

Ahsan, Md. Nazmul; Emran, M. Shahe; Jiang, Hanchen; Shilpi, Forhad

**Working Paper**

## What the Mean Measures of Mobility Miss: Learning About Intergenerational Mobility from Conditional Variance

GLO Discussion Paper, No. 1097

**Provided in Cooperation with:**

Global Labor Organization (GLO)

*Suggested Citation:* Ahsan, Md. Nazmul; Emran, M. Shahe; Jiang, Hanchen; Shilpi, Forhad (2022) : What the Mean Measures of Mobility Miss: Learning About Intergenerational Mobility from Conditional Variance, GLO Discussion Paper, No. 1097, Global Labor Organization (GLO), Essen

This Version is available at:

<https://hdl.handle.net/10419/258887>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# What the Mean Measures of Mobility Miss: Learning About Intergenerational Mobility from Conditional Variance <sup>1</sup>

Md. Nazmul Ahsan, Saint Louis University

M. Shahe Emran, IPD, Columbia University

Hanchen Jiang, University of North Texas

Forhad Shilpi, World Bank

First Draft: January 3, 2022

This Version: February 17, 2022

*Comments Welcome*

## ABSTRACT

A large literature on intergenerational mobility focuses on the conditional mean of children's economic outcomes to understand the role of family background, but ignores the information contained in conditional variance. Using exceptionally rich data free of coresidency bias, we provide evidence on three large developing countries (China, India, and Indonesia) that suggests a strong influence of father's education on conditional variance of children's schooling. We find substantial heterogeneity across countries, gender, and geography (rural/urban). Cohort based estimates suggest that the effects of father's education on the conditional variance has changed qualitatively, in some cases a positive effect in the 1950s cohort turning into a substantial negative effect in the 1980s cohort. We develop a methodology to incorporate the effects of family background on the conditional variance along with the standard conditional mean effects. We derive risk adjusted measures of relative and absolute mobility by accounting for an estimate of the risk premium for the conditional variance faced by a child. The estimates of risk adjusted relative and absolute mobility for China, India and Indonesia suggest that the standard measures substantially underestimate the effects of family background on children's educational opportunities, and may give a false impression of high educational mobility. The downward bias is specially large for the children born into the most disadvantaged households where fathers have no schooling, while the bias is negligible for the children of college educated fathers. The standard (but partial) measures may lead to incorrect ranking of regions and groups in terms of relative mobility. Compared to the risk adjusted measures, the standard measures are likely to underestimate gender gap and rural-urban gap in educational opportunities.

**Key Words:** Conditional Variance, Family Background, Intergenerational Educational Mobility, Risk Adjusted Mobility Measures, China, India, Indonesia

**JEL Codes:** I24, J62, O12

---

<sup>1</sup>Emails for correspondence: nazmul.ahsan@slu.edu (Md. Nazmul Ahsan); shahe.emran.econ@gmail.com (M. Shahe Emran); Hanchen.Jiang@unt.edu (Hanchen Jiang); fshilpi@worldbank.org (Forhad Shilpi).

## (1) Introduction

A large economic and sociological literature provides estimates of intergenerational persistence in economic status. A higher persistence across generations is interpreted as inequality of economic opportunities for children as their life chances are tied down closely to the socioeconomic status of their parents irrespective of their own choices and effort. The bulk of the measures used for understanding the transmission of economic status from one generation to the next are based on a conditional expectation function. The focus is on estimating the expected value of an indicator of socioeconomic status of children (e.g., permanent income, education ) conditional on parent's (usually father's) socioeconomic status (for surveys, see Solon (1999), Bjorklund and Salvanes (2011), Iversen et al. (2019), and Torche (2019)).

This vast and growing literature largely neglects any information contained in the conditional variance of children's economic outcomes.<sup>2</sup> This is a reasonable approach under two conditions: (i) the conditional variance of the relevant economic outcome does not vary in any systematic way with parental economic status, geographic location, gender, race and ethnicity etc.; (ii) parents and children are approximately risk neutral. A large body of evidence accumulated over many decades rejects risk neutrality, and strongly suggests an important role for risk aversion in economic choices under uncertainty (see, for example, Eeckhoudt et al. (2005)). There is no systematic evidence in the literature on the first condition, but there are a variety of economic mechanisms that can make the conditional variance a function of parent's economic status and geographic location, for example. Conditional variance in children's schooling may vary across the households in a village because of their different abilities to cope with adverse weather shocks. With better access to credit and insurance markets, the highly educated (high income) households are better able to deal with negative shocks such as flood and drought without any disruption to children's education. In contrast, such a negative income shock may force the uneducated poor parents to take the children out of school and

---

<sup>2</sup>Although largely ignored in the literature on intergenerational mobility, some studies in the related but distinct literature on inequality of opportunity (IOP) account for the fact that conditional variance is likely to depend on the "circumstances" a child is born into (see, for example, Bjorklund et al. (2012)). But their focus is very different. Please see the discussion in section 2 below. There is a small literature that exploits the information in conditional variance by estimating quantile regression models of intergenerational mobility. But the focus there is not on understanding the influence of parental socioeconomic status on conditional variance of children's outcomes. Please see section 2 below for a detailed discussion.

send them for child labor. This adds an element of uncertainty (on top of ability differences) for the children born into disadvantaged households, resulting in a higher conditional variance in completed schooling. The conditional variance of children’s schooling attainment is likely to *decline* with the education of parents when such economic shocks (income or health shocks) are the primary sources behind the observed variance in the data. *In this case, children born to higher educated parents not only have higher expected years of schooling (as found in numerous studies of intergenerational educational mobility), but also a lower variance in schooling attainment. Under the plausible assumption of risk aversion, this implies being born to higher educated parents brings double advantages for children part of which is ignored by the existing measures of intergenerational mobility.*

We analyze the relationship between family background and conditional variance of children’s outcome in the context of intergenerational educational mobility. We make two contributions to the literature. First, using data from three large developing countries (China, India, and Indonesia, with 42 percent of world population in 2000 (2.56 billion)), we provide the first empirical evidence that the conditional variance of children’s schooling is systematically related to his/her family background as captured by father’s education.<sup>3</sup> Second, we develop a methodology that combines the effects of father’s education on both the mean and conditional variance of children’s schooling. We propose new measures of relative and absolute mobility that adjust the standard mean effects by the risk premium associated with the conditional variance in educational outcomes faced by children. With risk neutrality, our proposed measures reduce to the canonical measures of intergenerational educational mobility widely used in the current literature (see, for example, Hertz et al. (2008), Azam and Bhatt (2015), and Narayan et al. (2018)). But, under the more plausible assumption of risk aversion, the measures of mobility developed in this paper incorporate the effects of family background operating through conditional variance.

For our empirical analysis, we use household survey data from China Family Panel Studies (CFPS) 2010, India Human Development Survey (IHDS) 2012, and Indonesia Family Life

---

<sup>3</sup>We are not aware of any studies on intergenerational mobility that estimates the effects of parent’s economic status on the conditional variance of children’s economic outcomes.

Survey (IFLS) 2014.<sup>4</sup> The estimates from the full sample (1950-1989 birth cohorts) suggest that the conditional variance in children’s schooling *declines* with father’s education in all three countries, thus confirming the conjecture that the children born to more educated fathers enjoy double advantages in the form of a lower variance in addition to a higher expected (mean) schooling attainment.

We find evidence of substantial heterogeneity across countries, geographic location (rural vs. urban), gender, and birth cohorts. Conditional variance in children’s schooling is the highest in India (18.76) and the lowest in Indonesia (13.58), with China in between (16.83). The influence of father’s education on conditional variance of children’s schooling follows a reverse cross-country pattern: Indonesia (-0.51), China (-0.48), and India (-0.38). Conditional variance is higher in the rural areas in a country, but the influence of father’s education on conditional variance is smaller in magnitude. The rural-urban difference is specially striking in India where the estimate is negative and large (-0.77) in the urban sample but small and statistically not significant (10 percent level) in the rural sample (-0.022). In contrast, the rural-urban difference is small in China: -0.55 (urban) and -0.52 (rural). We also find substantial gender differences with a larger negative effect on sons. The gender differences in India are the starkest: the estimated effect is negative in sons sample, but positive in daughters sample.<sup>5</sup> The results from cohort-based analysis suggest that the negative effect of father’s education on conditional variance has become stronger over time in all three countries. In rural and daughters samples in India and Indonesia, the estimate has turned from positive in the 1950s cohort to a strong negative effect in the 1980s cohort.<sup>6</sup>

We check some alternative explanations for the observed relations between conditional variance in children’s education and father’s education. We provide evidence that functional

---

<sup>4</sup>These surveys are chosen to ensure that the estimates are not biased because of sample truncation due to coresidency restrictions. It is well known that truncations biases the estimated variance downward (Cohen (1991)). Recent evidence suggests that coresidency causes substantial downward bias in the estimate of relative educational mobility as measured by IGRC; see Emran et al. (2018).

<sup>5</sup>Government policies and social norms can make the relation between father’s education and conditional variance of children’s schooling positive. For example, gender based social norms such as son preference and Purdah may results in low conditional variance in low educated households as parents target a reference level of schooling for the daughters, and the girls’ schooling attainment bunches around that reference point. This can also give rise to a positive effect in the conditional variance regression. Please see section 2 below.

<sup>6</sup>This suggests that the positive effect in the full sample (1950-1989) found earlier for rural India and the daughters in India is driven by the earlier cohorts.

form mis-specification is not responsible for the observed relations.<sup>7</sup> Taking advantage of data on cognitive ability in IFLS 2014 in Indonesia, we explore whether the estimated effect of father’s education is largely due to omitted ability heterogeneity of children. We find that the inclusion of quadratic controls for ability reduces the magnitude of the impact of father’s education on conditional variance, but the estimates still remain substantial and statistically significant at the 1 percent level.

For relative mobility, the estimates of risk adjusted IGRC (RIGRC) suggest that the workhorse measure of relative mobility in the literature, IGRC, substantially underestimates the impact of family background. The estimates for the full sample (1950-1989 cohorts) suggest that the downward bias on average is 26 percent in China, 41 percent in India, and 10.4 percent in Indonesia.<sup>8</sup>

Accounting for the influence of family background on conditional variance of schooling makes a dramatic difference in the estimated relative and absolute mobility for the children born to the most disadvantaged households (fathers with no schooling).<sup>9</sup> RIGRC estimates from the full sample (1950-1989 birth cohorts) for this subgroup shows that the standard IGRC provides a 37 percent upward biased estimate of relative mobility in China, and 63 percent and 28 percent upward bias in India and Indonesia respectively. In contrast, the gap between the RIGRC and IGRC estimates for the subgroup with college educated fathers is small. Absolute mobility is also substantially overestimated for the most disadvantaged subgroup without risk adjustments: conditional mean of years of schooling is overestimated by 48 percent in China, 127 percent in India, and 25 percent in Indonesia. Again, for absolute mobility of the children of college educated father, the risk adjustments does not make any substantial difference. *The upshot is that while the standard estimates of relative and absolute*

---

<sup>7</sup>Based on recent evidence, we allow for a quadratic mobility CEF in place of a linear functional form (see Becker et al. (2015, 2018), Emran et al. (2021), Ahsan et al. (2021)). We find that allowing for a quadratic CEF does not change the relation between the conditional variance in children’s schooling and father’s education in any significant manner.

<sup>8</sup>The smaller bias in Indonesia despite a large influence of father’s education on the conditional variance noted earlier reflects the fact that the ratio of the conditional variance to the conditional mean is much smaller. This ratio is important in determining the risk premium. Please see section (5) below.

<sup>9</sup>Note that IGRC, the measure of relative mobility in the workhorse linear model, does not vary with father’s education level. But the risk adjusted measure RIGRC varies across low and high educated households because of differences in the conditional variance and the conditional mean.

*mobility seem to capture reasonably well the educational opportunities of children born to college educated fathers, a failure to account for the effects of family background on conditional variance vastly overstates the educational opportunities of the most disadvantaged children with father having no schooling.*

Ignoring the conditional variance can also lead to wrong conclusions in inter-group comparisons. For example, In India, the urban and rural daughters appear to enjoy similar relative mobility according to the standard IGRC estimates (0.60 (urban) and 0.59 (rural)), but the RIGRC estimates reveal a substantial disadvantage faced by the rural daughters (0.92 (rural) and 0.79 (urban)). The estimates of both RIGRC and IGRC for decade wise birth cohorts show that the evolution of intergenerational educational mobility has been very different in China compared to India and Indonesia. China has become less mobile from the 1950s to the 1980s while mobility has improved monotonically from the 1950s to the 1980s in India and Indonesia, and the magnitude is substantial. While both measures pick the trend correctly, the standard IGRC substantially underestimates the improvements over time in India.

The rest of the paper is organized as follows. The next section discusses the relevant conceptual issues with a focus on the economic mechanisms that can give rise to a negative or positive effect of father's education on the conditional variance of children's schooling, and lays out the estimating equations. Section (3) is devoted to a discussion of the surveys and data sets used for our analysis: CFPS 2014 (China), IHDS 2012 (India), and IFLS 2014 for Indonesia. These three surveys are different from many other household surveys available in developing countries as the samples do not suffer from significant truncation. This is important as truncation of a sample is expected to reduce the estimate variance. Section (4) reports the evidence on the conditional variance. In section (5), we develop a methodology for estimating relative mobility that takes into account both the conditional mean and conditional variance, and provide estimates of the risk adjusted relative mobility measure. The paper concludes with summary of the findings and points out the central contributions of the paper to the literature.

## **(2) Conceptual Issues and Estimating Equations**

The standard estimating equation for intergenerational educational mobility is:

$$S_i^c = \alpha + \beta S_i^p + \varepsilon_i; \quad E(\varepsilon_i) = 0 \quad (1)$$

where  $S_i$  is the years of schooling of child  $i$  and superscripts  $c$  and  $p$  stand for child and parents respectively. The focus of the analysis is the parameter  $\beta$  which is known as intergenerational regression coefficient (IGRC, for short) in the literature.<sup>10</sup> It is implicitly assumed that the variance of the error term  $\varepsilon_i$  does not depend on father's education in any systematic way, and thus  $\beta$  alone adequately captures the influence of family background. This assumption is valid when the error term captures primarily the variations in children's ability uncorrelated with father's education, and there are no market imperfections. In a model with perfect credit and insurance markets, the optimal investment in a child's education depends only on his/her ability, the family background is irrelevant. Under the plausible assumption that the conditional variance of children's (innate) cognitive ability does not depend on family background, there is no additional information in the conditional variance of schooling attainment that could be useful for understanding the impact of family background on educational opportunities of children.

In a more realistic setting where the credit and insurance markets are imperfect (or missing), we would expect that the conditional variance would reflect the interactions of a child's ability with the credit constraint and risk coping strategies of a household. First, consider the implications of credit market imperfections in the absence of income or health shocks. We consider two types of credit market imperfections. In the first case, the poor (less educated) households pay a higher interest rate but can borrow as much as they want for educational investment (i.e., no quantitative credit rationing).<sup>11</sup> In this case, the poor (less educated) parents invest less, given the ability of a child, because of a higher interest rate, but the investment differences across children from the same family (or similar family background where fathers

---

<sup>10</sup> Among many studies relying on this specification, please see Hertz et al. (2008) and Narayan et al. (2018) for cross country evidence, Azam and Bhatt (2015), Emran and Shilpi (2015) and Asher et al. (2018) on India, Knight et al. (2011), Golley and Kong (2013), and Emran and Sun (2015) on China, other references on China and Indonesia. For recent surveys of this literature, see Iversen et al. (2019), Torche (2019), and Emran and Shilpi (2021).

<sup>11</sup> This model of credit market imperfections is adopted by Becker et al. (2018) in their recent theoretical analysis of intergenerational mobility.



have the same education) are determined solely by the ability differences among the children. We thus expect *lower average level* of education for the children of less educated parents, but the *conditional variance should not depend in any significant way on father's education* in this case. The second model of credit market imperfections focuses on the quantitative credit rationing, a special case of which is self financing by the parents (the case of missing credit market for investment in education). When the parents have limited investment funds, they might choose to invest in the most able child to maximize the expected income (Becker (1991)). Since the probability of success is higher for a child with high cognitive ability, it may be optimal for the parents to reallocate investment funds from other children, specially when returns to education are convex.<sup>12</sup> Such investment choices would increase the variance of children's schooling in the less educated credit constrained families as the less able children's education level is depressed and the education level of the high ability child is pushed up. Negative income shocks can amplify the effects of a binding credit constraint, as the family may need to allocate the funds earmarked for education investment to buy food. It is not uncommon for one sibling to drop out of school in response to a negative shock to supplement family income through child labor, while the more promising sibling continues with his/her study. However, as emphasized by Behrman et al. (1982), equity concerns for a low ability child may dominate the income maximizing motive, leading to a compensating investment allocation where the low ability child gets a larger share of the educational investment. If compensating investment rather than the reinforcing investment is the overriding behavioral response of parents facing scarcity, then we would expect lower conditional variance for the children born to low educated fathers.<sup>13</sup>

Government policies and social norms can also affect the conditional variance of children's education. When government policies such as free and compulsory primary schooling are well designed and implemented, it ensures that the children from the poor socioeconomic background attain primary schooling irrespective of a child's ability. This will reduce the conditional variance in the poor households by effectively eliminating the lower tail of the

---

<sup>12</sup>There is emerging evidence that returns to education function is convex in many developing countries. See Kingdon (2007) on India, and Fasih et al. (2012) for cross-country evidence.

<sup>13</sup>There is a large sociological literature on reinforcing vs. compensating parental investments in children's education. But most of the literature focuses on the developed countries. See, for example, Conley (2004).

counterfactual schooling distribution of children without any government policy interventions. Merit based scholarships provided by schools or government programs on the other hand can relax the credit constraints only for the most able child in a poor family and thus increase the conditional variance by expanding the upper tail of educational attainment.

Social norms can create reference points for the desired level of education of children which may vary significantly by gender, specially in the older cohorts. For example, strong son preference and Purdah may imply that girls in poor households go to school only if schooling is easily accessible and, more importantly, free. They drop out after primary schooling because secondary and higher schooling requires substantial private investments by the parents and the high schools may be far away. We might thus observe low conditional variance in the households with less educated parents because of bunching around primary schooling or other thresholds determined by social norms, particularly for daughters. The richer and more educated households may invest substantially in daughter’s education even with son preference, and their investment would be more closely aligned with the ability of a child irrespective of gender. The preceding discussion thus suggests that depending on government policy and social norms, we may in fact observe an increasing conditional variance with father’s education, specially for daughters in rural areas.

To understand the potential influence of family background as captured by father’s education, we estimate the following equation for conditional variance:

$$V(\varepsilon_i) = \theta_0 + \theta_1 S_i^p + v_i; \quad E(v_i) = 0 \quad (2)$$

We are not aware of any studies on intergenerational mobility that provide estimates of equation (2). In the related but distinct literature on inequality of opportunity that grew out of Roemer’s seminal work (Roemer (1998), Roemer and Trannoy (2016)) , there are a number of studies that estimate equation (2); see, for example, Bjorklund et al. (2012) and Hederos et al. (2017) in the context of income mobility in Sweden. However, their focus is very different, they are interested in estimating a clean measure of “effort” in order to decompose the observed income of children into two parts: one due to the circumstances a child is born into, and the other due to a child’s own effort. Similar to this paper, they recognize that the

residual from a linear regression of children’s education, for example, on a set of variables defining the “circumstances” is not a clean measure of effort as it partly reflects the effects of family background.<sup>14</sup> As measure of effort, they use the “sterilized residual” from the regression of the residual squared (the residual from the earlier stage) on circumstances.

There is a small literature on intergenerational mobility that exploits the information in conditional variance using quantile regressions. See, for example, Grawe (2004) on USA and Kishan (2018) on India. The focus in this approach on estimating different conditional mean functions corresponding to the quantiles of children’s education. Grawe (2004) provides an interesting analysis of the pitfalls in relying on functional form of the CEF to learn about credit constraints in the context of income mobility. His analysis suggests that a quantile regression approach can be useful in understanding the existence of credit constraints.

### **(3) Data and Variables**

We use the following household surveys for our empirical analysis: China Family Panel Studies (CFPS) for China, India Human Development Survey (IHDS) for India, and Indonesia Family Life Survey (IFLS) for Indonesia. These data sets are suitable for our analysis because they do not suffer from any significant sample truncation arising from coresidency restrictions commonly used to define household membership in a survey. A truncated sample is likely to underestimate the conditional variance, for example when the data miss observations on highly educated children who left the natal house for college.

The data for China come from the China Family Panel Study (CFPS) 2010 wave, which has a unique T-Table design that presents a complete family network, in which household members’ education information is also available. For more detailed discussions about the unique advantage of CFPS in analyzing intergenerational mobility related questions, please see Fan, Yi ang Zhang (2021) and Emran, Jiang, Shilpi (2020). The data for India come from the India Human Development Survey (IHDS) 2012 wave. We follow Emran, Jiang, Shilpi (2021) closely, which updates and expands the sample of father-child pairs for years of schooling in India in two major ways compared to the earlier studies such as in Azam

---

<sup>14</sup>The circumstances usually include parent’s education, occupation, race, ethnicity, geographic location, and gender.

and Bhatt (2015) and Azam (2016). Our sample includes not only the non-resident fathers but also other non-resident family members, and non-resident children of household heads in particular.

The data for Indonesia come from Indonesia Family Life Survey (IFLS) 2014 wave. IFLS's household roster, nonresident parents module, and mother's marriage module allow us to construct father-children pairs whose education information is not subject to truncation bias. More details about the sample construction procedure, readers are referred to Ahsan, Emran, Shilpi (2021) and Mazumder et al. (2019).

The summary statistics for our main estimation samples are reported in Table 1. We first report the average years of schooling for both father and children in our full sample born between 1950 and 1989 across three countries respectively. The average years of schooling for fathers is 4.24 in China, 3.63 in India, and 6.21 in Indonesia. The average years of schooling for children is 7.52 in China, 6.50 in India, and 9.52 in Indonesia. Therefore, Indonesia has the best education outcome for both fathers and children among the three countries while India has the lowest mean education for both generations.

We also report the summary statistics for our four main sub-samples: urban, rural, sons, and daughters in the following panels respectively. In each country, there is consistent rural-urban gap in education for both generations. Children in urban China and urban India have about 3 more years of schooling than children in rural areas, while the gap is smaller in Indonesia (2 years). All three countries exhibit different degree of gender gap in schooling among children: 1.3 years in China, 2.3 years in India, and 0.6 years in Indonesia. Gender gap in Indonesia is much smaller, consistent with a large literature showing that girls in Indonesia do not face any significant disadvantages compared to the boys.

#### **(4) Evidence on Conditional Variance**

Estimates of equations (1) (conditional mean) and (2) (conditional variance) for our full estimation samples (1950-1990 birth cohorts) are reported in Table 2. The estimates for the mobility equation (1) are in odd columns and those for the conditional variance equation (2) are in even columns. The evidence is consistent across the three countries: *conditional variance of children's schooling is a negative function of father's education*. Estimates from the mobility

equation show that father's education has a substantial positive influence on the expected schooling of children, consistent with a large literature that focuses solely on the mean effects. When considered together, the evidence on the mobility and conditional variance equations suggests that *being born to a higher educated father is equivalent to winning an education lottery with higher mean (expected years of schooling) and a lower variance*. There are some important cross-country heterogeneity: while father's impact on the expected education of children (IGRC) is the highest in India (0.62), the effect on conditional variance is the smallest (-0.38). The influence of father's education on conditional variance is of comparable magnitude in China (-0.48) and Indonesia (-0.51), but the estimate for the mean schooling is much smaller in China (0.38) compared to that in Indonesia (0.48).

#### **(4.1) Heterogeneity: Rural vs. Urban, and Sons vs. Daughters**

The top panel of Table 3 reports the estimates of equations (1) and (2) separately for rural and urban samples. The evidence suggests striking rural/urban differences which vary across countries. Conditional variance on average is higher in rural areas, although the rural-urban gap is small in China.<sup>15</sup> In India, the effects of father's education on conditional variance is large in urban sample (-0.77), but we cannot reject the null hypothesis of no influence in the rural sample (-0.02). As we discuss below this null effect hides important gender differences in the rural areas. The estimates are similar in magnitude across rural and urban areas in the case of China (-0.55 (urban) and -0.52 (rural)), and in Indonesia, the urban estimate is much larger (-0.71 (urban) and -0.29 (rural)).

The lower panel of Table 3 contains the estimates for sons and daughters samples. In India, the estimate for sons is negative, and large in magnitude (-0.93), but the estimate in daughter's sample is positive and numerically much smaller (0.33) (both estimates are significant at the 1 percent level). The evidence in Table 3 thus suggests that the idea that being born into a highly educated household confers you double dividends is valid only for the sons in India. However, the evidence below on the evolution of educational mobility across cohorts show that this conclusion is valid only for the older cohorts (see below). In China,

---

<sup>15</sup>The higher conditional variance in rural areas is consistent with the observation that the rural economy is more exposed to weather shocks and the credit and insurance markets are less developed.

higher education of a father lowers the conditional variance of schooling for both sons and daughters, but the magnitude of the impact is substantially larger for sons (-0.48 for sons, and -0.36 for daughters). The evidence is different in Indonesia: there is no significant difference across gender.<sup>16</sup>

In the online appendix, we discuss the estimates for four subsamples defined by gender and rural/urban location of a child (see Table A.1 in the online appendix section OA.1). The evidence on India suggests that the rural daughters face very different educational prospects: the impact of father's education is positive and numerically large for this subgroup, while the effect is negative in the other three subgroups. The finding that the rural daughters are qualitatively different from the other three groups also holds in China: there is no significant impact on conditional variance of rural daughter's schooling, while the effect is negative and significant in the other three subgroups.

#### **(4.2) The Evolution of Conditional Variance: Evidence from Decade-wise Birth Cohorts**

Table 4 reports the estimates for equations (1) and (2) for decade-wise birth cohorts: 1950-1959, 1960-1969, 1970-1979, 1980-1989. The evidence shows interesting pattern in the evolution of the influence of family background on conditional variance of children's schooling. If we focus only on the mean effect as is done in the existing literature, the evidence suggests that relative mobility has improved in India and Indonesia over time, while it has worsened in China. However, the impacts on the conditional variance shows a much stronger role of the family background in the recent decades which counteracts the improvements in the mean effects. In all three countries, the influence of father's education on the conditional variance is negative and substantial in magnitude in the 1980s, suggesting that the children born to educated parents gain in terms of a much lower conditional variance, in addition to a higher conditional mean. There are dramatic differences in the earlier cohorts across countries: the estimate is negative in China, positive in Indonesia, and a zero effect in India for the 1950s

---

<sup>16</sup>The standard mean effects (see the IGRC estimates in the odd numbered columns of Table 3) show that the influence of father's education is much higher for daughters in terms of the first moment (expected years of schooling) in China. The gender advantages thus are opposite in terms of the mean vs. conditional variance effects. We discuss a simple summary measure of relative mobility that combines these two aspects in section 5 below.

cohort. The estimate turns negative and significant in Indonesia in the 1960s, and in India a decade later in the 1970s. The influence of family background on conditional variance has increased dramatically, and relative mobility is substantially overestimated in both countries in the recent decades if we ignore the impact on conditional variance. In section (5) below, we combine the conditional mean and conditional variance effects to provide risk adjusted relative and absolute mobility measures.

The estimates disaggregated across gender and geography, and for different cohorts are reported in the online appendix Tables A.2, and A.3 (please see online appendix section OA.1). Again, the evidence suggests important heterogeneity across gender and rural-urban locations. The influence of family background on conditional variance in early cohorts is negative in urban and sons samples for India and China, but there is no significant effect in Indonesia. It is positive and numerically substantial in the rural and daughters samples for India and Indonesia, but no significant effect in China. The estimate turned negative in the 1980s even in the rural and daughters samples in all three countries.

### (4.3) Robustness Checks

The evidence discussed above suggests that the conditional variance of children's school depends systematically on father's education, and there are substantial heterogeneity across countries, regions (rural/urban), gender, and cohorts. We first check whether the observed patterns in conditional variance of children's schooling are primarily driven by functional form misspecification. As noted briefly earlier, there is a growing theoretical and empirical literature that suggests that the intergenerational educational mobility equation is quadratic (Becker et al. (2018) , Emran et al. (2020) ):<sup>17</sup>

$$S_i^c = \alpha + \beta S_i^p + \delta (S_i^p)^2 + \zeta_i \quad (3)$$

If the true conditional expectation function is given by equation (3), but we estimate the linear equation (1), the error term is  $\varepsilon_i = \delta (S_i^p)^2 + \zeta_i$ , and the conditional variance of

---

<sup>17</sup>Most of the studies on intergenerational income mobility use a specification linear in logs. Bratsberg et al. (2007) finds that it is convex in Norway, Denmark, and Finland, but closer to linear in USA and UK. However, Chetty et al. (2014) report evidence of a concave relation (see their Figure 1) in USA, and a recent analysis by Mitnik et al. (2018) provides evidence that the income mobility equation is convex in USA.

$\varepsilon_i$  is a function of father’s education simply because of a misspecified functional form. To check this, we estimate the mobility equation (3) and the impact of father’s education on the conditional variance defined in terms of  $\zeta_i$ . The estimates for various samples are reported in Tables A.4-a.8 in the online appendix section OA.2. The evidence suggests strongly that the relations between family background and conditional variance of children’s schooling uncovered in Tables 2-4 are not driven by functional form misspecification of the mobility CEF.

The next question we address is whether the estimated impact of father’s education largely reflects the omitted cognitive ability heterogeneity of children. For this analysis, we take advantage of the IFLS-2014 survey in Indonesia which collected data on multiple indicators of cognitive ability of a child (measurement taken in 2014 when the children are adult): raven test scores and two memory tests. We construct an index of cognitive ability in two steps. First, we construct the first principal component of the different measures of cognitive ability. In the second step, we regress the first principal component on age and age squared of a child to take out the “Flynn effect”. The residual from this regression is our index of cognitive ability of a child. We control for the ability index and its squared in the regression for conditional variance in equation (2) above. The estimates for the full sample are reported in online appendix Table A.4 (see online appendix section OA.3). The main message that comes out is that the estimated effects of father’s education on conditional variance of schooling of children are not driven by omitted ability heterogeneity. Even though ability controls reduce the estimated coefficient, the influence of father’s education still remains substantial and statistically significant at the 1 percent level. The estimates for other subsamples are available from the authors.

### **(5) Combining the Mean and Conditional Variance Effects: New (and More Complete) Measures of of Relative and Absolute Mobility**

The evidence presented above suggests strongly that it is important to understand the influence of family background on the conditional variance in addition to the standard mean effects. In this section, we develop an approach that combines the mean and variance effects using standard results from the theory of decisions under uncertainty.

Assume a concave payoff function (utility function) defined over the possible schooling



outcomes of a child  $i$ ,  $W(S_i^c)$ . Denote the expected schooling as  $E(S_i^c)$ , and  $\epsilon_i = S_i^c - E(S_i^c)$ . So we can rewrite  $W(S_i^c) = W(E(S_i^c) + \epsilon_i)$ . Using the intergenerational mobility equation (1) above,  $E(S_i^c) = \alpha + \beta S_i^p$ , which implies  $W(S_i^c) = W(\alpha + \beta S_i^p + \epsilon_i)$ .

We have the following:

$$EW(S_i^c) = W(\alpha + \beta S_i^p - \Pi_i) \quad (4)$$

where  $\Pi_i$  is the risk premium which depends on the variance of  $\epsilon_i$ . Using second order Taylor series expansions around the conditional mean on both sides of equation (4), the risk premium can be approximately written as:

$$\Pi_i \simeq \frac{1}{2} \frac{\sigma_i^2}{(\alpha + \beta S_i^p)} R \quad (5)$$

where  $Var(\epsilon_i) = \sigma_i^2$ , and  $R$  is the parameter of relative risk aversion in a CRRA utility/payoff function (see, for example, Eeckhoudt et al. (2005)). Using equation (2) and denoting an estimated parameter by a hat, we can have an estimate of the risk premium as below:

$$\hat{\Pi}_i \simeq \frac{1}{2} \frac{\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta} S_i^p)} R \quad (6)$$

Combining (4) and (6), we have:

$$EW(S_i^c) \simeq W\left(\hat{\alpha} + \hat{\beta} S_i^p - \frac{1}{2} \frac{\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta} S_i^p)} R\right) \quad (7)$$

Since  $W(\cdot)$  is a monotonically increasing function, the rankings remain the same if we use  $\hat{\alpha} + \hat{\beta} S_i^p - \frac{1}{2} \frac{\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta} S_i^p)} R$  instead of the RHS of equation (7).

We propose measures of absolute and relative mobility based on  $\hat{\alpha} + \hat{\beta} S_i^p - \frac{1}{2} \frac{\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta} S_i^p)} R$ .

This has some important advantages compared to the measures of mobility based on equation

(7) above, as we will see below. Let

$$\Psi_i(S_i^p) = \hat{\alpha} + \hat{\beta}S_i^p - \frac{1}{2} \frac{\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta}S_i^p)} R \quad (8)$$

$\Psi_i(S_i^p)$  is our measure of absolute mobility for child  $i$  which shows the risk adjusted expected years of schooling of children conditional on father's schooling (called  $RES_i$  for short).<sup>18</sup>

The measure of relative mobility is:

$$RIGRC_i = \frac{\partial \Psi}{\partial S_i^p} = \hat{\beta} - \frac{R}{2(\hat{\alpha} + \hat{\beta}S_i^p)} \left[ \hat{\theta}_1 - \frac{\hat{\beta} \{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}}{(\hat{\alpha} + \hat{\beta}S_i^p)} \right] \quad (9)$$

An important advantage of the measures of relative and absolute mobility in equations (8) and (9) is that they are readily comparable to the standard estimates of mobility (they are measured in the same units: years of schooling). A second important feature of the proposed measures is that they yield the standard measures of relative and absolute mobility currently used in the literature under risk neutrality. For example, consider the workhorse measure of relative educational mobility in the current literature called IGRC, estimated as the parameter  $\beta$  in equation (1). For the risk neutral case, we have  $R = 0$ , and relative mobility is equal to  $\beta$  (IGRC). Under risk aversion, the bias in the estimate when we omit the effects of family background on the conditional variance is given by the second term.

It also important to appreciate some of the differences between the standard measures and the risk-adjusted measures proposed here. Even though all the estimates of  $\beta$  as a measure of relative mobility we are aware of fall in the open interval  $(0, 1)$ , the risk adjusted measures may not be contained in this interval. For example, when the ratio of conditional variance to conditional mean is large, the risk premium in equation (9) can be large enough to make RIGRC estimate greater than 1.<sup>19</sup> This implies that the conventional argument that  $1 - \beta$  can be interpreted as a measure of mobility (while  $\beta$  is a measure of intergenerational

---

<sup>18</sup>This measure is similar to the other measures of absolute mobility based on the conditional mean function; see, for example, Chetty et al. (2014) in the context of intergenerational income mobility.

<sup>19</sup>This, however, does not mean an explosive process, as the magnitude of RIGRC declines with father's education.

persistence) may not be useful in this context. We propose the inverse of RIGRC for such an interpretation.<sup>20</sup>

To operationalize equations (8) and (9), we need an estimate of the CRRA coefficient  $R$ . A substantial literature suggests that a CRRA utility function with risk aversion parameter of 1 is consistent with a variety of evidence (see, for example, Chetty (2006) on USA, and Gendelman and Hernández-Murillo (2014) for cross country evidence including many developing countries). We will thus set  $R = 1$  for our estimation below.<sup>21</sup>

Note that when the influence of father’s education on the conditional variance is negative (i.e.,  $\theta_1 < 0$ ), the second term in equation (9) is unambiguously positive, and the estimate of risk adjusted relative immobility is necessarily larger than the standard estimate. However, the term in brackets can be negative even when  $\theta_1 > 0$ , for example, when the conditional variance term  $\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\}$  is large (more likely in rural areas subject to weather shocks to agriculture). When comparing different groups, the risk adjusted estimates may be very different from the canonical IGRC estimates even if the impact of father’s education on the conditional variance (i.e.,  $\hat{\theta}_1$ ) is similar across groups, because of differences in the magnitudes of  $\hat{\theta}_0$  across groups.

## Mobility Estimates Based on the Risk Adjusted Measures

### Mobility Across the Distribution of Father’s Education

The standard measure of relative mobility in the workhorse linear model given by the slope of the mobility equation, IGRC, does not vary across the distribution of father’s schooling. In contrast, the RIGRC estimates from a linear mobility model vary with father’s education level because the risk premium is different across different levels of parental education. As noted earlier, the risk premium depends on the ratio of conditional variance to conditional

---

<sup>20</sup>Note that we use the linear mobility CEF as the default specification for the mobility equation because it is almost universally used in the existing studies on intergenerational educational mobility with a few recent exceptions. As noted earlier, recent evidence suggests that the mobility CEF is likely to be concave or convex in many cases. In such cases, relative mobility varies across the distribution without any risk adjustments, and one can find that the marginal effect of father’s education on children’s schooling is larger than 1, especially in the lower tail (for concave CEF) or the upper tail (for convex CEF). Thus, in a nonlinear model, using the inverse of the marginal effect of father’s schooling as a measure of mobility seems more appropriate.

<sup>21</sup>While a CRRA coefficient of 1 across countries help understand the role played by the influence of family background on conditional variance, one might prefer to use different estimates of CRRA coefficient when the focus is on interregional and intergroup differences within the same country.

mean. Figures 1A (China), 1B (India), and 1C (Indonesia) present the graphs of the estimated conditional mean and conditional variance functions using the full sample (1950-1989). The graphs show that the ratio of conditional variance to conditional mean is large in the low educated households, and the ratio declines with father's education. This suggests that the risk premium at the lower end of the distribution is substantially higher, and we expect risk adjustments to substantially reduce the estimates of both relative mobility (RIGRC larger than the IGRC) and absolute mobility ( $RES$  lower than  $ES$ ) of the most disadvantaged children.

The estimates of the risk adjusted relative and absolute mobility for the full sample are reported in Table 5 along with the standard estimates for ease of comparison. Figures 2A (China), 2B (India), and 2C (Indonesia) present the graphs of RIGRC and IGRC estimates, and the corresponding estimates of absolute mobility ( $RES$  and  $ES$ ) are in Figures 3A (China), 3B (India) and 3C (Indonesia). Consistent with the discussion above, the evidence confirms that accounting for risk reveals a much worse educational opportunities for the children born to fathers with low or no education. The gap between RIGRC and IGRC estimates is the largest for the children of fathers with no schooling, and the same is true for the gap between  $ES$  (expected years of schooling) and  $RES$  (risk adjusted expected years of schooling). For relative mobility, the canonical IGRC estimate underestimates the influence of family background for this most disadvantaged subgroup of children by 41 percent in China, 63 percent in India, and 28 percent in Indonesia. A comparison of the  $RES$  estimates with the  $ES$  estimates (see Table 4) show that a failure to take into account the effects on conditional variance overestimates the expected years of schooling for this subgroup of children by 48 percent in China, and by about 26 percent in India and Indonesia. A second important conclusion that comes out of the evidence is that, for the children of college educated fathers, the standard estimates are reasonably close to the risk adjusted estimates. For example, the standard IGRC overestimates relative mobility of the children of college educated fathers by 6.2 percent and absolute mobility by 4.1 percent in India, and the corresponding numbers for Indonesia are 5.6 percent and 2.1 percent. The biases in the corresponding estimates for China are larger, but even then, the biases are about half of that found for the subgroup where fathers have no schooling. The evidence thus suggests that the failure to consider the implications of family

background for the second moment of data may not be as consequential for the children born into highly educated households.

The estimates of the risk adjusted and standard measures of relative and absolute mobility across the distribution for rural vs. urban areas are reported in Table 6A for all three countries. The estimates of gender differences are reported in Table 6B. The evidence suggests that the standard measures of mobility consistently overestimate the educational opportunities for the disadvantaged children (father with low education). The risk adjustments make a big difference specially for the rural areas and the daughters.

### **Relative Mobility Across Countries, Regions, and Gender**

Since the risk adjusted relative mobility vary across the distribution, it does not provide us with a summary statistic such as IGRC which can be easily compared across countries, regions, and different social groups. For such comparisons, we calculate a weighted RIGRC using the proportion of children as weights. As a summary measure of relative mobility, weighted RIGRC may be specially useful for policymakers.

The weighted RIGRC for various sub-samples defined by gender and geography (rural/urban) are reported in the odd numbered columns in Table 7 for our main estimation sample of 1950-1989 birth cohorts. For ease of comparison, the corresponding canonical IGRC estimates are in the even numbered columns. The estimates show that the RIGRC estimates are uniformly larger than the corresponding IGRC estimates, and the difference is substantial in magnitude. For example, the estimates for the aggregate sample in row 1 of Table 7 suggest that the downward bias in the standard IGRC estimate is 26 percent in China, 41 percent in India and 10.4 in Indonesia. The cross-country rankings do not change when we use RIGRC instead of IGRC estimates.

However, when comparing different subgroups (based on gender and geography), the rankings based on the weighted RIGRC may be different (compared to the rankings based on standard IGRC). For example, in India, the rural-urban gap in educational mobility seems negligible according to the standard IGRC estimates (a 4.6 percent higher estimate in rural areas), but the gap is much larger according to the weighted RIGRC estimates (20 percent larger estimate in rural). Similarly, the standard IGRC estimates suggest no significant gender

gap in India, while the RIGRC estimates reveal a substantially lower relative mobility for the daughters. In India, the urban and rural daughters enjoy similar educational mobility according to the standard IGRC estimates with a slight advantage in favor of the rural daughters (a 2.9 percent higher IGRC estimate for urban daughters). But the weighted RIGRC estimates reveal a substantial disadvantage faced by the rural daughters (a 16.5 percent higher estimate for rural daughters).

The estimates for decade wise birth cohorts show that the evolution of intergenerational educational mobility has been very different in China compared to India and Indonesia (see Table 8). China has become less mobile from the 1960s to the 1980s after experiencing a slight improvement from 1950s to 1960s. In contrast, the estimates of both weighted RIGRC and IGRC suggest that mobility has improved from the 1950s to the 1980s in India and Indonesia. While both measures pick the time trend correctly, the standard IGRC underestimates the improvements substantially, specially in India.

## (6) Conclusions

A large literature on intergenerational mobility focuses on the effects of family background on the conditional mean of children’s economic outcomes and ignores any information contained in the conditional variance. We provide evidence on three large developing countries (China, India, and Indonesia) that suggests a strong influence of father’s education on the conditional variance of children’s schooling. We find substantial heterogeneity across countries, gender, and geography (rural/urban). Cohort based estimates suggest that the effect of father’s education on the conditional variance has changed qualitatively, in some cases a positive effect in the 1950s cohort turning into a substantial negative effect in the 1980s cohort.

The evidence on the effects of family background on the mean and conditional variance suggests that being born into a more educated father brings in double advantages for children in the form of a lower expected variance in schooling in addition to the standard higher expected years of schooling. We develop a methodology to incorporate the influence of family background on the conditional variance along with the standard conditional mean estimates.

Based on the standard results from the theory of decisions under uncertainty, we adjust the canonical measure of intergenerational relative and absolute mobility by an estimate of the risk premium associated with the conditional variance in schooling attainment faced by children. The risk premium is determined by the ratio of conditional variance to conditional mean along with the coefficient of relative risk aversion. The estimates of the risk adjusted relative and absolute mobility for China, India and Indonesia suggest that the current practice of ignoring the conditional variance results in substantial downward bias in the estimated effects of family background on children’s educational opportunities. More important, the downward bias in the standard measures is the largest for the most disadvantaged children born into households where fathers have no schooling. The existing literature on intergenerational educational mobility thus substantially overestimates the intergenerational educational mobility of the disadvantaged children. The standard (but partial) measure may lead to incorrect ranking of countries in terms of relative mobility. The standard measure of relative mobility (IGRC) is likely to underestimate gender gap and rural-urban gap in educational opportunities.

## References

- Ahsan, N., Emran, M. S., and Shilpi, F. (2021). Complementarities and Intergenerational Educational Mobility: Theory and Evidence from Indonesia. MPRA Paper 111125, University Library of Munich, Germany.
- Asher, S., Novosad, P., and Rafkin, C. (2018). Intergenerational Mobility in India: Estimates from New Methods and Administrative Data. Working paper, World Bank.
- Azam, M. and Bhatt, V. (2015). Like Father, Like Son? Intergenerational Educational Mobility in India. *Demography*, 52(6):1929–1959.
- Becker, G. (1991). *A Treatise on the Family*. Harvard University Press.
- Becker, G., Kominers, S. D., Murphy, K. M., and Spenkuch, J. L. (2015). A Theory of Intergenerational Mobility. MPRA Paper 66334, University Library of Munich, Germany.
- Becker, G. S., Kominers, S. D., Murphy, K. M., and Spenkuch, J. L. (2018). A Theory of

- Intergenerational Mobility. *Journal of Political Economy*, 126(S1):7–25.
- Behrman, J., Pollak, R., and Taubman, P. (1982). Parental Preferences and Provision for Progeny. *Journal of Political Economy*, 90(1):52–73.
- Bjorklund, A., Jantti, M., and Roemer, J. (2012). Equality of opportunity and the distribution of long-run income in Sweden. *Social Choice and Welfare*, 39(2):675–696.
- Bjorklund, A. and Salvanes, K. G. (2011). Education and Family Background: Mechanisms and Policies. In Hanushek, E., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, volume 3, pages 201–247. Elsevier.
- Bratsberg, B., Røed, K., Raaum, O., Naylor, R., Jaśntti, M., Eriksson, T., and Ošterbacka, E. (2007). Nonlinearities in intergenerational earnings mobility: Consequences for cross-country comparisons. *Economic Journal*, 117(519):C72–C92.
- Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.
- Cohen, A. C. (1991). *Truncated and Censored Samples: Theory and Applications*. Boca Raton, FL: CRC Press.
- Conley, D. (2004). *The Pecking Order: Which Siblings Succeed and Why*. Pantheon Books, New York.
- Eeckhoudt, L., Gollier, C., and Schlesinger, H. (2005). *Economic and Financial Decisions under Risk*. Princeton University Press.
- Emran, M. S., Greene, W., and Shilpi, F. (2018). When Measure Matters: Coresidency, Truncation Bias, and Intergenerational Mobility in Developing Countries. *Journal of Human Resources*, 53(3):589–607.
- Emran, M. S., Jiang, H., and Shilpi, F. (2021). Is Gender Destiny? Gender Bias and Intergenerational Educational Mobility in India. GLO Discussion Paper Series 807, Global Labor Organization (GLO).
- Emran, M. S., Jiang, H., and Shilpi, F. J. (2020). Gender Bias and Intergenerational Educational Mobility : Theory and Evidence from China and India. Policy Research working paper WPS 9250, World Bank Group.



- Emran, M. S. and Shilpi, F. (2015). Gender, Geography, and Generations: Intergenerational Educational Mobility in Post-Reform India. *World Development*, 72:362–380.
- Emran, M. S. and Shilpi, F. (2021). Economic approach to intergenerational mobility: Measures, methods, and challenges in developing countries. In Iversen, V., Krishna, A., and Sen, K., editors, *Social mobility in developing countries: Concepts, methods, and determinants*.
- Emran, M. S. and Sun, Y. (2015). Magical transition? intergenerational educational and occupational mobility in rural China : 1988-2002. Policy Research Working Paper Series 7316, The World Bank.
- Fasih, T., Kingdon, G., Patrinos, H. A., Sakellariou, C., and Soderbom, M. (2012). Heterogeneous returns to education in the labor market. Policy Research Working Paper Series 6170, The World Bank.
- Golley, J. and Kong, S. T. (2013). Inequality in Intergenerational Mobility of Education in China. *China & World Economy*, 21:15–37.
- Grawe, N. D. (2004). Reconsidering the Use of Nonlinearities in Intergenerational Earnings Mobility as a Test for Credit Constraints. *Journal of Human Resources*, 39(3).
- Hederos, K., Jäntti, M., and Lindahl, L. (2017). Gender and inequality of opportunity in Sweden. *Social Choice and Welfare*, 49(3):605–635.
- Hertz, T., Jayasundera, T., Piraino, P., Selcuk, S., Smith, N., and Verashchagina, A. (2008). The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends. *The B.E. Journal of Economic Analysis & Policy*, 7(2):1–48.
- Iversen, V., Krishna, A., and Sen, K. (2019). Beyond poverty escapes — social mobility in developing countries: A review article. *World Bank Research Observer*, 34(2):239–273.
- Kingdon, G. G. (2007). The progress of school education in India. *Oxford Review of Economic Policy*, 23(2):168–195.
- Kishan, P. K. V. (2018). Is the Past Still Holding Us Back? A Study on Intergenerational Education Mobility in India. IIMA Working Papers WP 2018-01-03, Indian Institute of Management Ahmedabad, Research and Publication Department.
- Knight, J., Sicular, T., and Yue, X. (2011). Educational Inequality in China: The Intergenerational Dimension. University of Western Ontario, Centre for Human Capital and

- Productivity (CHCP) Working Papers 201113, University of Western Ontario.
- Mazumder, B., Rosales-Rueda, M., and Triyana, M. (2019). Intergenerational Human Capital Spillovers: Indonesia’s School Construction and Its Effects on the Next Generation. *AEA Papers and Proceedings*, 109:243–249.
- Mitnik, P., Bryant, V., and Grusky, D. (2018). A Very Uneven Playing Field: Economic Mobility in the United States. Working Papers 2018-097, Human Capital and Economic Opportunity Working Group.
- Narayan, A., der Weide, R. V., Cojocaru, A., Lakner, C., Redaelli, S., Mahler, D. G., Ramasubbaiah, R. G. N., and Thewissen, S. (2018). *Fair Progress? Economic Mobility across Generations Around the World*. Number 28428 in World Bank Publications. The World Bank.
- Roemer, J. and Trannoy, A. (2016). Equality of Opportunity: Theory and Measurement. *Journal of Economic Literature*, 54(4):1288–1332.
- Roemer, J. E. (1998). *Equality of Opportunity*. Harvard University Press.
- Solon, G. (1999). Intergenerational mobility in the labor market. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 3 of *Handbook of Labor Economics*, pages 1761–1800. Elsevier.
- Torche, F. (2019). Educational mobility in developing countries. WIDER Working Paper Series 2019-88.

**Table 1: Summary Statistics**

	CHINA		INDIA		INDONESIA	
	Mean	SD	Mean	SD	Mean	SD
	Full Sample					
Father's Edu	4.124	4.370	3.633	4.540	6.213	3.854
Children's Edu	7.521	4.430	6.501	5.168	9.524	4.154
Observations	N=94159		N=86748		N=18356	
	Urban					
Father's Edu	5.089	4.662	5.233	5.035	7.717	4.023
Children's Edu	9.376	4.173	8.446	5.048	10.836	3.876
Observations	N=35308		N=31216		N=5919	
	Rural					
Father's Edu	3.546	4.078	2.734	3.962	5.497	3.554
Children's Edu	6.408	4.202	5.408	4.907	8.899	4.136
Observations	N=58851		N=55532		N=12437	
	Sons					
Father's Edu	4.086	4.373	3.689	4.495	6.177	3.839
Children's Edu	8.169	4.143	7.557	4.972	9.822	4.022
Observations	N=46791		N=46701		N=8558	
	Daughters					
Father's Edu	4.163	4.367	3.569	4.590	6.245	3.867
Children's Edu	6.880	4.609	5.269	5.120	9.264	4.249
Observations	N=47368		N=40047		N=9798	

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia.

**Table 2: Family background and Conditional Mean and Conditional Variance  
( Full Sample Estimates)**

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.
Father's Edu	0.383*** (0.014)	<b>-0.483***</b> <b>(0.036)</b>	0.621*** (0.005)	<b>-0.379***</b> <b>(0.028)</b>	0.497*** (0.011)	<b>-0.514***</b> <b>(0.052)</b>
Constant	5.943*** (0.152)	<b>18.823***</b> <b>(0.424)</b>	4.244*** (0.043)	<b>20.134***</b> <b>(0.144)</b>	6.437*** (0.113)	<b>16.784***</b> <b>(0.429)</b>
Observations	94,159	<b>94,159</b>	86,748	86,748	18356	18356
R-squared	0.142	<b>0.009</b>	0.298	0.006	0.212	0.011
Mean of $\bar{Y}$	7.521	<b>16.83</b>	6.501	18.76	9.523	13.587

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia.

**Table 3: Heterogeneity Across Urban vs. Rural and Sons vs. Daughters**

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.
<b>Urban</b>						
Father's Edu	0.356*** (0.013)	<b>-0.548*** (0.053)</b>	0.563*** (0.007)	<b>-0.772*** (0.034)</b>	0.468*** (0.016)	<b>-0.707*** (0.065)</b>
Constant	7.564*** (0.147)	<b>17.449*** (0.586)</b>	5.498*** (0.074)	<b>21.478*** (0.250)</b>	7.225*** (0.171)	<b>16.935*** (0.598)</b>
Observations	35,308	35,308	31,216	31,216	5919	5919
R-squared	0.158	0.013	0.316	0.029	0.236	0.027
Mean of $\bar{Y}$	9.376	14.66	8.446	17.44	10.835	11.475
<b>Rural</b>						
Father's Edu	0.321*** (0.014)	<b>-0.524*** (0.044)</b>	0.589*** (0.007)	<b>-0.022 (0.040)</b>	0.467*** (0.012)	<b>-0.294*** (0.069)</b>
Constant	5.271*** (0.165)	<b>17.799*** (0.342)</b>	3.798*** (0.048)	<b>18.702*** (0.177)</b>	6.331*** (0.115)	<b>15.967*** (0.516)</b>
Observations	58,851	58,851	55,532	55,532	12437	12437
R-squared	0.097	0.013	0.226	0.000	0.161	0.003
Mean of $\bar{Y}$	6.408	15.94	5.408	18.64	8.899	14.351
<b>Sons</b>						
Father's Edu	0.329*** (0.014)	<b>-0.476*** (0.048)</b>	0.595*** (0.006)	<b>-0.927*** (0.025)</b>	0.461*** (0.013)	<b>-0.522*** (0.066)</b>
Constant	6.824*** (0.142)	<b>17.033*** (0.547)</b>	5.361*** (0.049)	<b>20.974*** (0.165)</b>	6.971*** (0.133)	<b>16.259*** (0.516)</b>
Observations	46,791	46,791	46,701	46,701	8558	8558
R-squared	0.121	0.009	0.290	0.038	0.194	0.012
Mean of $\bar{Y}$	8.169	15.09	7.557	17.55	9.821	13.03
<b>Daughters</b>						
Father's Edu	0.438*** (0.015)	<b>-0.364*** (0.052)</b>	0.643*** (0.006)	<b>0.334*** (0.040)</b>	0.528*** (0.013)	<b>-0.483*** (0.061)</b>
Constant	5.057*** (0.174)	<b>19.099*** (0.347)</b>	2.974*** (0.048)	<b>16.306*** (0.200)</b>	5.964*** (0.123)	<b>16.892*** (0.499)</b>
Observations	47,368	47,368	40,047	40,047	9798	9798
R-squared	0.172	0.006	0.332	0.004	0.231	0.010
Mean of $\bar{Y}$	6.880	17.58	5.269	17.50	9.263	13.875

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

**Table 4: Evolution Across Birth Cohorts**

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.
1980-1989	0.420*** (0.034)	<b>-0.766***</b> <b>(0.101)</b>	0.551*** (0.007)	<b>-0.644***</b> <b>(0.034)</b>	0.424*** (0.013)	<b>-0.478***</b> <b>(0.050)</b>
1970-1979	0.398*** (0.021)	<b>-0.445***</b> <b>(0.055)</b>	0.582*** (0.007)	<b>-0.294***</b> <b>(0.041)</b>	0.492*** (0.015)	<b>-0.299***</b> <b>(0.065)</b>
1960-1969	0.292*** (0.015)	<b>-0.435***</b> <b>(0.046)</b>	0.650*** (0.009)	<b>0.053</b> <b>(0.056)</b>	0.586*** (0.024)	<b>-0.328**</b> <b>(0.139)</b>
1950-1959	0.292*** (0.017)	<b>-0.275***</b> <b>(0.070)</b>	0.681*** (0.011)	<b>0.028</b> <b>(0.077)</b>	0.521*** (0.036)	<b>0.462**</b> <b>(0.228)</b>

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia.

**Table 5: Relative Mobility and Absolute Mobility (Full Sample)**  
**Risk Adjusted vs. Standard Estimates**

	CHINA			INDIA			INDONESIA		
	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES
No Sch	0.525 (0.019)	4.359 (0.195)	5.943 (0.152)	1.013 (0.011)	1.872 (0.069)	4.244 (0.043)	0.637 (0.014)	5.134 (0.140)	6.437 (0.113)
Primary	0.457 (0.019)	7.272 (0.126)	8.239 (0.111)	0.752 (0.006)	6.109 (0.042)	7.350 (0.035)	0.562 (0.012)	8.691 (0.082)	9.418 (0.075)
Junior High	0.440 (0.015)	8.615 (0.122)	9.386 (0.111)	0.686 (0.005)	9.674 (0.047)	10.455 (0.043)	0.546 (0.012)	10.351 (0.077)	10.908 (0.072)
Senior High	0.428 (0.015)	9.915 (0.134)	10.534 (0.125)	0.673 (0.005)	11.031 (0.053)	11.698 (0.049)	0.535 (0.011)	11.971 (0.087)	12.399 (0.083)
College	0.417 (0.015)	11.604 (0.168)	12.064 (0.160)	0.660 (0.005)	13.028 (0.063)	13.561 (0.060)	0.525 (0.011)	14.089 (0.114)	14.386 (0.110)
<b>IGRC</b>	0.383 (0.014)			0.621 (0.005)			0.497 (0.011)		

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The RIGRC refers to the Risk Adjusted IGRC. The RES refers to the Risk Adjusted Expected Schooling. The Linear ES refers to the Expected Schooling from a linear CEF mobility model. And the IGRC is the Intergenerational Regression Coefficient from a linear CEF mobility model.

**Table 6A: Relative Mobility and Absolute Mobility Across Urban vs. Rural Areas**

	CHINA			INDIA			INDONESIA		
	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES
Urban									
No Sch	0.446 (0.015)	6.411 (0.174)	7.564 (0.147)	0.833 (0.012)	3.545 (0.102)	5.498 (0.074)	0.593 (0.020)	6.053 (0.203)	7.225 (0.171)
Primary	0.411 (0.014)	8.970 (0.114)	9.700 (0.104)	0.681 (0.008)	7.255 (0.060)	8.314 (0.052)	0.533 (0.017)	9.400 (0.104)	10.033 (0.096)
Junior High	0.401 (0.013)	10.187 (0.105)	10.768 (0.099)	0.629 (0.007)	10.512 (0.052)	11.130 (0.048)	0.518 (0.017)	10.974 (0.082)	11.436 (0.078)
Senior High	0.393 (0.013)	11.377 (0.112)	11.836 (0.107)	0.618 (0.007)	11.758 (0.056)	12.256 (0.052)	0.507 (0.016)	12.511 (0.089)	12.840 (0.086)
College	0.385 (0.013)	12.933 (0.139)	13.260 (0.134)	0.605 (0.007)	13.591 (0.067)	13.946 (0.064)	0.498 (0.016)	14.521 (0.130)	14.712 (0.127)
<b>IGRC</b>	0.356 (0.013)			0.563 (0.007)			0.468 (0.016)		
Rural									
No Sch	0.473 (0.021)	3.583 (0.220)	5.271 (0.165)	0.973 (0.016)	1.336 (0.082)	3.798 (0.048)	0.583 (0.016)	5.071 (0.144)	6.331 (0.115)
Primary	0.402 (0.017)	6.177 (0.121)	7.195 (0.103)	0.711 (0.009)	5.362 (0.057)	6.741 (0.046)	0.523 (0.014)	8.357 (0.090)	9.134 (0.081)
Junior High	0.384 (0.016)	7.355 (0.102)	8.157 (0.088)	0.648 (0.008)	8.730 (0.073)	9.685 (0.065)	0.509 (0.013)	9.903 (0.092)	10.536 (0.085)
Senior High	0.372 (0.016)	8.488 (0.106)	9.119 (0.094)	0.636 (0.008)	10.013 (0.084)	10.862 (0.076)	0.500 (0.013)	11.416 (0.110)	11.937 (0.103)
College	0.362 (0.015)	9.588 (0.128)	10.081 (0.117)	0.623 (0.007)	11.901 (0.101)	12.628 (0.093)	0.492 (0.013)	13.398 (0.146)	13.806 (0.139)
<b>IGRC</b>	0.321 (0.014)			0.589 (0.007)			0.467 (0.012)		

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The RIGRC refers to the Risk Adjusted Intergenerational Regression Coefficient. The RES refers to the Risk Adjusted Expected Schooling. The Linear ES refers to the Expected Schooling from a linear CEF mobility model. And the IGRC is the Intergenerational Regression Coefficient from a linear CEF mobility model.



**Table 6B: Relative Mobility and Absolute Mobility Across Sons vs. Daughters**

	CHINA			INDIA			INDONESIA		
	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES
Sons									
No Sch	0.424 (0.018)	5.576 (0.173)	6.824 (0.142)	0.899 (0.009)	3.405 (0.069)	5.361 (0.049)	0.576 (0.017)	5.805 (0.160)	6.971 (0.133)
Primary	0.387 (0.016)	7.994 (0.108)	8.800 (0.097)	0.721 (0.007)	7.358 (0.039)	8.338 (0.034)	0.520 (0.014)	9.066 (0.092)	9.740 (0.085)
Junior High	0.376 (0.015)	9.137 (0.106)	9.788 (0.098)	0.664 (0.006)	10.798 (0.040)	11.315 (0.038)	0.506 (0.014)	10.605 (0.086)	11.124 (0.081)
Senior High	0.367 (0.015)	10.251 (0.122)	10.776 (0.115)	0.651 (0.006)	12.112 (0.047)	12.506 (0.045)	0.497 (0.014)	12.109 (0.100)	12.509 (0.095)
College	0.360 (0.015)	11.704 (0.161)	12.093 (0.154)	0.638 (0.006)	14.045 (0.059)	14.292 (0.057)	0.488 (0.013)	14.079 (0.135)	14.354 (0.130)
<b>IGRC</b>	0.329 (0.014)			0.595 (0.006)			0.461 (0.013)		
Daughters									
No Sch	0.638 (0.024)	3.169 (0.241)	5.057 (0.174)	1.180 (0.024)	0.232 (0.099)	2.974 (0.048)	0.694 (0.018)	4.547 (0.158)	5.964 (0.123)
Primary	0.524 (0.017)	6.585 (0.155)	7.685 (0.133)	0.767 (0.009)	4.737 (0.061)	6.189 (0.048)	0.599 (0.014)	8.369 (0.085)	9.134 (0.077)
Junior High	0.501 (0.017)	8.120 (0.147)	8.999 (0.132)	0.697 (0.007)	8.360 (0.074)	9.405 (0.065)	0.580 (0.014)	10.135 (0.082)	10.720 (0.076)
Senior High	0.486 (0.016)	9.599 (0.157)	10.313 (0.144)	0.685 (0.007)	9.741 (0.082)	10.691 (0.074)	0.567 (0.014)	11.854 (0.098)	12.305 (0.093)
College	0.476 (0.016)	11.041 (0.179)	11.627 (0.168)	0.673 (0.007)	11.776 (0.097)	12.620 (0.089)	0.557 (0.013)	14.101 (0.135)	14.419 (0.130)
<b>IGRC</b>	0.438 (0.015)			0.643 (0.006)			0.528 (0.013)		

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The RIGRC refers to the Risk Adjusted Intergenerational Regression Coefficient. The RES refers to the Risk Adjusted Expected Schooling. The Linear ES refers to the Expected Schooling from a linear CEF mobility model. And the IGRC is the Intergenerational Regression Coefficient from a linear CEF mobility model.

**Table 7: Comparing Weighted Risk Adjusted IGRC to Canonical IGRC**

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC
All	0.484	0.383	0.876	0.621	0.568	0.497
Urban	0.420	0.356	0.721	0.563	0.527	0.468
Rural	0.436	0.321	0.863	0.589	0.532	0.467
Sons	0.402	0.329	0.800	0.595	0.524	0.461
Daughters	0.571	0.438	0.980	0.643	0.607	0.528
Urban Sons	0.351	0.312	0.651	0.524	0.498	0.443
Urban Daughters	0.486	0.402	0.791	0.597	0.551	0.489
Rural Sons	0.357	0.270	0.829	0.592	0.487	0.431
Rural Daughters	0.519	0.375	0.921	0.580	0.571	0.500

Notes: (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The weights are the proportion of children at each level of father's education.

**Table 8: Evolution of Risk Adjusted IGRC by Birth Cohorts**

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC
1980-1989	0.507	0.420	0.705	0.551	0.468	0.424
1970-1979	0.493	0.398	0.822	0.582	0.540	0.492
1960-1969	0.369	0.292	0.993	0.650	0.704	0.586
1950-1959	0.399	0.292	1.054	0.681	0.597	0.521

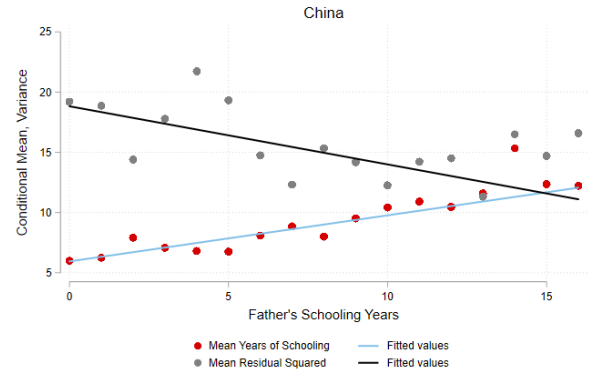
Notes: (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort. (3) (2) The weights are the proportion of children at each level of father's education.

**Table 9: Evolution of Risk Adjusted IGRC by Birth Cohorts  
Urban vs. Rural and Sons vs. Daughters**

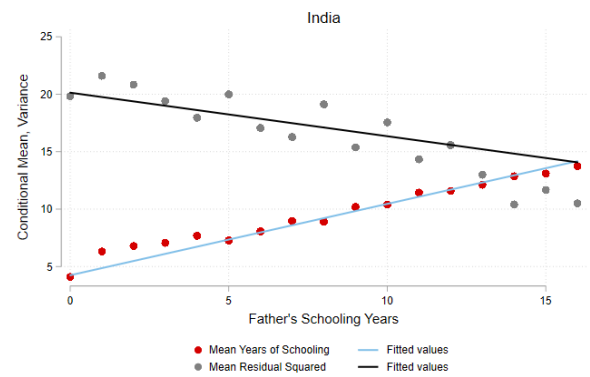
	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC
	<b>Urban</b>					
1980-1989	0.398	0.344	0.630	0.524	0.466	0.427
1970-1979	0.396	0.343	0.685	0.537	0.461	0.422
1960-1969	0.323	0.273	0.771	0.575	0.617	0.516
1950-1959	0.334	0.260	0.788	0.580	0.622	0.554
	<b>Rural</b>					
1980-1989	0.453	0.359	0.674	0.512	0.439	0.397
1970-1979	0.405	0.300	0.789	0.538	0.512	0.470
1960-1969	0.298	0.213	0.913	0.576	0.649	0.555
1950-1959	0.308	0.210	0.995	0.620	0.511	0.451
	<b>Sons</b>					
1980-1989	0.469	0.393	0.622	0.505	0.450	0.407
1970-1979	0.431	0.357	0.394	0.275	0.499	0.455
1960-1969	0.311	0.256	0.906	0.633	0.626	0.529
1950-1959	0.310	0.240	1.035	0.704	0.585	0.502
	<b>Daughters</b>					
1980-1989	0.543	0.447	0.783	0.585	0.482	0.438
1970-1979	0.553	0.439	0.913	0.605	0.580	0.529
1960-1969	0.425	0.326	1.105	0.653	0.758	0.626
1950-1959	0.499	0.349	1.275	0.620	0.612	0.555

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category. (3) (2) The weights are the proportion of children at each level of father's education.

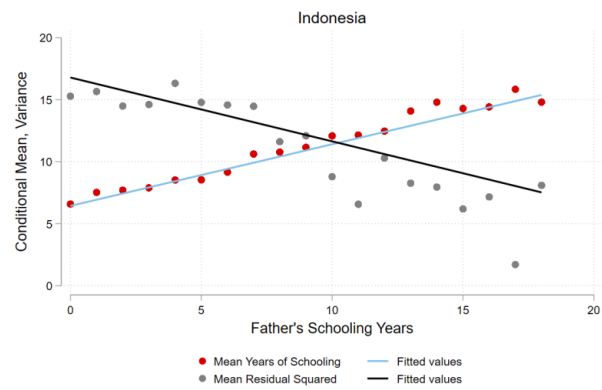
**Figure 1. Conditional Mean and Variance of Child's Schooling Against Father's Schooling**



**Panel A. China**

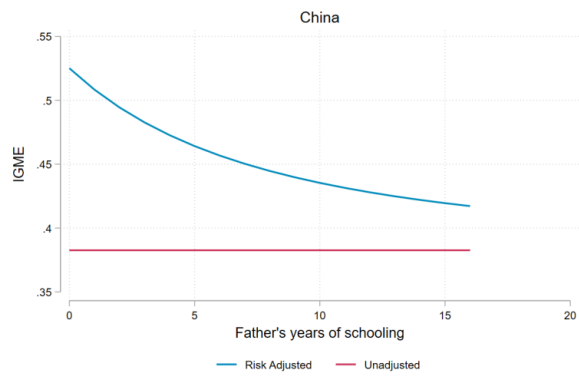


**Panel B. India**

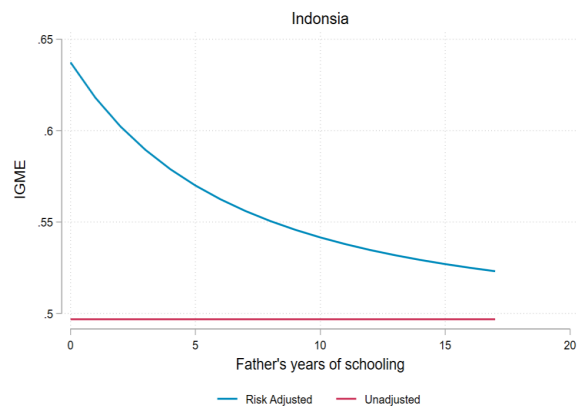


**Panel C. Indonesia**

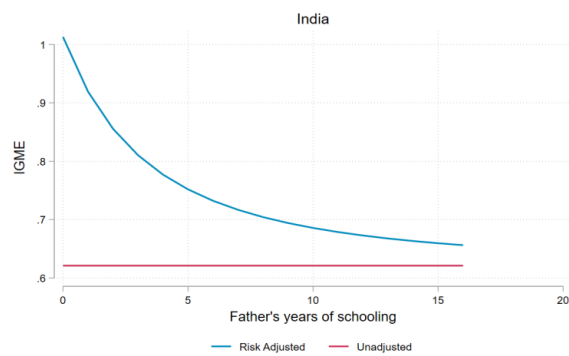
**Figure 2. Risk Adjusted and Linear Relative Mobility**



**Panel A. China**

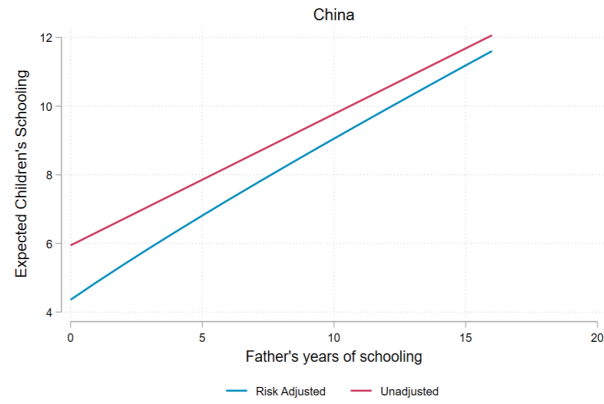


**Panel B. India**

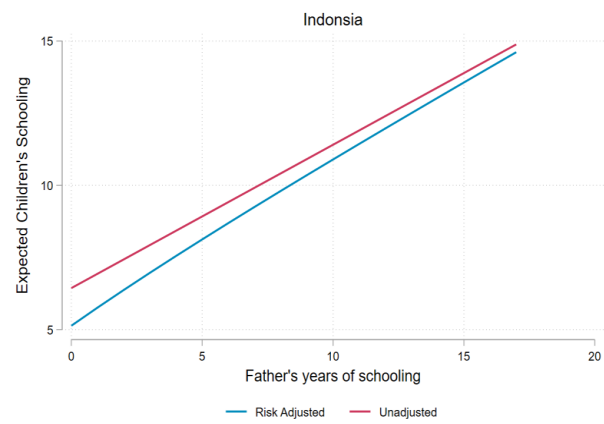


**Panel C. Indonesia**

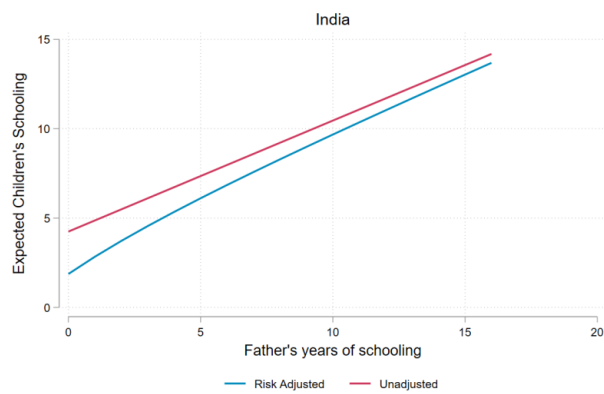
**Figure 3. Risk Adjusted and Linear Absolute Mobility**



**Panel A. China**



**Panel B. India**



**Panel C. Indonesia**

## ONLINE APPENDIX: NOT FOR PUBLICATION

### OA1. Additional Results on Residual Squared

**Table A.1: Intersections of Geography and Gender**

	CHINA		INDIA		INDONESIA	
	Yrs Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.
<b>Urban Sons</b>						
Father's Edu	0.312*** (0.012)	<b>-0.400*** (0.062)</b>	0.524*** (0.008)	<b>-1.007*** (0.035)</b>	0.443*** (0.020)	<b>-0.714*** (0.096)</b>
Constant	8.152*** (0.131)	<b>15.510*** (0.604)</b>	6.456*** (0.084)	<b>20.780*** (0.309)</b>	7.640*** (0.208)	<b>16.389*** (0.808)</b>
Observations	17,823	17,823	16,697	16,697	2649	2649
R-squared	0.136	0.007	0.307	0.058	0.224	0.028
Mean of $\bar{Y}$	9.732	13.48	9.264	15.39	11.043	10.902
<b>Urban Daughters</b>						
Father's Edu	0.402*** (0.015)	<b>-0.640*** (0.059)</b>	0.597*** (0.008)	<b>-0.384*** (0.049)</b>	0.489*** (0.019)	<b>-0.694*** (0.075)</b>
Constant	6.956*** (0.180)	<b>18.774*** (0.610)</b>	4.463*** (0.085)	<b>20.284*** (0.309)</b>	6.884*** (0.190)	<b>17.225*** (0.739)</b>
Observations	17,485	17,485	14,519	14,519	3270	3270
R-squared	0.184	0.018	0.336	0.007	0.247	0.026
Mean of $\bar{Y}$	9.013	15.50	7.504	18.33	10.667	11.851
<b>Rural Sons</b>						
Father's Edu	0.270*** (0.016)	<b>-0.631*** (0.053)</b>	0.592*** (0.008)	<b>-0.793*** (0.039)</b>	0.431*** (0.015)	<b>-0.323*** (0.083)</b>
Constant	6.267*** (0.166)	<b>16.681*** (0.551)</b>	4.972*** (0.058)	<b>20.436*** (0.199)</b>	6.901*** (0.137)	<b>15.577*** (0.596)</b>
Observations	28,968	28,968	30,004	30,004	5909	5909
R-squared	0.077	0.017	0.227	0.021	0.146	0.004
Mean of $\bar{Y}$	7.208	14.49	6.608	18.25	9.273	13.798
<b>Rural Daughters</b>						
Father's Edu	0.375*** (0.014)	<b>-0.275*** (0.069)</b>	0.580*** (0.009)	<b>0.793*** (0.050)</b>	0.500*** (0.017)	<b>-0.231*** (0.089)</b>
Constant	4.281*** (0.179)	<b>16.972*** (0.212)</b>	2.431*** (0.052)	<b>13.383*** (0.227)</b>	15.530*** (0.596)	<b>5.816*** (0.134)</b>
Observations	29,883	29,883	25,528	25,528	6528	6528
R-squared	0.128	0.004	0.260	0.022	0.177	0.002
Mean of $\bar{Y}$	5.632	15.98	3.997	15.52	9.273	13.798

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

**Table A.2: Evolution by Birth Cohorts  
Across Urban vs. Rural and Sons vs. Daughters**

	CHINA		INDIA		INDONESIA	
	Yrs Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.	Yrs. Sch.	Res. Sq.
	<b>Urban</b>					
1980-1989	0.344*** (0.027)	-0.845*** (0.128)	0.524*** (0.010)	-0.841*** (0.048)	0.427*** (0.018)	-0.561*** (0.072)
1970-1979	0.343*** (0.019)	-0.550*** (0.095)	0.537*** (0.010)	-0.658*** (0.053)	0.422*** (0.023)	-0.476*** (0.091)
1960-1969	0.273*** (0.014)	-0.465*** (0.056)	0.575*** (0.012)	-0.634*** (0.072)	0.516*** (0.039)	-0.957*** (0.194)
1950-1959	0.260*** (0.019)	-0.521*** (0.091)	0.580*** (0.016)	-0.690*** (0.100)	0.554*** (0.055)	0.243 (0.287)
	<b>Rural</b>					
1980-1989	0.359*** (0.038)	-0.787*** (0.106)	0.512*** (0.009)	-0.456*** (0.048)	0.397*** (0.015)	-0.384*** (0.064)
1970-1979	0.300*** (0.021)	-0.549*** (0.060)	0.538*** (0.011)	0.051 (0.059)	0.470*** (0.017)	-0.086 (0.091)
1960-1969	0.213*** (0.015)	-0.514*** (0.053)	0.576*** (0.014)	0.631*** (0.077)	0.555*** (0.031)	0.182 (0.174)
1950-1959	0.210*** (0.017)	-0.115 (0.079)	0.620*** (0.018)	0.584*** (0.112)	0.451*** (0.047)	0.589** (0.287)
	<b>Sons</b>					
1980-1989	0.393*** (0.033)	-0.774*** (0.113)	0.505*** (0.008)	-0.860*** (0.038)	0.407*** (0.017)	-0.485*** (0.071)
1970-1979	0.357*** (0.022)	-0.493*** (0.072)	0.548*** (0.009)	-0.956*** (0.041)	0.455*** (0.019)	-0.306*** (0.075)
1960-1969	0.256*** (0.015)	-0.394*** (0.058)	0.633*** (0.011)	-0.785*** (0.057)	0.529*** (0.031)	-0.528** (0.210)
1950-1959	0.240*** (0.017)	-0.383*** (0.082)	0.704*** (0.013)	-0.608*** (0.077)	0.502*** (0.056)	0.040 (0.329)
	<b>Daughters</b>					
1980-1989	0.447*** (0.036)	-0.724*** (0.111)	0.585*** (0.009)	-0.262*** (0.050)	0.438*** (0.016)	-0.473*** (0.063)
1970-1979	0.439*** (0.022)	-0.315*** (0.072)	0.605*** (0.010)	0.470*** (0.057)	0.529*** (0.018)	-0.263*** (0.086)
1960-1969	0.326*** (0.017)	-0.388*** (0.062)	0.653*** (0.012)	0.984*** (0.074)	0.626*** (0.030)	-0.049 (0.171)
1950-1959	0.349*** (0.021)	0.059 (0.110)	0.620*** (0.020)	1.126*** (0.119)	0.555*** (0.045)	0.918*** (0.256)



Notes: (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

**Table A.3: Evolution of Risk Adjusted IGRC by Birth Cohorts  
Across Geography and Gender**

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC	Weighted RIGRC	Canonical IGRC
	<b>Urban Sons</b>					
1980-1989	0.385	0.330	0.585	0.499	0.462	0.421
1970-1979	0.362	0.315	0.618	0.500	0.459	0.417
1960-1969	0.288	0.251	0.687	0.528	0.551	0.458
1950-1959	0.250	0.210	0.736	0.565	0.541	0.521
	<b>Urban Daughters</b>					
1980-1989	0.415	0.359	0.668	0.540	0.469	0.432
1970-1979	0.434	0.373	0.741	0.566	0.463	0.427
1960-1969	0.356	0.294	0.840	0.609	0.659	0.556
1950-1959	0.428	0.312	0.917	0.581	0.689	0.586
	<b>Rural Sons</b>					
1980-1989	0.422	0.339	0.607	0.478	0.420	0.381
1970-1979	0.359	0.271	0.745	0.538	0.462	0.427
1960-1969	0.242	0.178	0.904	0.606	0.567	0.494
1950-1959	0.263	0.180	1.079	0.684	0.559	0.455
	<b>Rural Daughters</b>					
1980-1989	0.484	0.381	0.730	0.532	0.456	0.411
1970-1979	0.446	0.326	0.819	0.522	0.560	0.514
1960-1969	0.350	0.247	0.905	0.521	0.698	0.593
1950-1959	0.367	0.251	0.947	0.496	0.451	0.463

Notes: (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

## OA2. Robustness Check: Linear vs. Quadratic CEF Model

**Table A.4: Full Sample Estimates with Linear CEF and Quadratic CEF**

	CHINA		INDIA		INDONESIA	
Mobility CEF Specification	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Outcome Var	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.
Father's Edu	-0.483*** (0.036)	-0.484*** (0.037)	-0.379*** (0.028)	-0.379*** (0.028)	-0.514*** (0.052)	-0.508*** (0.052)
Constant	18.823*** (0.424)	18.821*** (0.431)	20.134*** (0.144)	20.099*** (0.146)	16.784*** (0.429)	16.728*** (0.428)
Observations	94,159	94,159	86,748	86,748	18356	18356
R-squared	0.009	0.009	0.006	0.005	0.011	0.011
Mean of $\bar{Y}$	16.83	16.83	18.76	18.72	13.587	13.569

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia.

**Table A.5: Heterogeneity Across Urban vs. Rural and Sons vs. Daughters**

	<b>CHINA</b>		<b>INDIA</b>		<b>INDONESIA</b>	
Mobility CEF Specification	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Outcome Var	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.
	<b>Urban</b>					
Father's Edu	-0.548*** (0.053)	-0.546*** (0.054)	-0.772*** (0.034)	-0.773*** (0.033)	-0.707*** (0.065)	-0.707*** (0.065)
Constant	17.449*** (0.586)	17.436*** (0.593)	21.478*** (0.250)	21.452*** (0.251)	16.935*** (0.598)	16.930*** (0.599)
Observations	35,308	35,308	31,216	31,216	5919	5919
R-squared	0.013	0.013	0.029	0.029	0.027	0.027
Mean of $\bar{Y}$	14.66	14.66	17.44	17.41	11.475	13.568
	<b>Rural</b>					
Father's Edu	-0.524*** (0.044)	-0.528*** (0.044)	-0.022 (0.040)	-0.023 (0.039)	-0.294*** (0.069)	-0.294*** (0.069)
Constant	17.799*** (0.342)	17.810*** (0.339)	18.702*** (0.177)	18.660*** (0.178)	15.967*** (0.516)	15.931*** (0.515)
Observations	58,851	58,851	55,532	55,532	12437	12437
R-squared	0.013	0.013	0.000	0.000	0.003	0.003
Mean of $\bar{Y}$	15.94	15.94	18.64	18.60	14.351	14.314
	<b>Sons</b>					
Father's Edu	-0.476*** (0.048)	-0.478*** (0.049)	-0.927*** (0.025)	-0.934*** (0.025)	-0.522*** (0.066)	-0.516*** (0.066)
Constant	17.033*** (0.547)	17.033*** (0.554)	20.974*** (0.165)	20.960*** (0.166)	16.259*** (0.516)	16.216*** (0.514)
Observations	46,791	46,791	46,701	46,701	8558	8558
R-squared	0.009	0.009	0.038	0.039	0.012	0.012
Mean of $\bar{Y}$	15.09	15.08	17.55	17.52	13.03	13.025
	<b>Daughters</b>					
Father's Edu	-0.364*** (0.052)	-0.365*** (0.052)	0.334*** (0.040)	0.335*** (0.040)	-0.483*** (0.061)	-0.477*** (0.061)
Constant	19.099*** (0.347)	19.095*** (0.351)	16.306*** (0.200)	16.296*** (0.200)	16.892*** (0.499)	16.824*** (0.499)
Observations	47,368	47,368	40,047	40,047	9798	9798
R-squared	0.006	0.006	0.004	0.004	0.010	0.010
Mean of $\bar{Y}$	17.58	17.58	17.50	17.49	13.875	13.846

Notes: (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

**Table A.6: Intersections of Geography and Gender**

	<b>CHINA</b>		<b>INDIA</b>		<b>INDONESIA</b>	
Mobility CEF Specification	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Outcome Var	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.
<b>Urban Sons</b>						
Father's Edu	-0.400*** (0.062)	-0.399*** (0.063)	-1.007*** (0.035)	-1.009*** (0.035)	-0.714*** (0.096)	-0.715*** (0.096)
Constant	15.510*** (0.604)	15.498*** (0.610)	20.780*** (0.309)	20.778*** (0.308)	16.389*** (0.808)	16.393*** (0.805)
Observations	17,823	17,823	16,697	16,697	2649	2649
R-squared	0.007	0.007	0.058	0.058	0.028	0.028
Mean of $\bar{Y}$	13.48	13.47	15.39	15.38	10.902	10.901
<b>Urban Daughters</b>						
Father's Edu	-0.640*** (0.059)	-0.638*** (0.060)	-0.384*** (0.049)	-0.385*** (0.049)	-0.694*** (0.075)	-0.691*** (0.076)
Constant	18.774*** (0.610)	18.761*** (0.616)	20.284*** (0.309)	20.268*** (0.311)	17.225*** (0.739)	17.196*** (0.744)
Observations	17,485	17,485	14,519	14,519	3270	3270
R-squared	0.018	0.018	0.007	0.007	0.026	0.026
Mean of $\bar{Y}$	15.50	15.50	18.33	18.31	11.851	11.845
<b>Rural Sons</b>						
Father's Edu	-0.631*** (0.053)	-0.633*** (0.052)	-0.793*** (0.039)	-0.805*** (0.038)	-0.323*** (0.083)	-0.319*** (0.083)
Constant	16.681*** (0.551)	16.688*** (0.547)	20.436*** (0.199)	20.425*** (0.200)	15.577*** (0.596)	15.530*** (0.596)
Observations	28,968	28,968	30,004	30,004	5909	5909
R-squared	0.017	0.017	0.021	0.022	0.004	0.004
Mean of $\bar{Y}$	14.49	14.48	18.25	18.20	13.798	13.773
<b>Rural Daughters</b>						
Father's Edu	-0.275*** (0.069)	-0.281*** (0.069)	0.793*** (0.050)	0.793*** (0.049)	-0.231*** (0.089)	-0.237*** (0.090)
Constant	16.972*** (0.212)	16.989*** (0.211)	13.383*** (0.227)	13.370*** (0.227)	15.857*** (0.620)	15.837*** (0.620)
Observations	29,883	29,883	25,528	25,528	6528	6528
R-squared	0.004	0.004	0.022	0.022	0.002	0.002
Mean of $\bar{Y}$	15.98	15.98	15.52	15.51	13.798	14.534

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

**Table A.7: Evolution of Mobility by Birth Cohorts**

	<b>CHINA</b>		<b>INDIA</b>		<b>INDONESIA</b>	
Mobility CEF Specification	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Outcome Var	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.
1980-1989	-0.766*** (0.101)	-0.772*** (0.106)	-0.644*** (0.034)	-0.644*** (0.033)	-0.478*** (0.050)	-0.478*** (0.050)
1970-1979	-0.445*** (0.055)	-0.452*** (0.056)	-0.294*** (0.041)	-0.291*** (0.041)	-0.299*** (0.065)	-0.297*** (0.065)
1960-1969	-0.435*** (0.046)	-0.441*** (0.047)	0.053 (0.056)	0.061 (0.054)	-0.328** (0.139)	-0.324** (0.139)
1950-1959	-0.275*** (0.070)	-0.281*** (0.068)	0.028 (0.077)	0.022 (0.073)	0.462** (0.228)	0.470** (0.228)

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia.

**Table A.8: Evolution of Mobility by Birth Cohorts  
Across Urban vs. Rural and Sons vs. Daughters**

	CHINA		INDIA		INDONESIA	
Mobility CEF Specification	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Outcome Var	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.	Res. Sq.
	<b>Urban</b>					
1980-1989	-0.845*** (0.128)	-0.846*** (0.136)	-0.841*** (0.048)	-0.843*** (0.047)	-0.561*** (0.072)	-0.561*** (0.073)
1970-1979	-0.550*** (0.095)	-0.551*** (0.099)	-0.658*** (0.053)	-0.657*** (0.053)	-0.476*** (0.091)	-0.470*** (0.090)
1960-1969	-0.465*** (0.056)	-0.470*** (0.057)	-0.634*** (0.072)	-0.631*** (0.070)	-0.957*** (0.194)	-0.957*** (0.194)
1950-1959	-0.521*** (0.091)	-0.524*** (0.091)	-0.690*** (0.100)	-0.694*** (0.096)	0.243 (0.287)	0.229 (0.287)
	<b>Rural</b>					
1980-1989	-0.787*** (0.106)	-0.787*** (0.101)	-0.456*** (0.048)	-0.458*** (0.047)	-0.384*** (0.064)	-0.386*** (0.065)
1970-1979	-0.549*** (0.060)	-0.553*** (0.060)	0.051 (0.059)	0.057 (0.057)	-0.086 (0.091)	-0.086 (0.091)
1960-1969	-0.514*** (0.053)	-0.514*** (0.053)	0.631*** (0.077)	0.656*** (0.074)	0.182 (0.174)	0.184 (0.177)
1950-1959	-0.115 (0.079)	-0.150** (0.075)	0.584*** (0.112)	0.577*** (0.105)	0.589** (0.287)	0.594** (0.287)
	<b>Sons</b>					
1980-1989	-0.774*** (0.113)	-0.784*** (0.119)	-0.860*** (0.038)	-0.863*** (0.038)	-0.485*** (0.071)	-0.487*** (0.072)
1970-1979	-0.493*** (0.072)	-0.500*** (0.073)	-0.956*** (0.041)	-0.957*** (0.041)	-0.306*** (0.075)	-0.303*** (0.075)
1960-1969	-0.394*** (0.058)	-0.399*** (0.058)	-0.785*** (0.057)	-0.783*** (0.056)	-0.528** (0.210)	-0.532** (0.209)
1950-1959	-0.383*** (0.082)	-0.388*** (0.080)	-0.608*** (0.077)	-0.630*** (0.072)	0.040 (0.329)	0.059 (0.331)
	<b>Daughters</b>					
1980-1989	-0.724*** (0.111)	-0.728*** (0.113)	-0.262*** (0.050)	-0.262*** (0.049)	-0.473*** (0.063)	-0.469*** (0.064)
1970-1979	-0.315*** (0.072)	-0.322*** (0.073)	0.470*** (0.057)	0.471*** (0.057)	-0.263*** (0.086)	-0.262*** (0.086)
1960-1969	-0.388*** (0.062)	-0.396*** (0.061)	0.984*** (0.074)	0.986*** (0.072)	-0.049 (0.171)	-0.048 (0.169)
1950-1959	0.059 (0.110)	0.051 (0.108)	1.126*** (0.119)	1.121*** (0.121)	0.918*** (0.256)	0.919*** (0.256)

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) Each row uses a sub-sample of children who were born in the given birth cohort and the given category.

### OA3. Robustness Check: Control for Ability

**Table A.9 : Estimates with Ability Controls in Indonesia**

	<b>Yrs. Sch</b>	<b>Res. Sq.</b>
<b>Full Sample</b>		
Father's Edu	0.497*** (0.011)	-0.420*** (0.057)
Constant	6.437*** (0.113)	14.806*** (0.452)
R-squared	0.212	0.030
Observations	18356	18356
<b>Urban Only</b>		
Father's Edu	0.468*** (0.016)	0.468*** (0.016)
Constant	7.225*** (0.171)	7.225*** (0.171)
R-squared	0.236	0.236
Observations	5919	5919
<b>Rural Only</b>		
Father's Edu	0.467*** (0.012)	0.467*** (0.012)
Constant	6.331*** (0.115)	6.331*** (0.115)
R-squared	0.161	0.161
Observations	12437	12437
<b>Sons Only</b>		
Father's Edu	0.461*** (0.013)	0.461*** (0.013)
Constant	6.971*** (0.133)	6.971*** (0.133)
R-squared	0.194	0.194
Observations	8558	8558
<b>Daughters Only</b>		
Father's Edu	0.528*** (0.013)	0.528*** (0.013)
Constant	5.964*** (0.123)	5.964*** (0.123)
R-squared	0.231	0.231
Observations	9798	9798

*Notes:* (1) The data are from the IFLS 2014 round for Indonesia. The regression includes the cognitive ability index and its square. The cognitive ability index was constructed taking the first principal component of Raven test scores and two memory tests net of age and age square.

## OA4. Estimated Relative and Absolute Mobility

**Table A.10: Relative Mobility and Absolute Mobility  
Across Sons vs. Daughters in Urban Area**

	CHINA			INDIA			INDONESIA		
	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES
<b>Urban Sons</b>									
No Sch	0.373 (0.014)	7.200 (0.151)	8.152 (0.131)	0.733 (0.012)	4.847 (0.108)	6.456 (0.084)	0.552 (0.024)	6.568 (0.243)	7.640 (0.208)
Primary	0.352 (0.013)	9.369 (0.106)	10.023 (0.098)	0.630 (0.009)	8.211 (0.061)	9.078 (0.055)	0.503 (0.021)	9.710 (0.124)	10.298 (0.116)
Junior High	0.346 (0.013)	10.415 (0.104)	10.958 (0.098)	0.588 (0.009)	11.242 (0.050)	11.700 (0.048)	0.490 (0.021)	11.199 (0.100)	11.627 (0.095)
Senior High	0.340 (0.013)	11.444 (0.115)	11.894 (0.109)	0.578 (0.008)	12.408 (0.056)	12.749 (0.054)	0.481 (0.021)	12.654 (0.113)	12.956 (0.108)
College	0.335 (0.012)	12.795 (0.144)	13.142 (0.138)	0.567 (0.008)	14.124 (0.071)	14.322 (0.069)	0.472 (0.020)	14.559 (0.166)	14.728 (0.161)
IGRC	0.312 (0.012)			0.524 (0.008)			0.443 (0.020)		
<b>Urban Daughters</b>									
No Sch	0.527 (0.019)	5.607 (0.220)	6.956 (0.180)	0.944 (0.019)	2.191 (0.133)	4.463 (0.085)	0.628 (0.024)	5.633 (0.231)	6.884 (0.190)
Primary	0.471 (0.017)	8.574 (0.134)	9.371 (0.121)	0.722 (0.010)	6.216 (0.079)	7.449 (0.067)	0.557 (0.020)	9.150 (0.110)	9.816 (0.102)
Junior High	0.456 (0.016)	9.963 (0.118)	10.578 (0.110)	0.661 (0.009)	9.646 (0.077)	10.434 (0.070)	0.540 (0.020)	10.795 (0.088)	11.281 (0.083)
Senior High	0.446 (0.016)	11.315 (0.122)	11.785 (0.116)	0.648 (0.009)	10.954 (0.084)	11.628 (0.077)	0.529 (0.019)	12.398 (0.103)	12.747 (0.099)
College	0.438 (0.016)	12.639 (0.143)	12.993 (0.137)	0.635 (0.009)	12.878 (0.099)	13.419 (0.093)	0.519 (0.019)	14.493 (0.156)	14.701 (0.153)
IGRC	0.402 (0.015)			0.597 (0.008)			0.489 (0.019)		

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The RIGRC refers to the Risk Adjusted Intergenerational Marginal Effect. The RES refers to the Risk Adjusted Expected Schooling. The Linear ES refers to the Expected Schooling from a linear CEF mobility model. And the IGRC is the Intergenerational Regression Coefficient from a linear CEF mobility model.



**Table A11: Relative Mobility and Absolute Mobility  
Across Sons vs. Daughters in Rural Area**

	CHINA			INDIA			INDONESIA		
	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES	RIGRC	RES	Linear ES
<b>Rural Sons</b>									
No Sch	0.378 (0.021)	4.936 (0.206)	6.267 (0.166)	0.916 (0.014)	2.917 (0.084)	4.972 (0.058)	0.525 (0.019)	5.773 (0.165)	6.901 (0.137)
Primary	0.338 (0.018)	7.071 (0.105)	7.889 (0.092)	0.719 (0.009)	6.894 (0.050)	7.932 (0.043)	0.481 (0.016)	8.770 (0.100)	9.489 (0.091)
Junior High	0.326 (0.018)	8.067 (0.087)	8.699 (0.078)	0.660 (0.008)	10.318 (0.063)	10.892 (0.058)	0.470 (0.016)	10.195 (0.102)	10.783 (0.095)
Senior High	0.317 (0.017)	9.031 (0.101)	9.510 (0.092)	0.647 (0.008)	11.624 (0.074)	12.076 (0.070)	0.462 (0.016)	11.592 (0.123)	12.076 (0.116)
College	0.310 (0.017)	9.971 (0.133)	10.321 (0.126)	0.634 (0.008)	13.544 (0.093)	13.852 (0.089)	0.455 (0.015)	13.425 (0.168)	13.801 (0.160)
IGRC	0.270 (0.016)			0.592 (0.008)			0.431 (0.015)		
<b>Rural Daughters</b>									
No Sch	0.580 (0.028)	2.299 (0.262)	4.281 (0.179)	1.073 (0.035)	-0.322 (0.119)	2.431 (0.052)	0.637 (0.023)	4.453 (0.174)	5.816 (0.134)
Primary	0.463 (0.018)	5.355 (0.155)	6.529 (0.128)	0.682 (0.013)	3.703 (0.087)	5.330 (0.065)	0.559 (0.019)	7.993 (0.097)	8.814 (0.087)
Junior High	0.439 (0.017)	6.705 (0.141)	7.652 (0.120)	0.623 (0.011)	6.934 (0.118)	8.229 (0.100)	0.543 (0.018)	9.645 (0.108)	10.312 (0.100)
Senior High	0.423 (0.016)	7.997 (0.146)	8.776 (0.127)	0.613 (0.011)	8.169 (0.133)	9.388 (0.116)	0.533 (0.018)	11.258 (0.140)	11.811 (0.132)
College	0.413 (0.016)	9.251 (0.164)	9.900 (0.147)	0.603 (0.011)	9.992 (0.158)	11.128 (0.141)	0.524 (0.018)	13.370 (0.196)	13.810 (0.187)
IGRC	0.375 (0.014)			0.580 (0.009)			0.500 (0.017)		

*Notes:* (1) The data are from children who were born between 1950 and 1989 using the CFPS 2010 round for China, the IHDS 2012 round for India, and the IFLS 2014 round for Indonesia. (2) The RIGRC refers to the Risk Adjusted Intergenerational Marginal Effect. The RES refers to the Risk Adjusted Expected Schooling. The Linear ES refers to the Expected Schooling from a linear CEF mobility model. And the IGRC is the Intergenerational Regression Coefficient from a linear CEF mobility model.