged 20-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father of child *c* has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree. (5) Standard errors in parentheses are clustered at primary sampling unit level; *** p<0.01, ** p<0.05, * p<0.1.

**Table A5: Intergenerational Persistence in Schooling in Rural India (Age 16-35)**

| | LINEAR CEF | | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|---|
| | Sons (S) | Daughters (D) | D – S | | Sons (S) | Daughters (D) | D – S |
| $\hat{\psi}_1$ | 0.416 | 0.502 | 0.085 | | 0.502 | 0.655 | 0.153 |
| | (0.008) | (0.009) | (0.009) | | (0.022) | (0.023) | (0.027) |
| $\hat{\psi}_2$ | | | | | -0.008 | -0.014 | -0.006 |
| | | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 6.891 | 4.468 | -2.423 | | 6.816 | 4.356 | -2.460 |
| | (0.098) | (0.109) | (0.110) | | (0.100) | (0.108) | (0.112) |
| $N$ | 20229 | 19637 | 39866 | | 20229 | 19637 | 39866 |

**Estimates of Mobility from the Quadratic CEF**

| | Absolute Mobility | | | | Relative Mobility | | |
|---|---|---|---|---|---|---|---|
| | S | D | D – S | | S | D | D – S |
| $EH_0^c$ | 6.551 | 4.462 | -2.089 | $IGME_0^c$ | 0.502 | 0.655 | 0.153 |
| | (0.077) | (0.078) | (0.073) | | (0.022) | (0.023) | (0.027) |
| $EH_5^c$ | 8.871 | 7.393 | -1.478 | $IGME_5^c$ | 0.426 | 0.518 | 0.092 |
| | (0.055) | (0.076) | (0.071) | | (0.009) | (0.009) | (0.010) |
| $EH_{10}^c$ | 10.809 | 9.640 | -1.169 | $IGME_{10}^c$ | 0.350 | 0.381 | 0.031 |
| | (0.049) | (0.077) | (0.071) | | (0.013) | (0.016) | (0.019) |
| $EH_{15}^c$ | 12.366 | 11.204 | -1.162 | $IGME_{15}^c$ | 0.273 | 0.244 | -0.029 |
| | (0.099) | (0.139) | (0.156) | | (0.027) | (0.033) | (0.039) |
| $EH_{17}^c$ | 12.883 | 11.637 | -1.246 | $IGME_{17}^c$ | 0.243 | 0.189 | -0.054 |
| | (0.151) | (0.201) | (0.234) | | (0.033) | (0.039) | (0.047) |

*Notes*: (1) The data come from the IHDS 2012 round with children aged 16-35. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled for in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations. (3) $EH_k^c$ is expected schooling when the father of child *c* has *k* years of schooling, and $IGME_k^c$ is the Intergenerational Marginal Effect (IGME) when the father has *k* years of schooling. *k*=0, 5, 10, 15, 17. (4) 15 years of schooling refer to college degree, and 17 years to a Master's degree.

## OA.7: Mobility Estimates from the First Child Sample (18-30 Age Range)

**Table A6: Estimates of Intergenerational Mobility in India from the First-Born Child Sample (Age 18-30)**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D-S** | **Sons (S)** | **Daughters (D)** | **D-S** |
| | | | **Urban India** | | | |
| $\hat{\psi}_1$ | 0.442 | 0.515 | 0.073 | 0.545 | 0.601 | 0.056 |
| | (0.013) | (0.012) | (0.015) | (0.037) | (0.035) | (0.045) |
| $\hat{\psi}_2$ | | | | -0.007 | -0.006 | 0.001 |
| | | | | (0.002) | (0.002) | (0.003) |
| $\hat{\psi}_0$ | 7.959 | 6.236 | -1.723 | 7.790 | 6.126 | -1.664 |
| | (0.184) | (0.175) | (0.214) | (0.199) | (0.179) | (0.228) |
| $N$ | 4521 | 5424 | 9945 | 4521 | 5424 | 9945 |
| | | | **Rural India** | | | |
| $\hat{\psi}_1$ | 0.450 | 0.510 | 0.060 | 0.513 | 0.623 | 0.110 |
| | (0.010) | (0.011) | (0.013) | (0.027) | (0.030) | (0.036) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.010 | -0.005 |
| | | | | (0.002) | (0.002) | (0.003) |
| $\hat{\psi}_0$ | 6.897 | 4.529 | -2.368 | 6.846 | 4.447 | -2.399 |
| | (0.126) | (0.124) | (0.142) | (0.129) | (0.125) | (0.146) |
| $N$ | 9063 | 11375 | 20438 | 9063 | 11375 | 20438 |

*Notes*: (1) The data used are from the IHDS 2012 round with the first-born child aged 18-30. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.

## OA.8: Mobility Estimates for Matrilineal vs. Patrilineal States in India (18-30 years Age Range)

**Table A7: Estimates of Intergenerational Mobility in Urban India**
**Patrilineal States vs. Matrilineal States (Age 18-30)**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D-S** | **Sons (S)** | **Daughters (D)** | **D-S** |
| | | | **Patrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.425 | 0.502 | 0.070 | 0.511 | 0.595 | 0.088 |
| | (0.012) | (0.012) | (0.013) | (0.035) | (0.034) | (0.040) |
| $\hat{\psi}_2$ | | | | -0.006 | -0.007 | -0.001 |
| | | | | (0.002) | (0.002) | (0.002) |
| $\hat{\psi}_0$ | 8.159 | 6.225 | -0.895 | 8.025 | 6.109 | -0.903 |
| | (0.175) | (0.179) | (0.127) | (0.188) | (0.184) | (0.147) |
| *N* | 7082 | 6469 | 13551 | 7082 | 6469 | 13551 |
| | | | **Matrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.341 | 0.346 | 0.006 | 0.511 | 0.487 | -0.030 |
| | (0.044) | (0.027) | (0.038) | (0.122) | (0.094) | (0.135) |
| $\hat{\psi}_2$ | | | | -0.011 | -0.010 | 0.002 |
| | | | | (0.006) | (0.006) | (0.007) |
| $\hat{\psi}_0$ | 9.312 | 8.997 | 0.147 | 8.798 | 8.661 | 0.311 |
| | (0.434) | (0.314) | (0.363) | (0.608) | (0.399) | (0.567) |
| *N* | 646 | 599 | 1245 | 646 | 599 | 1245 |

*Notes*: (1) The data used are from the IHDS 2012 round with children aged 18-30. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) The patrilineal and matrilineal classification follows that of Jayachandran and Pande (2017). (3) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.

**Table A8: Estimates of Intergenerational Mobility in Rural India**
**Patrilineal States vs. Matrilineal States (Age 18-30)**

| | LINEAR CEF | | | QUADRATIC CEF | | |
|---|---|---|---|---|---|---|
| | **Sons (S)** | **Daughters (D)** | **D-S** | **Sons (S)** | **Daughters (D)** | **D-S** |
| | | | **Patrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.418 | 0.492 | 0.078 | 0.474 | 0.605 | 0.136 |
| | (0.009) | (0.011) | (0.012) | (0.025) | (0.029) | (0.034) |
| $\hat{\psi}_2$ | | | | -0.005 | -0.010 | -0.005 |
| | | | | (0.002) | (0.002) | (0.003) |
| $\hat{\psi}_0$ | 7.244 | 4.311 | -2.078 | 7.195 | 4.229 | -2.111 |
| | (0.119) | (0.129) | (0.082) | (0.122) | (0.129) | (0.088) |
| $N$ | 12799 | 12474 | 25273 | 12799 | 12474 | 25273 |
| | | | **Matrilineal States in India** | | | |
| $\hat{\psi}_1$ | 0.469 | 0.543 | 0.074 | 0.681 | 0.822 | 0.139 |
| | (0.035) | (0.036) | (0.035) | (0.102) | (0.095) | (0.107) |
| $\hat{\psi}_2$ | | | | -0.017 | -0.024 | -0.007 |
| | | | | (0.007) | (0.006) | (0.008) |
| $\hat{\psi}_0$ | 7.209 | 6.872 | -0.198 | 6.868 | 6.557 | -0.175 |
| | (0.455) | (0.431) | (0.310) | (0.482) | (0.453) | (0.340) |
| $N$ | 925 | 834 | 1759 | 925 | 834 | 1759 |

*Notes*: (1) The data used are from the IHDS 2012 round with children aged 18-30. The dependent variable in the regression is children's years of schooling. Number of children in a household is controlled in each regression. (2) The patrilineal and matrilineal classification follows that of Jayachandran and Pande (2017). (3) $\hat{\psi}_1$ is the estimated linear coefficient in the mobility equation, $\hat{\psi}_2$ is the estimated quadratic coefficient in the mobility equation, and $\hat{\psi}_0$ is the estimated intercept in the mobility equation. N is the number of observations.