OPPORTUNITY AND RISK [1]

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ABSTRACT

The standard measures of intergenerational mobility do not account for risk. We develop a broader approach where conditional variance of children's outcome is a summary statistic for life-time risks. Conditional variance of children's schooling declines with father's education. We derive risk-adjusted measures of educational mobility by accounting for the risk premium implied by conditional variance. Estimates of risk-adjusted mobility in China, India, and Indonesia suggest that the standard measures overestimate relative and absolute educational mobility. The overestimation is substantial for the disadvantaged children and daughters, but negligible for the children of college-educated fathers.

Key Words: Intergenerational Mobility, Life-time Risks, Conditional Variance, Risk-adjusted Relative and Absolute Mobility, Education, China, India, Indonesia

JEL Codes: I24, J62, O12

(1) Introduction

A large body of economic and sociological literature provides estimates of intergenerational persistence in economic status.[2] 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 standard measures used for understanding the transmission of economic status from one generation to the next are based on the conditional mean function.[3] The focus is on estimating the expected value of an indicator of the socioeconomic status of children (e.g., permanent income, education) conditional on the parent's (usually father's) socioeconomic status. This approach is built on the idea of mobility as "origin independence", and is consistent with the inequality of opportunity (IOP) approach (Roemer (1998)).[4] Equality of opportunity in this perspective implies that the expected life outcomes of children do not depend on the inherited family background (i.e., mean independence).

We focus on the role of life-time risks in understanding economic opportunities of children. The implications of heterogeneity in risk exposure and risk coping capabilities across socioeconomic backgrounds for measuring intergenerational mobility are central to our analysis. A focus on life-time risks and risk aversion could be especially important for the children born to poor (and uneducated) parents. The poor and uneducated households are likely to be more exposed to economic and climate shocks, and they have less risk-coping capabilities. We develop an approach where conditional variance of children's life-time economic outcome is a summary statistic for the risks faced by a child while growing up (i.e., conditional on family background). It is important to recognize that the risk captured by conditional variances

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[2]For surveys of the economic literature, please see, Solon (1999), Bjorklund and Salvanes (2011), Black and Devereux (2011), Heckman and Mosso (2014), Mogstad and Torsvik (2021) and Cholli and Durlauf (2022), and for the sociological literature see Hout (2015), Torche (2015). For surveys on developing countries, see Iversen et al. (2019), Torche (2019), and Emran and Shilpi (2021).

[3]Two most widely-used measures of intergenerational income mobility are intergenerational elasticity (IGE) and intergenerational rank-rank slope. The IGE is estimated as the slope of a log-log conditional mean function for income, while the rank-rank slope is the slope of the regression of percentile income rank of children on the percentile income rank of parents. Similarly, three widely-used measures of intergenerational educational mobility are estimated as the slopes of the relevant conditional mean functions: intergenerational regression coefficient (IGRC), intergenerational (Pearson) correlation (IGC), and rank-rank slope based on schooling ranks in each generation.

[4]The fundamental premise of the IOP approach is that children should not be held responsible for the "circumstances" inherited by birth such as parent's schooling, occupation, race, gender, ethnicity etc. The ideas of equality of opportunity and individual responsibility lead to the distinction between fair and unfair inequality. See the discussion by Roemer (1998), and Hufe et al. (2022).

of children's life outcomes such as schooling attainment is largely the outcome of parental decisions facing credit constraints and various shocks as a child grows up (Currie and Almond (2011), Almond et al. (2018)). Schooling attainment of children born into educated high-income households are not affected substantially by negative income or health shocks as their parents have better access to credit market and higher savings. In contrast, the poor and uneducated parents are often forced to discontinue the schooling of their children when hit by adverse shocks. This increases substantially the life-time risks to the schooling attainment of the children of poor and uneducated parents. Parental choices are thus part of the risk environment inherited by birth. In the terminology of the inequality of opportunity approach (Roemer (1998)), parental choices constitute "circumstances" children are born into.[5]

We make three contributions to the literature. First, using data from three large developing countries (China, India, and Indonesia, with 42 percent of world population in 2000), we provide the first evidence that life-time educational risks as captured by conditional variance of children's schooling are systematically related to their father's education, showing a robust negative association.[6] This extends the idea of mobility as origin independence to life-time risks in a consistent manner, and allows us to develop risk-adjusted measures of mobility that are anchored in the work-horse conditional mean-based measures. Second, we develop a methodology that combines the influences of father's education on both the mean and the conditional variance of children's schooling.[7] We derive more complete measures of relative and absolute mobility that adjust the standard conditional mean-based measures of mobility by the risk premium associated with the conditional variance. The risk premium is evaluated at the birth of a child, and varies with father's education because both conditional variance and mean are functions of father's education.[8] The "accident" of birth, in this perspective, is like a lottery ticket that induces a conditional distribution of schooling outcomes given parental education. The core insight of our approach is to evaluate this lottery ticket from an ex-

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[5]This also includes any differences in parenting style across parents with different levels of education.

[6]In this paper, we use education and schooling interchangeably. It is widely understood that education is a broader concept and includes other forms of learning. For a discussion on these issues, see Behrman (2019).

[7]We use 'association' and 'influence' interchangeably, and emphasize that we do not present any causal evidence. The goal of our analysis is to develop broader measures of relative and absolute mobility that take into account the implications of risk exposure and risk aversion.

[8]In many existing studies, relative mobility is measured by the slope of a linear conditional mean function, and thus relative mobility does not vary across the distribution (see, for example, Hertz et al. (2008) on educational mobility, and Solon (1992) and Chetty et al. (2014) on income mobility). With risk adjustments, relative educational mobility varies across father's schooling as it depends on the risk premium.

ante perspective of a risk-averse child to understand how the value of the lottery varies with parental education (more broadly, family background). With risk neutrality, our proposed measures reduce to the canonical measures of intergenerational educational mobility widely used in the current literature (Bjorklund and Salvanes (2011), Torche (2019), and Iversen et al. (2021)). For summary measures at the national level, we report weighted risk-adjusted mobility estimates using the proportion of children in each bin (defined by father's education level) as weights. Third, under the plausible assumption of risk aversion, we estimate the risk adjusted measures of relative and absolute educational mobility in China, India, and Indonesia, and compare them with the estimates of the standard conditional mean-based measures used in the existing literature. Evidence suggests that the standard measures without risk adjustments considerably overstate relative and absolute mobility, especially for the most disadvantaged children, and can change the rankings in inter-group comparisons.[9]

The approach developed here is of wider interest for three reasons: (i) the risk-adjusted measures can be easily applied to the analysis of intergenerational income mobility;[10] (ii) it is suitable for estimating causal effects of policies because the risk-adjusted measures are anchored in the standard measures, and the impact of policies on life-time risks (as measured by conditional variance) can provide us additional insights into the economic mechanisms; and (iii) the policymakers may find the risk-adjusted measures more appropriate for guiding policy priorities, especially when disadvantaged children face disproportionately higher risks in life outcomes due to climate change.

For our empirical analysis, we use household survey data from the China Family Panel Studies (CFPS) 2010 for China, the India Human Development Survey (IHDS) 2012 for India, and the Indonesia Family Life Survey (IFLS) 2014 for Indonesia.[11] We focus on the 18-40 year old children for our main empirical analysis. This is motivated by the fact that the data on the older cohorts in India (IHDS) are not comparable to the other two countries.[12] We check

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[9]We use the term "disadvantaged children" for the children of fathers with less than primary schooling, and the "most disadvantaged children" for the children of fathers with no schooling.

[10]For income mobility, the focus is on the conditional variance of *permanent income* of children given the *permanent income* of parents; but, to the best of our knowledge, there is no such analysis in the existing literature. The analysis of income mobility, however, involves an additional aspect: *income volatility* experienced by an individual throughout life. We thank Matthew Lindquist for illuminating discussions on these issues.

[11]These surveys are chosen to ensure that the estimates are not biased because of sample truncation due to coresidency restrictions, see Emran et al. (2018).

[12]For India, we do not have information on siblings of the household head and spouse. The data on older cohorts in India thus suffer from truncation.

the robustness of the conclusions using alternative age cohorts including 18-35 and 22-40 year age ranges.

We implement the maximum likelihood estimation (MLE) procedure developed by Western and Bloome (2009) to estimate jointly the conditional mean and conditional variance functions.[13] The estimates suggest a robust finding: life-time educational risks faced by children (as measured by conditional variance of children's schooling) *declines* substantially with father's education in all three countries. For our main sample (18-40 age cohorts), the estimated influence of father's education on conditional variance of children's schooling are: India (-0.760), Indonesia (-0.525), and China (-0.629). To have a sense of the implied magnitudes, compare the children of college-educated fathers with the children of fathers with primary schooling (a 10 years gap in father's schooling). The point estimate in India suggests that the conditional variance faced by children of college-educated fathers is 7.6 years lower. This is substantial in magnitude given the fact that the mean conditional variance in the sample is 17.44 years. Evidence thus provides strong support for the view that the children born to more educated fathers enjoy double advantages in the form of a lower life-time educational risk in addition to a higher expected schooling attainment (conditional mean). There is substantial heterogeneity in the strength of the association between life-time educational risks and father's schooling across rural vs. urban locations, and gender, even though the association remains consistently negative. We provide evidence that the observed negative relationship between educational risks and father's schooling is not driven by the parametric functional form assumptions (using nonparametric plots from binscatter regressions), and omitted ability heterogeneity.[14] A substantial part of the influence of father's education on children's schooling risks can be accounted for by location and cohort fixed effects, suggesting that spatial heterogeneity in climate and labor market shocks, and access to markets and schools are important economic mechanisms.

The most important finding from our analysis is that the conclusions about relative and absolute mobility are markedly different when the risk-adjusted measures are used instead of the standard measures based on the conditional mean function. The differences between

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[13]The estimates and conclusions are robust if we use OLS to estimate the equations separately. Estimates are available upon request.

[14]The analysis of the omitted ability heterogeneity takes advantage of multiple measures of cognitive ability of children available for Indonesia in the IFLS survey. Such data on cognitive ability are not available in the household surveys for China (CFPS) and India (IHDS).

these measures depend on the risk premium which is determined by the ratio of conditional variance to the conditional mean of children's schooling (given father's education).[15] For relative mobility, the workhorse measure in the literature, intergenerational regression coefficient (IGRC), substantially underestimates the influence of parental education compared to the risk-adjusted IGRC (henceforth RIGRC) estimates, and thus the existing evidence considerably overestimates the extent of intergenerational educational mobility.

Accounting for risks makes a dramatic difference in the estimated relative and absolute mobility for the disadvantaged subgroups: children born to fathers with low or no schooling, girls, and rural children. The standard IGRC estimates considerably underestimate the gender disparity and rural-urban gap in relative mobility in China and India. Of special interest to the policymakers are the children of fathers with no schooling, as they are likely to be the most disadvantaged segment of the population.[16] RIGRC estimates from our main sample for this subgroup of children show that the standard IGRC overestimates relative mobility by 35.63 percent in China, 46.58 percent in India, and 20.94 percent in Indonesia. Similar results hold when we adopt a broader definition of the disadvantaged group of children whose fathers have less than primary schooling, following the recent analysis of Alesina et al. (2021). 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 34.15 percent in China, 55.21 percent in India, and 13.92 percent in Indonesia.[17] For absolute mobility of the children of college educated father, the risk adjustments again do not make any substantial difference. The upshot is that while the existing estimates of relative and absolute mobility in the literature seem to capture reasonably well the educational opportunities of children born to college or more educated fathers, a failure to account for the influences of family background on conditional variance substantially overstates the educational opportunities of the most disadvantaged children. An important implication for the policymakers is

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[15]When comparing different countries and subgroups (sons-daughters, rural-urban), the risk premium can be smaller (larger) even when the influence of father's education on the conditional variance is larger (smaller) depending on the magnitude of conditional mean.

[16]In many developing countries, this is an important subgroup: in our sample of children of 18-40 years age, 31 percent of fathers have no schooling in China, 42 percent in India, and 7 percent in Indonesia.

[17]We also find comparable overestimation of absolute mobility for the children of fathers with less than primary schooling.

that the standard measures of mobility may lead to increasingly severe underestimation of the disadvantages faced by children born to uneducated parents as they become more exposed and vulnerable to the vagaries of climate change.

The rest of the paper is organized as follows. Section (2) reviews the relevant literature to put the contributions of the paper in perspective. Section (3) 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 life-time educational risks faced by children as measured by the conditional variance of children's schooling. This section also lays out the estimating equations for the educational risk function and conditional mean function.[18] Section (4) is devoted to a discussion of the surveys and data sets used for our analysis: the CFPS 2014 (China), the IHDS 2012 (India), and the IFLS 2014 (Indonesia). Section (5) reports the evidence on the influence of father's education on the conditional variance of children's schooling. In section (6), we explore the role of place (location) and time (birth cohort) in explaining the association between father's education and conditional variance of children's schooling. Section (7) develops measures of relative and absolute mobility that takes into account both the conditional mean and conditional variance channels, and provide estimates of the risk adjusted mobility measures for children in China, India, and Indonesia. The paper concludes with a summary of the findings and points out the central contributions of the paper to the literature.

(2) Related Literature

The literature on intergenerational mobility in developed countries primarily focuses on persistence in permanent income, while the studies on developing countries focus on intergenerational educational persistence.[19] Recent contributions on intergenerational income and/or educational mobility include, among others, Chetty et al. (2014), Black et al. (2020), Mogstad (2017), Berman (2022), Carneiro et al. (2021), Asher et al. (2023), Van Der Weide et al. (2023), Acciari et al. (2022), Adermon et al. (2021), Abramitzky et al. (2021), Katz and Krueger (2017), Card et al. (2022), and Emran et al. (2018). To the best of our knowledge, this is the first paper to study the implications of heterogeneity in risk exposure, risk coping

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[18]Conditional variance as a function of father's schooling is also called educational risk function in this paper.

[19]The focus on education is primarily because of paucity of long-term panel data with good quality income information. See the discussion by Iversen et al. (2019) and Emran and Shilpi (2021).

ability, and risk aversion for measures of intergenerational mobility.

There is a small economic literature that partially exploits the information in conditional variance using quantile regressions. But the focus again is on the *conditional mean function* albeit at various quantiles of children's income or education. See, for example, Grawe (2004) on income mobility in the United States, and Kishan (2018) on educational mobility in India.

A large literature on inequality of opportunity that grew out of the influential contribution of Roemer (1998) uses within group variance (conditional variance) as a measure of children's effort, but does not consider the role of risks.[20] There are some studies that account for the fact that the within group variance may vary by socioeconomic status of children, and define effort by the sterilized residual after netting out the influence of family background on the within group variance (Bjorklund et al. (2012) and Hederos et al. (2017)). Note that if the conditional variance in a society is not influenced by family background because it is largely driven by children's own effort and choices, then such a society enjoys high mobility according to the inequality of opportunity perspective (given a conditional mean function).

There is a long tradition in sociology and economics that uses transition matrices to characterize the joint distribution of outcomes in children's and parents' generations. There are many measures of mobility based on transition matrix proposed in the literature (see, for example, Shorrocks (1978), and Fields and Ok (1996)), but, as noted by Jäntti and Jenkins (2015), most of them are not widely adopted by empirical researchers.[21] Quantile transition probabilities are more widely used as a measure of absolute mobility (see, for example, Chetty et al. (2014), and Bhattacharya and Mazumder (2011)). Perhaps more importantly, we are not aware of any studies that use measures of mobility derived from transition matrix to analyze the role of life-time risks and risk aversion.

That there is a link between mobility and risk is discussed in the context of intra-generational income mobility. The focus is on positional mobility, i.e., mobility as movement: transitory income shocks can lead to short-term mobility across income groups which dissipates in the long-term (see, for example, Gottschalk and Moffitt (2009) and Chen and Couch (2013)). For a survey of this literature and a useful discussion on a large number of measures of intra-

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[20]The groups are defined in terms of children's socioeconomic status defined by a vector of inherited circumstances such as parental education, occupation, sex, ethnicity etc.

[21]For a recent analysis of intergenerational educational mobility in 8 European countries using transition matrices, see Apouey et al. (2022).

generational and intergenerational income mobility, see Jäntti and Jenkins (2015). A related literature analyzes rising income and earnings volatility and residual wage inequality, especially in the context of the USA. On income and earnings volatility, see, among others, Gottschalk et al. (1994), Gottschalk and Moffitt (2009), Moffitt and Zhang (2018). For residual wage inequality, see, for example, Juhn et al. (1993), Lemieux (2006), and Katz et al. (1999). The studies on residual wage inequality focus on the evolution of the conditional variance of wage given education and experience. But most of this literature is not concerned with the influences of family background. We are aware of two papers that study the association between family background and *volatility* of children's income: Shore (2011) and Jäntti and Lindahl (2012).

(3) Conceptual Issues and Estimating Equations

(3.1) Conceptual Issues

The standard estimating equation for intergenerational educational mobility is:

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

where S_i^c is the years of schooling of child i and S_i^p is the schooling level of the parent. The focus of the analysis is on the parameter β which is known as intergenerational regression coefficient (IGRC) in the literature.[22] We note here that the mobility measures developed in this paper and the empirical findings do not depend on the parametric approach. As part of robustness checks, we report later nonparametric estimates using binscatter regressions (see Cattaneo et al. (2019)).[23]

It is implicitly assumed that the variance of the error term ε_i does not depend on a parent's (father in our empirical analysis) education in any systematic way, and thus β 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 under the assumption of no market imperfections. In a model with a perfect credit market, the optimal investment in a child's education depends only on his/her ability, the family background is irrelevant (Becker (1991)). Under the plausible assumption that the variance

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[22]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) on India, Dartanto et al. (2021) on Indonesia, Knight et al. (2011), Golley and Kong (2013), and Emran and Sun (2015) on China. For recent surveys of the literature on developing countries, see Iversen et al. (2019), Torche (2019), and Emran and Shilpi (2021).

[23]The nonparametric plots are implemented with STATA code binsreg.

of children's (innate) cognitive ability does not depend on father's education level, there is no additional information in the conditional variance of schooling attainment that could be useful for understanding the influence of family background on the educational opportunities of children.

In a more realistic setting where the credit markets are imperfect (or missing), we would expect conditional variance to capture educational risks faced by children, reflecting the interactions of a child's innate cognitive ability with the credit constraint and risk-coping strategies of a household. First, consider the implications of credit market imperfections in the absence of any exogenous 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 investments (i.e., no quantitative credit rationing).[24] In this case, the poor (less educated) parents invest less, given the ability of a child because of a higher interest rate. More important for our analysis, the investment differences across children from the same family background (as measured by fathers having the same education level) are determined solely by the ability differences among the children. We thus expect a lower average level of education for the children of less educated parents, but children's educational risks (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.[25] Such investment choices are likely to increase the conditional variance of children's schooling in the less-educated, credit-constrained families as the less able child's education level is depressed and the education level of the high-ability child is pushed up.[26]

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[24]This model of credit market imperfections is adopted by Becker et al. (2015, 2018) in their recent theoretical analysis of intergenerational mobility.

[25]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.

[26]We emphasize again here that the parental choices are part of the risk environment faced by a child, i.e.,

Negative income and health shocks amplify the effects of a binding credit constraint faced by an uneducated (low-income) household. Life-time educational risks may vary with the family background because of differences in exposure to and capabilities for coping with adverse shocks, for example, labor market shocks, weather shocks, and natural disasters.[27] There is substantial evidence that less-educated (and poor) households live in unfavorable geographic locations, and they are much more vulnerable to the weather shocks and climate change (Frankenberg et al. (2013)). Evidence from the "Young Lives" project finds ".. in Ethiopia, a startling 81% of children in our poorest households had experienced at least one extreme weather event, compared to only 22% in the least poor households. Similar trends can be seen in India (65% v 18%), Peru (63% v 12%) and Vietnam (50% v 17%)" (Porter (2021)). With higher income and savings, and better access to credit markets, the highly educated parents are better able to deal with negative shocks without any disruption to their children's education (Muttarak and Lutz (2014)). In contrast, a negative income or health shock may force the uneducated poor parents to take their children out of school and send them for child labor. Even when adverse shocks do not force the parents to take a child out of school, the learning outcomes (and eventual academic progression) may suffer because of stress and strain on the cognitive bandwidth of a child (Mullainathan and Shafir (2013)), along with food deprivation because of skipping meals. The timing of such shocks is also important for the credit constrained households. When income or health shocks occur during a child's school years, it is likely to affect adversely his/her schooling attainment, while others from similar family background (including siblings) who went to school in a different time period without such shocks would achieve higher schooling (given innate ability). The higher exposure to risks and lower risk-coping ability thus result in increased educational risks, with a higher conditional variance of the completed schooling of the children born to poor and uneducated parents, compared to a benchmark where conditional variance is driven solely by innate ability heterogeneity of children.[28]

Educational risks as measured by conditional variance of children's schooling attainment

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they are "circumstances" a child is born into, not chosen by himslef/herself. Thus, they are part of the family background effect we are interested in.

[27]Floods, droughts, and extreme heat are becoming more frequent and increasingly severe with climate change, making it more important to take into account the implications of risks in understanding inequality of opportunity.

[28]As noted above, this benchmark holds, for example, when credit market is perfect.

are likely to *decline* with the education of parents when such economic shocks are important sources of 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 that being born to higher educated parents brings double advantages for children, part of which is ignored by the standard measures in the existing literature on intergenerational mobility.

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 reinforcing investment is the overriding behaviorial response of parents facing scarcity, then we may observe a lower conditional variance for the children born to low-educated fathers.[29] This may make the relationship between father's schooling and conditional variance of children's schooling positive.

Government policies can also affect the relationship between life-time educational risks faced by children and their socioeconomic status. When government policies such as free compulsory primary schooling are well designed and implemented, they ensure that the children from 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 counterfactual schooling distribution of children without any policy interventions. This will again tend to make the association between educational risks and father's schooling positive. In contrast, merit based scholarships provided by schools or government programs usually 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 of poor children. This is likely to make the relationship between father's schooling and children's educational risks negative. The upshot of the above discussion is that (i) it is highly unlikely that life-time educational risks as captured by conditional variance remain constant across the distribution of father's schooling, and (ii) the relationship between chil-

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[29]Ye and Yi (2017) develop a model where there is complementarity between initial endowment and investment, and parental preference shows inequality aversion. They show that the rich (more educated) parents adopt the reinforcing investment strategy while the poor (low-educated) parents use compensating investments facing credit constraints.

dren's educational risks and father's schooling cannot be pinned down unambiguously on the basis of theoretical arguments alone. Hence, it is important to provide empirical evidence on this issue.

(3.2) Children's Schooling Risks and Father's Education: Estimating Equation

To understand the potential influence of father's education on children's educational risks, we estimate the following equation:

$$V\left(\varepsilon_i\right) = \theta_0 + \theta_1 S_i^p + v_i; \quad E(v_i) = 0 \tag{2}$$

where ε_i is the error term from the conditional mean function of children's schooling given parent's level of schooling (equation 1).[30] $V\left(\varepsilon_i\right)$ is our measure of life-time educational risks faced by children. Equation (2) is called educational risk function or conditional variance function interchangeably in this paper. The error term in the educational risk function, v_i, captures the part of conditional variance unrelated to family background. This may include factors such as the idiosyncratic part of innate ability of a child, and the differences in effort not driven by family environment. Note that the approach we develop in this paper does not depend on any parametric functional form assumption for the conditional variance and conditional mean functions. It is straightforward to adapt the analysis of educational risks and family background in terms of a nonparametric conditional variance function approach. We report nonparametric estimates (plots) using binscatter regression later in the paper (see subsection (5.2) below). We are not aware of any studies on intergenerational mobility in the economic literature that provide estimates of equation (2).[31]

(4) Data and Variables

We use the following household surveys for our empirical analysis: the China Family Panel Studies 2010 (CFPS, 2010) for China, the India Human Development Survey 2012 (IHDS, 2012) for India, and the Indonesia Family Life Survey 2014 (IFLS, 2014) for Indonesia. As noted earlier, we chose these surveys primarily because they do not suffer from any signifi-

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[30]We rely on a linear specification for the conditional variance function, similar to the Breusch-Pagan model of heteroskedasticity. An alternative is to use a multiplicative formulation, as suggested by Harvey (1976). In an earlier working paper version of this paper (with a different title), Ahsan et al. (2022), we derive the risk-adjusted measures of mobility for the multiplicative case. However, it is important to appreciate that the critical difference from the econometric literature is that heteroskedasticy in our application is the object of interest, generated by plausible economic mechanisms.

[31]As noted earlier, there are a few studies on inequality of opportunity that estimate equation (2) to retrieve the residual as a measure of children's effort.

cant truncation of the sample that arises from coresidency in the case of standard household surveys[32] and population censuses in developing countries. The sample truncation in the standard household surveys results from the fact that they do not collect information on the nonresident children or parents. In this section, we discuss the sample construction procedure briefly for each of the surveys, and provide additional discussions in the online appendix (please see section G of the online appendix).

The China Family Panel Study (CFPS) 2010 has a unique T-Table design that presents the complete family network, in which household members' education information is available irrespective of their residency status at the time of the survey. For a more detailed discussion on the advantage of the CFPS in analyzing intergenerational mobility-related questions, please see online appendix section GI, and Fan et al. (2021) and Emran et al. (2020). The data for India come from the India Human Development Survey (IHDS) 2012 wave. We follow Emran, Jiang, Shilpi (2021) closely. We take advantage of the nonresident household member module to find the information on the children where not at the household at the time of the survey. For more details, please see online appendix section GII. The data for Indonesia come from the 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. For more details about the sample construction procedure, readers are referred to the online appendix section GIII, and Ahsan et al. (2021) and Mazumder et al. (2019).

We focus on the younger cohorts (18-40 year old in the survey year) for our analysis. This is motivated by the fact that, for India, we do not have information on the siblings of the household head and spouse, and, as a result, the sample of older cohorts of children is truncated. We use 18-40 years age cohorts of children as our main sample, and check the robustness of the conclusions using alternative age ranges.[33]

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 main sample

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[32]Sample truncation occurs when the information on both the independent and dependent variables in the regression is missing. Such truncation is usually not random, which results in biased estimates. Some widely-used household surveys subject to truncation are Demographic and Health Survey (DHS) and Living Standards and Measurement Survey (LSMS).

[33]We checked a number of age ranges. The results for the 22-40 years, and 18-35 years age cohorts are reported in the online appendix. The results for other age ranges, for example, 18-38 cohorts are available upon request.

consisting of children 18-40 year old in a survey. The average years of schooling for fathers is 5.54 in China, 4.64 in India, and 6.73 in Indonesia. The average years of schooling for children is 8.41 in China, 7.90 in India, and 10.48 in Indonesia. Therefore, Indonesia has the best schooling outcomes for both generations while India has the lowest mean education for both children and fathers.

We also report the summary statistics for our four main sub-samples: urban and rural areas, sons, and daughters in the following panels of Table 1 respectively. In each country, there is a consistent rural-urban gap in education for both generations. Children in urban China and urban Indonesia have about 2 more years of schooling than children in rural areas, while the gap is the largest in India (2.5 years). Among these three countries, only India exhibits a substantial gender gap in children's schooling: sons have 1.83 years of more schooling that the daughters on average. The average gender gap in China and Indonesia is much smaller. As we discuss below, this gender convergence in average schooling in China masks some important gender gaps in relative and absolute mobility.

(5) Children's Schooling Risks and Father's Education: Evidence from China, India, and Indonesia

The conditional mean and conditional variance functions can be estimated by ordinary least squares (OLS) separately. The variance function (risk function) can be estimated by OLS after retrieving the residuals from the estimated conditional mean function by OLS, but it is not efficient under a wide variety of assumptions (Western and Bloome (2009), Davidian and Carroll (1987)). We implement the MLE procedure developed by Western and Bloome (2009) for joint estimation of the conditional mean and conditional variance functions.[34]

Estimates of equations (1) (conditional mean function) and (2) (conditional variance function) for our main sample (18-40 year age cohorts) are reported in Table 2. The estimates for the conditional mean function are in odd columns and those for the conditional variance function are in even columns. The evidence is consistent across the three countries: educational risks as measured by conditional variance of children's schooling is a negative function of father's education.[35] Estimates of the conditional mean function show that father's educa-

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[34]It is implemented with the STATA codes provided by Western and Bloome (2009) with necessary modifications. The conclusions in this paper remain intact if we use OLS to estimate the equations separately. The OLS estimates are available upon request.

[35]All the estimates are significant at the 1 percent level. One might wonder whether the high conditional

14

tion has a substantial *positive* association with the expected schooling of children, consistent with a large literature that focuses solely on the conditional mean. When considered together, the evidence on the conditional mean and conditional variance equations suggests that being born to a higher-educated father is equivalent to an education lottery with a higher expected years of schooling and a lower life-time educational risk.

There are some important cross-country heterogeneity: father's influence on both expected schooling of children (IGRC=0.54) and educational risks (-0.76) are the highest in India. The influence of father's education on children's expected schooling is of comparable magnitude in China (0.42) and Indonesia (0.41), but the estimate for educational risks is larger in China (-0.62) compared to that in Indonesia (-0.53).

(5.1) Subgroup Heterogeneity: Rural-Urban and Sons-Daughters

Rural vs. Urban

The top two panels of Table 3 report the estimates of equations (1) and (2) separately for urban and rural samples. The first important point is that a higher level of father's education is associated with a lower conditional variance faced by a child irrespective of geographic location, suggesting that being born to more educated parents yields double dividends in both rural and urban areas. There are striking rural-urban differences in the slope of the conditional variance function in India and Indonesia, but little differences in the intercepts. In China, there are no significant rural-urban differences, both in the slope and intercept of the conditional variance function.

In India, the association between father's education and conditional variance (i.e., the slope of the conditional variance function) is much stronger in the urban sample (-0.92) than that in the rural sample (-0.60). In Indonesia, the strength of the association is lower in both rural and urban areas compared to the other two countries, with the urban estimate about 76 percent larger than the rural estimate.[36] A smaller influence of father's education

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variance at the lower end of the distribution could be partly because schooling is bounded from below at zero. However, cutting off the lower part of a distribution is likely to reduce the variance. Moreover, the top of the distribution of schooling is bounded from above. If bounding at the end points is driving the variance, then we should see similar variance at zero and the highest schooling levels of fathers which is contradicted by the evidence.

[36]An analysis of the sources of the rural-urban differences is beyond the scope of this paper, and is left for future research. Plausible explanations include differences in the occupational structure. For example, in rural areas, higher education is usually associated with nonfarm occupations producing nontraded services consumed within the village. While nonfarm production process is less subject to weather shocks, any shock

15

on conditional variance in rural areas does not imply that the risk premium is lower, as the risk premium is an inverse function of the conditional mean which is smaller in rural areas (please see the formula for the risk premium in equation (6) below).

Sons vs. Daughters

The lower two panels of Table 3 contain the estimates for the son's and daughter's samples. Evidence suggests that children of higher-educated parents enjoy lower educational risks irrespective of gender. In China and India, the association of father's education with children's educational risks is larger in magnitude for sons (relative to daughters), with no significant gender differences in Indonesia. The gender gap in the estimated intercepts of the conditional variance function is also small in Indonesia. Among the three countries, the gender gap in the slope estimate of the educational risk function is the largest in India, with the estimate for sons about 170 percent larger: (sons: -0.97) and (daughters: -0.36).[37] China falls in between, with the influence on sons larger, but the gender gap (16 percent) is much smaller than that in India.

The estimates of the conditional mean of children's schooling (see the IGRC estimates in the odd-numbered columns of Table 3) show that the point estimate is substantially higher for daughters in China and India. In contrast, in Indonesia, the estimated conditional mean function also does not vary significantly across gender (both slope and intercept). The evidence thus suggests gender convergence in Indonesia in the slope and intercept of both the conditional variance and conditional mean functions.[38] We propose and estimate a measure of relative mobility that combines the mean and conditional variance channels in section 7 below.

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to agriculture also affects the nonfarm business in a village through demand (see Emran et al. (2003)). Thus the reduction in variance of income with higher education (nonfarm occupations) may be less in rural areas.

[37]Both estimates are significant at the 1 percent level. An analysis of the causes of this gender difference is beyond the scope of this paper. A plausible conjecture is that the decisions regarding a son's schooling are much more responsive to economic forces including credit constraint and labor market opportunities which vary substantially with father's education. In contrast, daughter's schooling might be determined primarily by social norms. For example, even the more educated fathers may not send their daughters to a high school located in a distant village (Tilak (1993), Scott (1985)). This may result in bunching of girls' education at around certain levels (e.g., primary), thus lowering the variance.

[38]This is consistent with a substantial literature showing gender convergence in education for the younger cohorts in Indonesia. See, for example, Levine and Kevane (2003), Afkar et al. (2020).

(5.2) Robustness Checks

Alternative Age Ranges

Our main results are based on 18-40 year age cohorts in the survey year in a country. We checked whether the main conclusions are robust to changes in the age ranges. We estimate the conditional mean and conditional variance functions for a number of alternative age ranges including 18-35, and 22-40. The 18-35 age range is considered to check if the inclusion of relatively older children might bias the estimates for India because of the inclusion of some household heads and spouses as children. The 22-40 age range is motivated by the consideration that some children may not have completed their schooling at age 18. An age cut-off of 22 would allow 4-year college completion by children.

Online appendix section AI contains the estimates. Table A1 reports the national level estimates for 18-35 (upper panel) and 22-40 (lower panel) age ranges. The estimates are similar to the estimates for our main sample (18-40) reported earlier in Table 2. The estimates for rural-urban and sons-daughters subgroups are reported in online appendix Tables A2 (18-35) and A3 (22-40). Again, the subgroup estimates are not substantially different from the corresponding estimates based on our main sample of 18-40 age cohorts.

Functional Form of the Conditional Mean Function

The next robustness check deals with the question of whether the observed patterns in the educational risk function are primarily driven by functional form mis-specification of the conditional mean function. There is a growing theoretical and empirical literature that suggests that, in many cases, the conditional mean function is likely to be quadratic in parental schooling (see Becker et al. (2018), and Becker et al. (2015)):

$$S_i^c = \alpha + \beta S_i^p + \delta \left(S_i^p\right)^2 + \zeta_i \tag{3}$$

If the true conditional mean function is given by equation (3), but we estimate the linear equation (1), the error term is $\varepsilon_i = \delta \left(S_i^p\right)^2 + \zeta_i$, and the variance of ε_i is a function of the father's education simply because of a misspecified functional form.[39]

To check this, we estimate the mobility equation (3) and the influence of father's education

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[39]Most of the studies on intergenerational *income mobility* use a specification linear in logs. Bratsberg et al. (2007) find that it is convex in Norway, Denmark, and Finland, but closer to linear in the United States and the United Kingdom. However, Chetty et al. (2014) report evidence of a concave relation (see their Figure 1) in the United States, and a recent analysis by Mitnik et al. (2018) provides evidence that the income mobility equation is convex in the United States.

on the conditional variance of children's schooling defined in terms of ζ_i. The estimates are reported in the online appendix section AII: Table A4 for the 18-40 sample, Table A5 for the 18-35 and 22-40 age cohorts. Tables A6 (rural-urban) and A7 (sons-daughters) contain the estimates for different subgroups for our main sample (18-40).

One might wonder whether we get similar results if we use a nonparametric approach for estimating the conditional mean function. To this end, we estimate the conditional mean function nonparametrically using binscatter regression (see Cattaneo et al. (2019)), please see Figure A1 in online appendix AII. Next, we retrieve the residuals to define the life-time educational risks faced by children. Then we estimate the nonparametric relationship between educational risks and father's schooling which shows a clear negative association across all three countries (see Figure A1 in online appendix AII).[40] The evidence, taken together, suggests strongly that the relationship between father's schooling and children's educational risks as measured by the conditional variance of children's schooling uncovered in Tables 2-3 are not driven by functional form mis-specification of the conditional mean function.

Ability Heterogeneity: Evidence from Indonesia

The next question we address is whether the estimated influence of father's education on conditional variance largely reflects the omitted cognitive ability heterogeneity of children unrelated to father's education. 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 (measurements taken in 2014 when the children are adults): 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 our main sample (18-40 year age cohorts) are reported in online appendix Table A8, including the subgroups: rural-urban and sons-daughters. The corresponding estimates for 18-35 and 22-40 age cohorts are in the online appendix Tables A9 and A10 respectively. The main message that comes out is that the estimated influence of father's education on conditional variance of schooling of children is not driven by omitted

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[40]Binscatter plots are implemented using the binsreg command in STATA.

ability heterogeneity.[41] This is true for both the national sample, and the subgroups: rural-urban, and sons-daughters. Even though ability controls reduce the estimated coefficient on father's education, the influence of father's education still remains substantial and statistically significant at the 1 percent level.[42]

(6) Place, Time, and Children's Life-time Schooling Risks

Understanding heterogeneity across geographic location (place) and birth cohorts (time) has been a major focus of the literature on intergenerational mobility. The influential theoretical analysis of Solon (2004) emphasizes the importance of understanding the variation in intergenerational mobility across geographic space and over time. A substantial literature provides evidence on the role of neighborhood.[43] The influential work of Chetty and his co-authors has underscored the primacy of place in understanding economic opportunities across commuting zones in the United States.[44] However, the existing literature deals primarily with the importance of place and time in conditional mean-based measures of opportunity and intergenerational mobility.

In section (2) above, we discussed a variety of economic mechanisms that can result in a negative relation between the conditional variance of children's schooling (life-time educational risk) and their father's level of schooling. Place and time capture many of these mechanisms in a convenient way. The timing, frequency and severity of economic shocks, and parental ability to deal with them depend on location and time period. Weather shocks such as floods and drought, and market shocks such as local labor market downturns are tied to the location of a household. Location also determines access to schools, the set of markets available to a household, and transaction costs involved in participating in the urban labor and product markets. The locational heterogeneity in risk exposure is expected to be increasingly important because of climate change as less educated poor households are in general located

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[41]The conclusions remain the same if we control for ability heterogeneity in the quadratic conditional mean function. The estimates are available upon request.

[42]Note that the ability measures partly capture the effects of family background as they are measured in 2014 when the children are of adult age. It is thus likely that we over-control for the effects of innate cognitive ability heterogeneity.

[43]See, for example, Raaum et al. (2006), Solon et al. (2000), Chyn and Katz (2021), and Chetty and Hendren (2018).

[44]It is important for policymakers to understand whether the place a child grows up exerts a substantial influence on his/her opportunities in addition to family characteristics. Evidence in favor of an important spatial effect suggests that place-based policies (as opposed to people-targeted policies) are effective for addressing inequality of opportunity (Chetty (2018)).

in more vulnerable areas (Frankenberg et al. (2013)). The nature of shocks and access to markets and schools evolve over time, which can be captured by birth cohort fixed effects.

To check whether place and time are of first-order importance for understanding the relation between father's schooling and conditional variance in children's schooling, we include location (primary sampling unit) and birth year fixed effects in the conditional variance equation (2). The estimates are reported in Table 4. The first column reproduces the estimates without any fixed effects reported earlier as a benchmark. The second column contains the estimates with location fixed effects, the third column includes location×birth year fixed effects. A comparison of the first and second columns suggests that place is an important factor in understanding the relation between father's schooling and children's educational risks: the magnitude of association between father's schooling and conditional variance goes down by 35.60 percent in China, by 19.87 percent in India, and 23.24 percent in Indonesia when we include location fixed effects. The evidence that the role played by location is the strongest in China is consistent with the fact that Hukou restrictions limited spatial mobility in China for many decades. The estimates with location×birth year fixed effects in column 3 capture the influences of location and cohort the most comprehensively: the estimated influence of father's education declines by 50 percent in China, by 38.16 percent in India, and by 32.38 percent in Indonesia. These conclusions do not depend on the age range chosen: please see online appendix section B for 18-35 (Table B1) and 22-40 (Table B2).

(7) Risk-adjusted Measures of Relative and Absolute Mobility

The evidence presented above suggests that it is important to understand the influence of family background on the life-time educational risks as measured by conditional variance in addition to the influences on the mean. In this section, we develop an approach that combines the mean and conditional variance channels using standard results from the theory of decisions under risk. The analysis below is couched in terms of intergenerational educational mobility given our empirical applications for China, India, and Indonesia. We, however, emphasize that the approach developed below can be readily applied to the analysis of intergenerational income mobility, to explore the role of income risks inherited by birth as captured by the conditional variance of children's permanent income (i.e., conditional on parental permanent income).

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 conditional on parental education as $E(S_i^c \mid S_i^p)$, and $\epsilon_i = S_i^c - E(S_i^c \mid S_i^p)$. So we can rewrite $W(S_i^c) = W(E(S_i^c \mid S_i^p) + \epsilon_i)$. Using the intergenerational mobility equation (1) above, $E(S_i^c \mid S_i^p) = \alpha + \beta S_i^p$, which implies $W(S_i^c) = W(\alpha + \beta S_i^p + \epsilon_i)$.

We have the following:

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

where Π_i is the risk premium which depends on the variance of ε_i.

Since W(.) is a monotonically increasing function, the rankings remain unchanged if we focus on $\alpha + \beta S_i^p - \Pi_i$ for our measures of mobility. In this formulation, the risk premium is a sufficient statistic for the influence of family background on intergenerational educational mobility through conditional variance. We discuss below that this approach has some important advantages, and relates intuitively to the standard measures of relative and absolute mobility based on the conditional mean under the assumption of risk neutrality.

We assume a constant relative risk aversion (CRRA) form of the W(.) function with relative risk aversion parameter R. The risk premium can be written as:

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

where $Var(\varepsilon_i) = \sigma_i^2$.[45] Using the conditional variance function equation (2), and denoting an estimated parameter by a hat, we can write an estimate of the risk premium conditional on parent's education as below:

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

Let

$$\Psi_i(S_i^p) = \hat{\alpha} + \hat{\beta} S_i^p - \hat{\Pi}_i(S_i^p) = \hat{\alpha} + \hat{\beta} S_i^p - \frac{1}{2} \frac{\left\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\right\}}{\left(\hat{\alpha} + \hat{\beta} S_i^p\right)} R \tag{7}$$

$\Psi_i(S_i^p)$ 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). 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

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[45]For a derivation of the risk premium formula with a concave payoff function, see, for example, Eeckhoudt et al. (2005). Taylor series approximation of a concave W(.) function around the conditional mean can be used for deriving the risk premium along with the fact that the mean of the residuals is zero, i.e., $E(\hat{\varepsilon}_i) = 0$. Please see online appendix section C.

mobility.

The measure of relative mobility is risk-adjusted IGRC (RIGRC):

$$RIGRC_i = \frac{\partial \Psi}{\partial S_i^p} = \hat{\beta} - \frac{R}{2\left(\hat{\alpha} + \hat{\beta}S_i^p\right)} \left[\hat{\theta}_1 - \frac{\hat{\beta}\left\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\right\}}{\left(\hat{\alpha} + \hat{\beta}S_i^p\right)}\right] \qquad (8)$$

An important advantage of the measures of relative and absolute mobility in equations (7) and (8) is that they are readily comparable to the standard estimates of mobility (they are measured in the same units: years of schooling). A second perhaps more 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 the risk-neutral case, we have $R = 0$, and risk-adjusted relative mobility (RIGRC) from equation (8) becomes:

$$RIGRC_i = \frac{\partial \Psi}{\partial S_i^p} = \hat{\beta}$$

. As noted earlier, $\hat{\beta}$ (IGRC) is the workhorse measure of relative mobility in the existing literature without risk adjustments. Similarly, plugging in $R = 0$ in equation (7) yields the standard conditional mean function which is used for estimating absolute educational mobility without risk adjustments.[46]

To operationalize equations (7) and (8), we need an estimate of the CRRA coefficient R. The existing literature suggests that a CRRA utility function with a risk aversion parameter of 1 is consistent with a variety of evidence (see, for example, Chetty (2006) on the United States, and Gendelman and Hernández-Murillo (2014) for cross-country evidence including many developing countries). We thus set $R = 1$ for our estimation below. We, however, emphasize that the main conclusions below do not depend on this particular value of the coefficient of relative risk aversion.[47] We check the robustness of the conclusions for $R = 1.3, 1.5, 1.7$. The estimates for $R = 1.5$ for our main sample are reported in the online appendix section E.[48] While a CRRA coefficient invariant across countries helps understand the role played by conditional variance, one might prefer to use country and group-specific estimates of the CRRA coefficient when the focus is on interregional and intergroup differences within the

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[46]Note that the measures of risk-adjusted relative and absolute mobility can be applied to intergenerational income mobility, by replacing educational attainment by permanent income of children and parents (usually measured by average income over many years).

[47]In fact, our approach is flexible in the sense that one can use a different model of behavior under risk, but as long as it is feasible to estimate the implied risk premium, the basic approach developed here remains valid.

[48]Estimates for the other values of R are available upon request.

same country.[49]

Since the evidence reported earlier suggests that the influence of father's education on the conditional variance is negative (i.e., $\theta_1 < 0$), the second term in equation (8) is unambiguously *positive*, and the estimate of risk-adjusted relative *immobility* is necessarily *larger* than the standard estimate. The important point here is that the standard conditional mean-based measures thus overestimate the degree of mobility by ignoring the conditional variance function. However, note that the term in brackets can be negative even when $\theta_1 > 0$, for example, when the conditional variance term $\left\{\hat{\theta}_0 + \hat{\theta}_1 S_i^p\right\}$ is large relative to the conditional mean. 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.

(7.1) Estimates of risk-adjusted Measures: Mobility across the Distribution of Father's Education

The standard measure of relative mobility in the workhorse linear model, IGRC, does not vary across the distribution of father's schooling because the slope is constant in this case. 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 function to conditional mean function, given father's education. Figures 1A (China), 1B (India), and 1C (Indonesia) present the graphs of the estimated risk premium as a function of parental education. We present both linear and fractional polynomial plots. The most important finding from these figures is that risk premium is large in the low-educated households, and it declines with father's education, and this pattern holds in all three countries. We thus expect risk adjustments to substantially reduce the estimates of both relative mobility (RIGRC *larger* than the IGRC) and absolute mobility (RES *smaller* than ES) of the disadvantaged children (fathers with little or no schooling).

The estimates of the risk-adjusted relative mobility for the full sample are reported in Table 5 along with the standard estimates for ease of comparison. The corresponding estimates of absolute mobility are in Table 6. Figures 2A (China), 2B (India), and 2C (Indonesia)

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[49]We discuss in section (7.1) substantial evidence that the poor and uneducated are likely to be more risk averse.

present the graphs of RIGRC and IGRC estimates, and the corresponding estimates of absolute mobility: RES ((risk-adjusted expected years of schooling)) and ES (expected years of schooling) are in Figures 3A (China), 3B (India) and 3C (Indonesia). Consistent with the discussion above, the evidence confirms that accounting for risk reveals much worse educational opportunities for the children born to fathers with low or no education. The gap between the 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 and RES. For relative mobility, the canonical IGRC estimate underestimates the influence of family background for this most disadvantaged subgroup of children (i.e., fathers with no schooling) by 35.63 percent in China, 46.58 percent in India, and 20.94 percent in Indonesia. The existing evidence based on IGRC thus is likely to substantially overestimate the educational opportunities of the children of fathers with no schooling.

For absolute mobility, a comparison of the RES estimates with the ES estimates (see Table 6) shows that a failure to take into account the conditional variance channel overestimates the expected years of schooling for this subgroup of children (fathers with no schooling) by 32.49 percent in China, 54.23 percent in India, and 12.77 percent in Indonesia.

A second important conclusion from the evidence in Tables 5 and 6, and Figures 2 and 3 is that, for the children of college educated fathers, the standard (unadjusted) estimates are reasonably close to the risk-adjusted estimates. For both relative and absolute mobility, we cannot reject the null hypothesis of equality of standard and risk-adjusted estimates for the children of college educated fathers in all three countries (at the 10 percent significance level). Evidence thus suggests that the failure to consider the conditional variance channel is of little or no consequence for the children born into highly educated households. These conclusions do not depend on the exact age range chosen to define the estimation sample. In the online appendix section C, we report estimates for 18-35 age cohorts and 22-40 age cohorts.

Note that the estimates in Tables 5 and 6 are based on the assumption that the degree of risk aversion does not vary across households. However, there is growing evidence that risk aversion is affected by education and exposure to natural disasters. The disadvantaged groups are likely to be more risk averse both because of their low education level and more exposure to climate shocks and natural disasters.[50] This implies that the magnitudes of overestimation

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[50]The existing evidence suggests that education level and risk aversion are negatively related (for a survey see Outreville (2015)). There is substantial evidence that exposure to natural disasters makes people more

of educational opportunities of the most disadvantaged children discussed above are likely to be lower bounds.

(7.2) Risk-Adjusted Mobility Measures: Rural-Urban and Sons-Daughters

Evidence on the risk-adjusted vs. standard measures across the distribution of father's schooling for rural vs. urban areas are presented in a series of graphs in Figure 4 (relative mobility) and Figure 5 (absolute mobility). The corresponding graphs for sons vs. daughters are in Figure 6 (relative mobility) and Figure 7 (absolute mobility). Online appendix section D reports the relative mobility estimates for these subgroups, and online appendix section E contains the estimates of absolute mobility. The disaggregated evidence is consistent with the twin conclusions above that the standard measures substantially overestimate the relative and absolute mobility of children born to disadvantaged households with low or no education, while they provide a reliable picture of educational mobility faced by children of highly educated fathers (college or more).

The risk adjustments make a big difference for the rural areas and for the daughters. Evidence suggests that the standard IGRC estimates are likely to considerably underestimate the opportunity gap between rural and urban areas, and also the gender gap between girls and boys. The findings in this subsection are robust to alternative age ranges used to define the estimation sample. Please see online appendix sections D (relative mobility) and E (absolute mobility) for the estimates for 18-35 and 22-40 year age cohorts.

(7.3) Weighted RIGRC: Summary Measures for Comparing Relative Mobility across Countries and Subgroups

Since the risk-adjusted relative mobility varies across the distribution, it does not provide us with a summary statistic which can be easily compared across countries, regions, and different social groups. Such summary measures may be specially useful for policymakers. To this end, we calculate weighted RIGRC using the proportion of children at each level of father's education as weights.

We provide two summary measures: a global summary measure that provides a weighted average of RIGRC estimates across the entire distribution of father's schooling, and a measure for the disadvantaged children focusing on the fathers with less than primary schooling.[51] This

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risk averse; see Maitra et al. (2021) for a survey of the relevant studies.

[51]This is similar to the analysis of Alesina et al. (2021) which also focuses on the educational opportunities of children born to fathers with less than primary schooling.

second measure is conceptually similar to the income mobility measure of Chetty et al. (2014) that focuses on the lower half of the parental income distribution to understand the economic opportunities of the children with disadvantaged socioeconomic background. In our data sets, the proportion of children in this disadvantaged subgroup is 61.21 percent in India, 35 percent in China, and 31 percent in Indonesia. Primary schooling is 6 years in Indonesia and China, and 5 years in India. To ensure consistency across countries, we define disadvantaged children as the children of fathers with 6 years or less schooling in all three countries. All the qualitative conclusions below remain intact when we instead use 5 years as primary schooling cut-off in India.

The estimates of the global measure, i.e., weighted RIGRC across the full distribution of fathers schooling, are reported in odd-numbered columns of Table 7 for our main estimation sample of 18-40 year age cohorts. The first row refers to the estimates at the national level, and the other rows contain the estimates for various subgroups. For ease of comparison, the corresponding standard IGRC estimates are reproduced in the even-numbered columns. The evidence shows that the weighted RIGRC estimates are uniformly larger than the corresponding standard IGRC estimates, and the difference is substantial in magnitude, especially in China and India. For example, the estimates for the national sample in row 1 of Table 7 suggest that the magnitude of underestimation in the standard IGRC estimate is 22.09 percent in China, 28.47 percent in India, and 11.30 percent in Indonesia. The weighted RIGRC estimates confirm the conclusion that a failure to take into account the influence of family background on conditional variance can be especially misleading in understanding the extent of disadvantages faced by daughters and the children growing up in rural areas. The standard IGRC estimates lead to misleading conclusions, suggesting that there is no significant rural-urban gap in educational opportunities in India while the weighted RIGRC estimates reveal that the rural children face substantial disadvantage.

The corresponding weighted estimates for the disadvantaged children, i.e., children of fathers with lower than primary schooling, are reported in Table 8. A comparison of Tables 7 and 8 suggests that the standard measure of relative mobility, IGRC, underestimates the disadvantages faced by the children of less educated fathers dramatically. The extent of underestimation is the largest for the daughters, suggesting that the existing evidence on the gender gap in educational mobility may be painting an overly optimistic picture. For

daughters, the underestimation is 40.39 percent in China, 39.37 percent in India, and 21.18 percent in Indonesia.

Note that unlike income, there is a lump in the schooling distribution of fathers at zero, with 42 percent of children in this subgroup in India, 7 percent in Indonesia, and 31 percent in China. Thus, a policymaker can also focus on the relative mobility of this *most disadvantaged subgroup* using the estimated $RIGRC_0$ in Table 5.

The estimated weighted risk-adjusted relative and absolute mobility for 18-35 and 22-40 year samples of children are reported in online appendix section F. The evidence is consistent with the conclusions reached above based on the 18-40 year children sample.

(8) Conclusions

The existing literature on intergenerational mobility relies on measures of relative and absolute mobility that do not account for risk. We argue that conditional variance is a useful summary measure of children's life-outcome risks, i.e., risks about life-time economic outcomes such as schooling attainment and permanent income (and wealth). We estimate the influence of family background on conditional mean and conditional variance functions jointly using the MLE procedure developed by Western and Bloome (2009) in the context of intergenerational transmission of schooling.

We provide evidence on three large developing countries with 42 percent of world population in 2000 (China, India, and Indonesia) that suggests a strong negative influence of father's education on life-time schooling risks faced by children. There is substantial heterogeneity in the educational risk function (conditional variance function) across countries, gender, and geography (rural/urban). The evidence on the effects of family background on the mean and conditional variance suggests that being born to a more educated father brings in double advantages for children: a lower variance in schooling attainment in addition to higher expected years of schooling.

We develop a methodology to incorporate the influence of family background on children's educational risks along with the standard conditional mean-based estimates of relative and absolute mobility. Exploiting the standard results from the theory of decisions under risk, we adjust the standard measures of intergenerational relative and absolute mobility by an estimate of the risk premium associated with the conditional variance in schooling attainment faced by children at birth. The risk premium is determined by the ratio of conditional variance

27

to conditional mean along with the coefficient of relative risk aversion.

The estimates of the risk-adjusted relative and absolute educational mobility for China, India and Indonesia suggest that the current practice of ignoring the educational risk channel results in considerable overestimation of relative and absolute educational mobility. More important, the magnitude of overestimation in the standard measures is the largest for the most disadvantaged children born into households where fathers have little or no schooling. The standard (but partial) measures widely used in the current literature substantially underestimate the gender gap and rural-urban gap in educational opportunities. The approach developed and implemented in this paper is of wider interest for both the researchers and the policymakers: (i) it can be readily applied to the analysis of intergenerational income mobility; and (ii) facing the challenges of climate change, the policymakers may find the risk-adjusted measures more appropriate for designing policies.

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Table 1. Summary Statistics

	CHINA		INDIA		INDONESIA	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
	Full Sample					
Father's Edu	5.538	4.460	4.640	4.824	6.732	4.141
Children's Edu	8.406	4.301	7.900	4.924	10.476	3.490
Observations	N=45,100		N=70,101		N=15,466	
	Urban					
Father's Edu	6.914	4.534	6.353	5.119	7.524	4.176
Children's Edu	10.645	3.900	9.520	4.657	11.171	3.281
Observations	N=15,203		N=24,424		N=9,486	
	Rural					
Father's Edu	4.838	4.255	3.724	4.392	5.477	3.757
Children's Edu	7.268	4.041	7.034	4.843	9.374	3.529
Observations	N=29,897		N=45,677		N=5,980	
	Sons					
Father's Edu	5.513	4.475	4.746	4.778	6.743	4.204
Children's Edu	8.830	4.069	8.778	4.521	10.485	3.455
Observations	N=21,961		N=36,494		N=7,058	
	Daughters					
Father's Edu	5.561	4.447	4.525	4.870	6.724	4.087
Children's Edu	8.004	4.473	6.947	5.161	10.469	3.520
Observations	N=23,139		N=33,607		N=8,408	

Notes: (1) "Father's Edu" stands for the father's education, and "Children's Edu" stands for the children's education. Both the father's and the children's education are measured in years of schooling. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 2. Conditional Variance and Conditional Mean Functions
Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Father's Edu	0.421***	**-0.618*** **	0.541***	**-0.760*** **	0.406***	**-0.525*** **
	(0.022)	**(0.058)**	(0.005)	**(0.023)**	(0.010)	**(0.036)**
Constant	6.072***	18.385***	5.392***	20.968***	7.743***	12.888***
	(0.232)	(0.704)	(0.052)	(0.157)	(0.124)	(0.436)
Mean of Y	8.406	14.963	7.900	17.441	10.48	9.357
Observations	45,100	45,100	70,101	70,101	15,466	15,466

Notes: (1) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (2) The Conditional Variance and Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (3) "Mean of Y" refers to average years of schooling of children. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 3. Heterogeneity Across Urban vs. Rural and Sons vs. Daughters
Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Urban						
Father's Edu	0.357***	**-0.671*****	0.509***	**-0.922***	0.370***	**-0.557***
	(0.018)	**(0.093)**	(0.007)	**(0.032)**	(0.013)	**(0.040)**
Constant	8.178***	17.227***	6.287***	20.759***	8.385***	12.566***
	(0.206)	(1.048)	(0.088)	(0.305)	(0.148)	(0.474)
Observations	15,203	15,203	24,424	24,424	9,486	9,486
Mean of Y	10.645	12.589	9.520	14.901	11.17	8.372
Rural						
Father's Edu	0.362***	**-0.642***	0.513***	**-0.600***	0.390***	**-0.316***
	(0.024)	**(0.060)**	(0.007)	**(0.034)**	(0.014)	**(0.062)**
Constant	5.516***	17.057***	5.123***	20.611***	7.239***	12.035***
	(0.251)	(0.613)	(0.061)	(0.183)	(0.156)	(0.633)
Observations	29,897	29,897	45,677	45,677	5,980	5,980
Mean of Y	7.268	13.952	7.034	18.376	9.374	10.31
Sons						
Father's Edu	0.379***	**-0.624***	0.485***	**-0.967***	0.386***	**-0.542***
	(0.023)	**(0.077)**	(0.006)	**(0.025)**	(0.012)	**(0.042)**
Constant	6.740***	17.115***	6.475***	19.652***	7.880***	12.955***
	(0.222)	(0.817)	(0.057)	(0.211)	(0.138)	(0.485)
Observations	21,961	21,961	36,494	36,494	7,058	7,058
Mean of Y	8.830	13.675	8.778	15.063	10.48	9.298
Daughters						
Father's Edu	0.463***	**-0.542***	0.590***	**-0.359***	0.423***	**-0.510***
	(0.024)	**(0.061)**	(0.006)	**(0.036)**	(0.012)	**(0.046)**
Constant	5.428***	18.782***	4.276***	19.992***	7.622***	12.826***
	(0.254)	(0.651)	(0.060)	(0.192)	(0.135)	(0.496)
Observations	23,139	23,139	33,607	33,607	8,408	8,408
Mean of Y	8.004	15.768	6.947	18.366	10.47	9.395

Notes: (1) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (2) Each panel reports estimates using the relevant subsample of data. (3) The Conditional Variance and Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (4) "Mean of Y" refers to average years of schooling of children. (5) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 4. Place, Time, and Risk: Conditional Variance Function with Location and Time Fixed Effects
Children of Age 18-40 Years

	(1)	(2)	(3)
Panel A. China			
Father's Edu	-0.618***	-0.398***	-0.296***
	(0.058)	(0.054)	(0.065)
Constant	18.385***	17.168***	16.601***
	(0.704)	(0.301)	(0.359)
Observations	45,100	45,100	45,100
Panel B. India			
Father's Edu	-0.760***	-0.609***	-0.470***
	(0.023)	(0.032)	(0.044)
Constant	20.968***	20.269***	19.710***
	(0.157)	(0.149)	(0.197)
Observations	70,101	70,101	70,101
Panel C. Indonesia			
Father's Edu	-0.525***	-0.403***	-0.355***
	(0.036)	(0.0367)	(0.0467)
Constant	12.89***	12.07***	11.82***
	(0.436)	(0.247)	(0.310)
Observations	15,466	15,466	15,466
Location FE	No	Yes	No
Birth Year FE	No	No	No
Location * Birth Year FE	No	No	Yes

Notes: (1) The dependent variable is conditional variance of children's schooling from estimates in Table 2. (2) The conditional variance function is jointly estimated with the conditional mean function by maximum likelihood estimator of Western and Bloome (2009). (3) Column 1 reproduces the results in Table 2 without any fixed effects. Column 2 includes the location fixed effects (FE) at the Primary Sample Unit (PSU) level. Column 3 includes the fixed effects (FE) for the PSU location interacted with birth year. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 5. Relative Mobility among Children of Age 18-40 Years
Risk-Adjusted Intergenerational Regression Coefficient (RIGRC) versus Intergenerational Regression Coefficient (IGRC)

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
No School	0.571	0.421	0.793	0.541	0.491	0.406
	(0.028)	(0.022)	(0.008)	(0.005)	(0.011)	(0.010)
Primary School	0.497	0.421	0.649	0.541	0.457	0.406
	(0.023)	(0.022)	(0.006)	(0.005)	(0.010)	(0.010)
Junior High	0.480	0.421	0.598	0.541	0.448	0.406
	(0.023)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)
Senior High	0.468	0.421	0.587	0.541	0.441	0.406
	(0.022)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)
College	0.457	0.421	0.574	0.541	0.435	0.406
	(0.022)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)

Notes: (1) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) The RIGRC estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 6. Absolute Mobility among Children of Age 18-40 Years
Risk-Adjusted Expected Schooling (RES) versus Expected Schooling (ES)

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
No School	4.583	6.072	3.496	5.392	6.866	7.743
	(0.279)	(0.232)	(0.071)	(0.052)	(0.136)	(0.124)
Primary School	7.749	8.601	7.030	8.095	9.696	10.179
	(0.141)	(0.128)	(0.043)	(0.037)	(0.078)	(0.075)
Junior High	9.212	9.865	10.130	10.798	11.052	11.397
	(0.115)	(0.107)	(0.038)	(0.037)	(0.062)	(0.061)
Senior High	10.633	11.130	11.315	11.879	12.385	12.615
	(0.128)	(0.124)	(0.042)	(0.042)	(0.059)	(0.062)
College	12.481	12.815	13.055	13.501	14.136	14.239
	(0.184)	(0.187)	(0.050)	(0.052)	(0.076)	(0.083)

Notes: (1) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (2) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 7. Summary Measures of Mobility:
Comparing Weighted Risk-Adjusted IGRC to IGRC
Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC
All	0.514	0.421	0.695	0.541	0.458	0.406
Urban	0.412	0.357	0.604	0.509	0.415	0.370
Rural	0.452	0.362	0.679	0.513	0.442	0.39
Sons	0.453	0.379	0.588	0.485	0.435	0.386
Daughters	0.573	0.463	0.807	0.590	0.479	0.423

Notes: (1) Weighted RIGRC estimates use the proportion of children at each level of father's schooling as the relevant weight. (2) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table 8. Summary Measure of Mobility:
Comparing Weighted Risk-Adjusted IGRC to IGRC
The Disadvantaged Children (Fathers with Less than Primary Schools)

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC
All	0.568	0.421	0.754	0.541	0.492	0.406
Urban	0.440	0.357	0.659	0.509	0.450	0.370
Rural	0.498	0.362	0.726	0.513	0.458	0.390
Sons	0.489	0.379	0.624	0.485	0.468	0.386
Daughters	0.650	0.463	0.899	0.590	0.513	0.423

Notes: (1) Weighted RIGRC estimates use the proportion of children at each level of father's schooling as the relevant weight. (2) The disadvantaged subgroup consists of the lower 35 percent of father's schooling distribution in China, 61 percent in India, and 31 percent in Indonesia. (3) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Figure 1. Risk Premium and Father's Education

Panel A. China

Panel B. India

Panel C. Indonesia
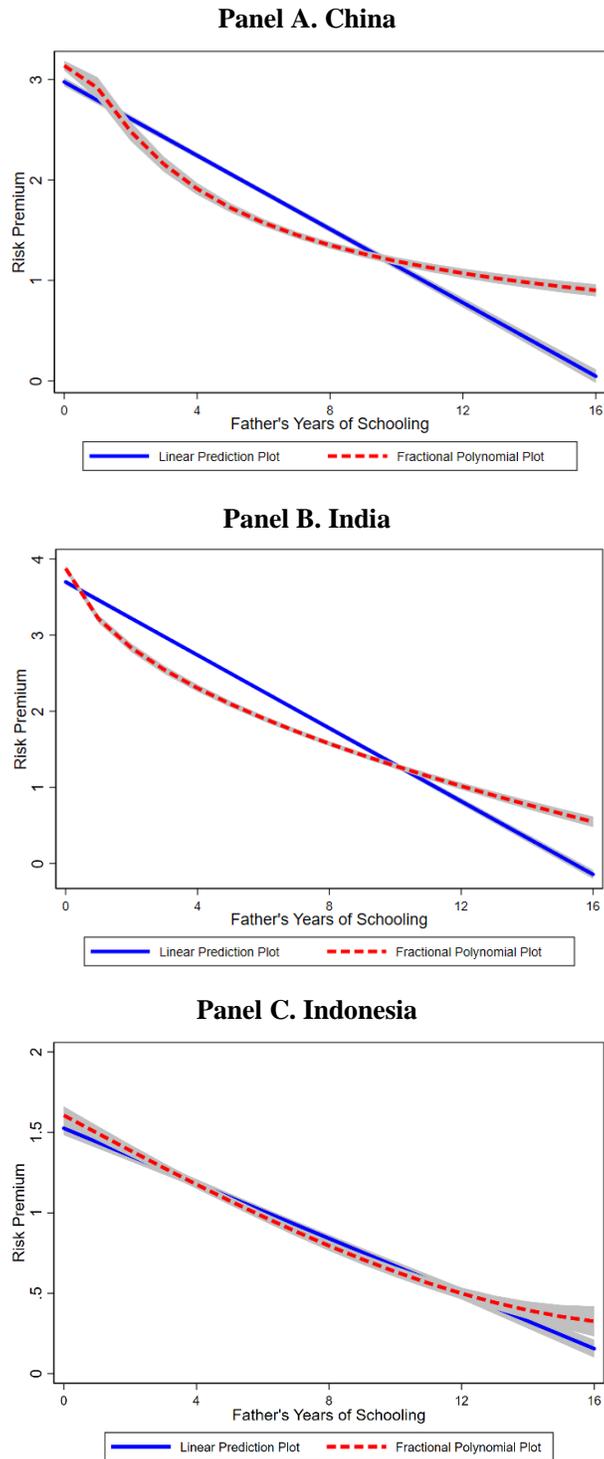
Notes: (1) The risk premium is estimated using equation (6) in the text, assuming a Constant Relative Risk Aversion (CRRA) coefficient, R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) The sample sizes are 45,100 in China, 70,101 in India, and 15,466 in Indonesia, respectively.

Figure 2. Relative Mobility
Risk-Adjusted Intergenerational Regression Coefficient (RIGRC) versus Intergenerational Regression Coefficient (IGRC)

Panel A. China
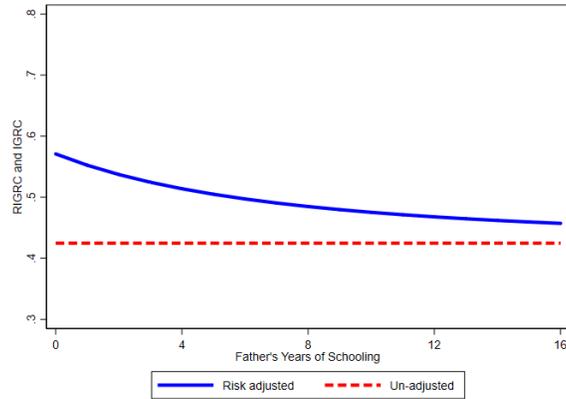
Panel B. India
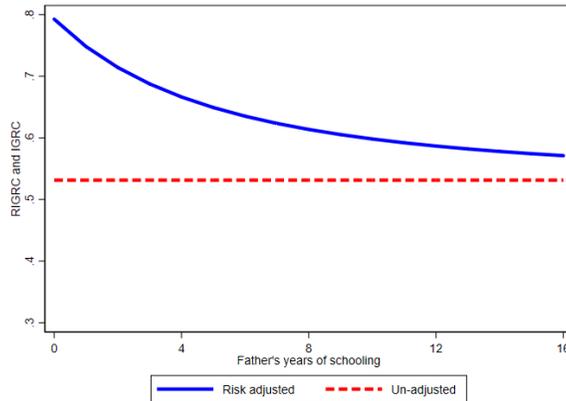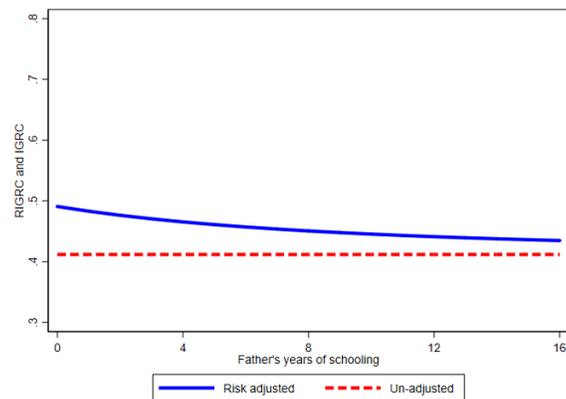
Panel C. Indonesia

Notes: (1) The risk adjusted intergenerational regression coefficient (RIGRC) is estimated using equation (8) in the text assuming that the CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) The sample sizes are 45,100 in China, 70,101 in India, and 15,466 in Indonesia, respectively.

Figure 3. Absolute Mobility
Risk-Adjusted Expected Schooling (RES) versus Expected Schooling (ES)
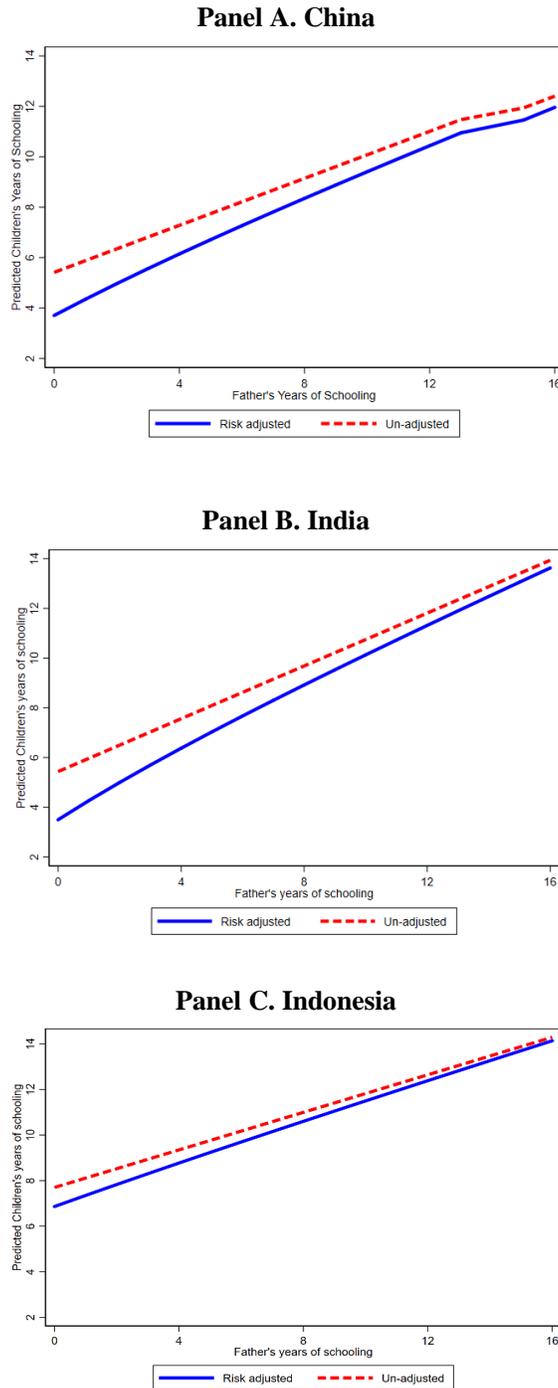
Panel A. China

Panel B. India

Panel C. Indonesia

Notes: (1) Risk adjusted expected schooling (RES) is estimates using equation (7) in the main text assuming a CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) The sample sizes are 45,100 in China, 70,101 in India, and 15,466 in Indonesia, respectively.

Figure 4. Relative Mobility: Urban versus Rural Areas

Panel A. Urban Areas

Panel B. Rural Areas

Notes: (1) The risk adjusted intergenerational regression coefficient (RIGRC) is estimated using equation (8) in the text assuming that the CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) In Panel A, the sample sizes are 15,203 in urban China, 24,424 in urban India, and 9,486 in urban Indonesia, respectively. In Panel B, the sample sizes are 29,897 in rural China, 45,677 in rural India, and 5,980 in rural Indonesia, respectively.

Figure 5. Absolute Mobility: Urban versus Rural Areas
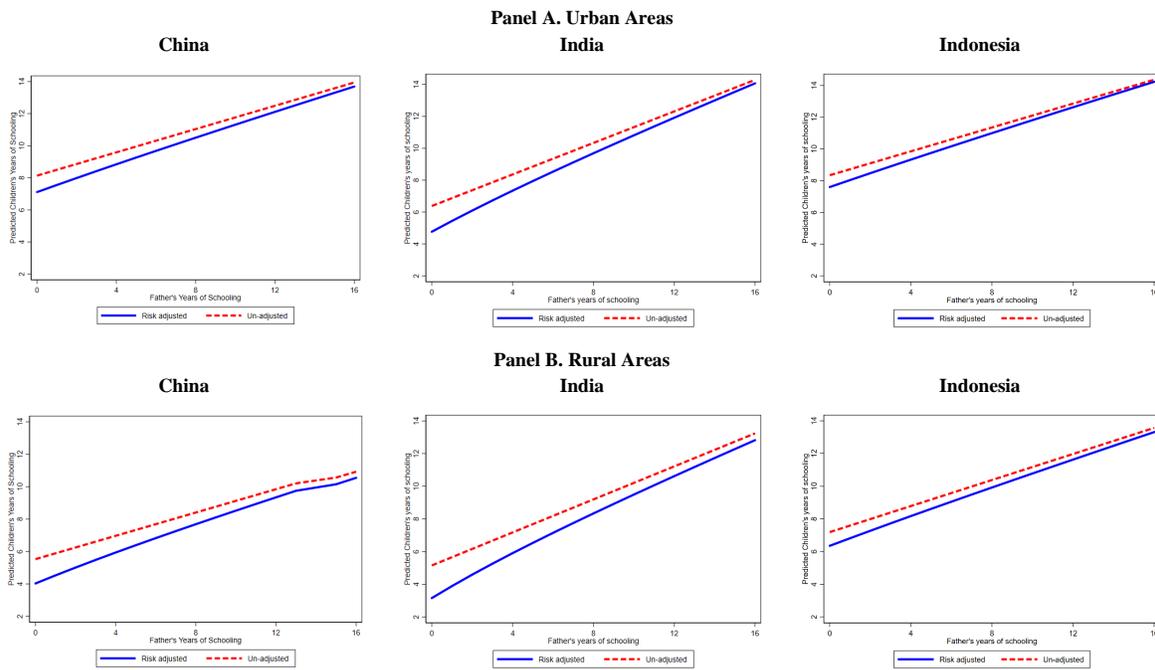
Panel A. Urban Areas

Panel B. Rural Areas

Notes: (1) Risk adjusted expected schooling (RES) is estimates using equation (7) in the main text assuming a CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) In Panel A, the sample sizes are 15,203 in urban China, 24,424 in urban India, and 9,486 in urban Indonesia, respectively. In Panel B, the sample sizes are 29,897 in rural China, 45,677 in rural India, and 5,980 in rural Indonesia, respectively.

Figure 6. Relative Mobility: Sons versus Daughters

Panel A. Sons

China   **India**   **Indonesia**

Panel B. Daughters

China   **India**   **Indonesia**

Notes: (1) The risk adjusted intergenerational regression coefficient (RIGRC) is estimated using equation (8) in the text assuming that the CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) In Panel A, the sample sizes are 21,961 among sons in China, 36,494 among sons in India, and 7,058 among sons in Indonesia, respectively. In Panel B, the sample sizes are 23,139 among daughters in China, 33,607 among daughters in India, and 8,408 among daughters in Indonesia, respectively.

Figure 7. Absolute Mobility: Sons versus Daughters

Panel A. Sons

Notes: (1) Risk adjusted expected schooling (RES) is estimates using equation (7) in the main text assuming a CRRA coefficient R=1. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) In Panel A, the sample sizes are 21,961 among sons in China, 36,494 among sons in India, and 7,058 among sons in Indonesia, respectively. In Panel B, the sample sizes are 23,139 among daughters in China, 33,607 among daughters in India, and 8,408 among daughters in Indonesia, respectively.

NOT FOR PUBLICATION

ONLINE APPENDIX TO:

Opportunity and Risk

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Appendix Section A. Conditional Mean and Conditional Variance Functions: Robustness Checks

Section AI. Alternative Age Ranges

Table A1 Conditional Variance and Conditional Mean Functions
Alternative Age Ranges for Children

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var
	Panel A. Age 18-35 Years					
Father's Edu	0.419***	-0.729***	0.519***	-0.812***	0.384***	-0.553***
	(0.030)	(0.086)	(0.006)	(0.024)	(0.011)	(0.038)
Constant	6.346***	18.789***	5.728***	20.666***	8.017***	12.773***
	(0.299)	(0.946)	(0.057)	(0.179)	(0.135)	(0.473)
Observations	29,548	29,548	56,994	56,994	12,419	12,419
Mean of Y	8.925	14.306	8.274	16.682	10.66	8.976
	Panel B. Age 22-40 Years					
Father's Edu	0.424***	-0.528***	0.570***	-0.585***	0.435***	-0.476***
	(0.022)	(0.056)	(0.006)	(0.029)	(0.011)	(0.042)
Constant	6.002***	18.440***	5.015***	20.943***	7.550***	13.092***
	(0.227)	(0.678)	(0.053)	(0.168)	(0.126)	(0.462)
Observations	40,292	40,292	55,007	55,007	13,192	13,192
Mean of Y	8.278	15.608	7.511	18.382	10.39	9.979

Notes: (1) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (2) The Conditional Variance and Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (3) "Mean of Y" refers to average years of schooling of children. (4) The data include children aged between 18 and 35 years in Panel A and children aged between 22 and 40 years in Panel B, respectively, which are obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A2. Heterogeneity Across Urban vs. Rural and Sons vs. Daughters
Children of Age 18-35 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Urban						
Father's Edu	0.339***	-0.699***	0.494***	-0.951***	0.351***	-0.577***
	(0.024)	(0.127)	(0.008)	(0.035)	(0.013)	(0.043)
Constant	8.644***	17.001***	6.546***	20.389***	8.620***	12.403***
	(0.268)	(1.403)	(0.099)	(0.347)	(0.156)	(0.521)
Observations	9,600	9,600	19,742	19,742	7,583	7,583
Mean of $\bar{Y}$	11.216	11.692	9.835	14.055	11.31	7.968
Rural						
Father's Edu	0.364***	-0.771***	0.490***	-0.679***	0.371***	-0.358***
	(0.033)	(0.088)	(0.007)	(0.035)	(0.015)	(0.067)
Constant	5.837***	17.632***	5.499***	20.406***	7.548***	12.044***
	(0.326)	(0.878)	(0.067)	(0.205)	(0.175)	(0.696)
Observations	19,948	19,948	37,252	37,252	4,836	4,836
Mean of $\bar{Y}$	7.822	13.423	7.447	17.707	9.625	10.04
Sons						
Father's Edu	0.382***	-0.703***	0.468***	-0.944***	0.367***	-0.583***
	(0.029)	(0.104)	(0.006)	(0.028)	(0.013)	(0.046)
Constant	6.925***	17.389***	6.665***	19.056***	8.112***	12.998***
	(0.282)	(1.040)	(0.062)	(0.239)	(0.150)	(0.540)
Observations	14,250	14,250	30,131	30,131	5,593	5,593
Mean of $\bar{Y}$	9.269	13.080	9.004	14.341	10.64	8.976
Daughters						
Father's Edu	0.455***	-0.700***	0.567***	-0.518***	0.400***	-0.531***
	(0.032)	(0.084)	(0.007)	(0.036)	(0.013)	(0.048)
Constant	5.797***	19.495***	4.730***	20.561***	7.933***	12.596***
	(0.328)	(0.908)	(0.068)	(0.208)	(0.149)	(0.531)
Observations	15,298	15,298	26,863	26,863	6,826	6,826
Mean of $\bar{Y}$	8.604	15.175	7.454	18.074	10.67	8.966

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (3) The Conditional Variance and Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (4) "Mean of Y" refers to average years of schooling of children. (5) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A3. Heterogeneity Across Urban vs. Rural and Sons vs. Daughters
Children of Age 22-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Urban						
Father's Edu	0.368***	-0.647***	0.539***	-0.833***	0.404***	-0.528***
	(0.019)	(0.097)	(0.008)	(0.038)	(0.014)	(0.048)
Constant	8.138***	17.459***	5.997***	21.040***	8.169***	12.797***
	(0.208)	(1.094)	(0.091)	(0.323)	(0.156)	(0.525)
Observations	13,894	13,894	19,296	19,296	8,002	8,002
Mean of Y	10.626	13.088	9.280	15.969	11.11	8.953
Rural						
Father's Edu	0.349***	-0.566***	0.532***	-0.355***	0.408***	-0.240***
	(0.023)	(0.059)	(0.008)	(0.042)	(0.016)	(0.071)
Constant	5.429***	16.943***	4.716***	20.347***	7.082***	12.199***
	(0.245)	(0.568)	(0.062)	(0.198)	(0.158)	(0.665)
Observations	26,398	26,398	35,711	35,711	5,190	5,190
Mean of Y	7.042	14.323	6.555	19.121	9.278	10.91
Sons						
Father's Edu	0.383***	-0.547***	0.520***	-0.934***	0.414***	-0.486***
	(0.022)	(0.074)	(0.006)	(0.030)	(0.014)	(0.050)
Constant	6.700***	17.223***	6.221***	20.298***	7.717***	13.068***
	(0.218)	(0.798)	(0.060)	(0.226)	(0.141)	(0.511)
Observations	19,500	19,500	28,316	28,316	6,031	6,031
Mean of Y	8.735	14.317	8.569	16.085	10.42	9.899
Daughters						
Father's Edu	0.466***	-0.440***	0.608***	-0.050	0.453***	-0.467***
	(0.023)	(0.063)	(0.007)	(0.043)	(0.013)	(0.053)
Constant	5.328***	18.714***	3.810***	18.827***	7.405***	13.090***
	(0.251)	(0.636)	(0.062)	(0.217)	(0.141)	(0.537)
Observations	20,792	20,792	26,691	26,691	7,161	7,161
Mean of Y	7.849	16.334	6.389	18.616	10.37	10.03

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (3) The Conditional Variance and Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (4) "Mean of Y" refers to average years of schooling of children. (5) The data include children aged between 22 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Section AII. Quadratic Conditional Mean Function and Nonparametric Plots (Binscatter)

Table A4. Conditional Variance and Quadratic Conditional Mean Function
Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Father's Edu	0.371***	-0.619***	0.648***	-0.763***	0.335***	-0.523***
	(0.046)	(0.060)	(0.013)	(0.023)	(0.027)	(0.036)
Father's Edu Squared	0.004*		-0.009***		0.005***	
	(0.002)		(0.001)		(0.001)	
Constant	6.128***	18.383***	5.291***	20.946***	7.924***	12.868***
	(0.255)	(0.721)	(0.053)	(0.157)	(0.142)	(0.436)
Observations	45,100	45,100	70,101	70,101	15,466	15,466
Mean of Y	8.406	14.956	7.900	17.441	10.48	9.357

Notes: (1) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (2) The Conditional Variance and Quadratic Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (3) "Mean of Y" refers to average years of schooling of children. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A5. Conditional Variance and Quadratic Conditional Mean Function
Alternative Age Ranges

	CHINA		INDIA		INDONESIA	
	Yrs Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Panel A. Age 18-35 Years						
Father's Edu	0.378***	-0.730***	0.620***	-0.815***	0.293***	-0.550***
	(0.065)	(0.088)	(0.015)	(0.024)	(0.030)	(0.038)
Father's Edu Squared	0.004		-0.008***		0.006***	
	(0.003)		(0.001)		(0.002)	
Constant	6.398***	18.789***	5.626***	20.652***	8.255***	12.740***
	(0.339)	(0.969)	(0.060)	(0.179)	(0.160)	(0.473)
Observations	29,548	29,548	56,994	56,994	12,419	12,419
Mean of Y	8.925	14.301	8.274	16.652	10.66	8.960
Panel B. Age 22-40 Years						
Father's Edu	0.352***	-0.531***	0.648***	-0.584***	0.342***	-0.476***
	(0.044)	(0.058)	(0.015)	(0.028)	(0.030)	(0.042)
Father's Edu Squared	0.006***		-0.006***		0.006***	
	(0.002)		(0.001)		(0.002)	
Constant	6.079***	18.440***	4.947***	20.925***	7.783***	13.074***
	(0.249)	(0.700)	(0.054)	(0.168)	(0.148)	(0.463)
Observations	40,292	40,292	55,007	55,007	13,192	13,192
Mean of Y	8.278	15.593	7.511	18.365	10.39	9.963

Notes: (1) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (2) The Conditional Variance and Quadratic Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (3) "Mean of Y" refers to average years of schooling of children. (4) The data include children aged between 18 and 35 years in Panel A and children aged between 22 and 40 years in Panel B, respectively, which are obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A6. Heterogeneity Across Urban vs. Rural
Quadratic Conditional Mean Function, Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Urban						
Father's Edu	0.296***	-0.669***	0.624***	-0.926***	0.309***	-0.556***
	(0.037)	(0.095)	(0.021)	(0.032)	(0.036)	(0.040)
Father's Edu Squared	0.005**		-0.009***		0.004**	
	(0.002)		(0.001)		(0.002)	
Constant	8.281***	17.201***	6.124***	20.741***	8.562***	12.553***
	(0.229)	(1.070)	(0.093)	(0.303)	(0.189)	(0.479)
Observations	15,203	15,203	24,424	24,424	9,486	9,486
Mean of Y	10.645	12.579	9.520	14.860	11.17	8.366
Rural						
Father's Edu	0.425***	-0.648***	0.649***	-0.606***	0.262***	-0.322***
	(0.053)	(0.058)	(0.018)	(0.034)	(0.034)	(0.063)
Father's Edu Squared	-0.006*		-0.012***		0.010***	
	(0.003)		(0.001)		(0.002)	
Constant	5.465***	17.079***	5.025***	20.585***	7.515***	12.036***
	(0.267)	(0.595)	(0.062)	(0.183)	(0.174)	(0.628)
Observations	29,897	29,897	45,677	45,677	5,980	5,980
Mean of Y	7.268	13.943	7.034	18.329	9.374	10.27

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (3) The Conditional Variance and Quadratic Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (4) "Mean of Y" refers to average years of schooling of children. (5) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A7. Heterogeneity Across Sons vs. Daughters
Quadratic Conditional Mean Function, Children of Age 18-40 Years

	CHINA		INDIA		INDONESIA	
	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.	Yrs. Sch.	Cond. Var.
Sons						
Father's Edu	0.316***	-0.626***	0.558***	-0.971***	0.323***	-0.541***
	(0.048)	(0.079)	(0.016)	(0.025)	(0.032)	(0.042)
Father's Edu Squared	0.006**		-0.006***		0.004**	
	(0.003)		(0.001)		(0.002)	
Constant	6.809***	17.116***	6.400***	19.657***	8.040***	12.935***
	(0.247)	(0.839)	(0.061)	(0.209)	(0.163)	(0.484)
Observations	21,961	21,961	36,494	36,494	7,058	7,058
Mean of Y	8.830	13.663	8.778	15.047	10.48	9.290
Daughters						
Father's Edu	0.429***	-0.542***	0.689***	-0.361***	0.346***	-0.509***
	(0.048)	(0.062)	(0.017)	(0.035)	(0.035)	(0.046)
Father's Edu Squared	0.003		-0.008***		0.005***	
	(0.003)		(0.001)		(0.002)	
Constant	5.466***	18.781***	4.193***	19.970***	7.823***	12.807***
	(0.276)	(0.662)	(0.060)	(0.193)	(0.164)	(0.497)
Observations	23,139	23,139	33,607	33,607	8,408	8,408
Mean of Y	8.004	15.764	6.947	18.338	10.47	9.384

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "Yrs. Sch." stands for years of schooling of children, and "Cond. Var." is short for the conditional variance of children's schooling. (3) The Conditional Variance and Quadratic Conditional Mean Functions are estimated jointly by maximum likelihood estimator of Western and Bloome (2009). (4) "Mean of Y" refers to average years of schooling of children. (5) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Figure A1. Conditional Variance and Conditional Mean Functions based on Binscatter Method

Panel A. China
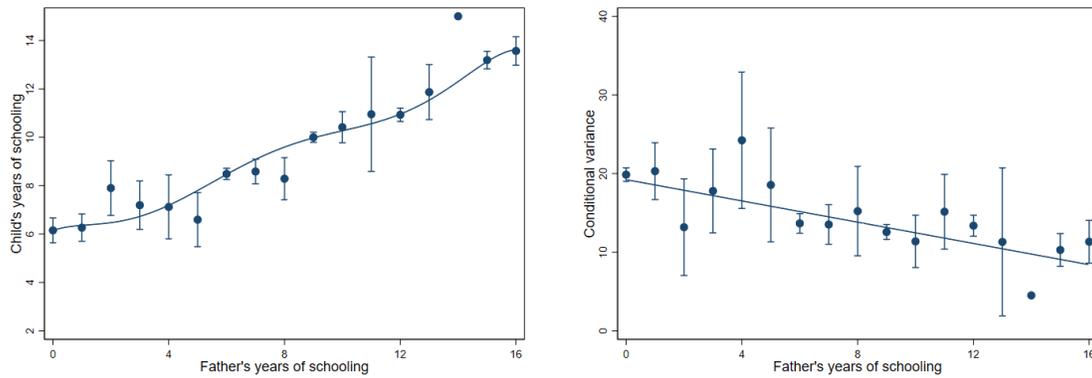
Panel B. India
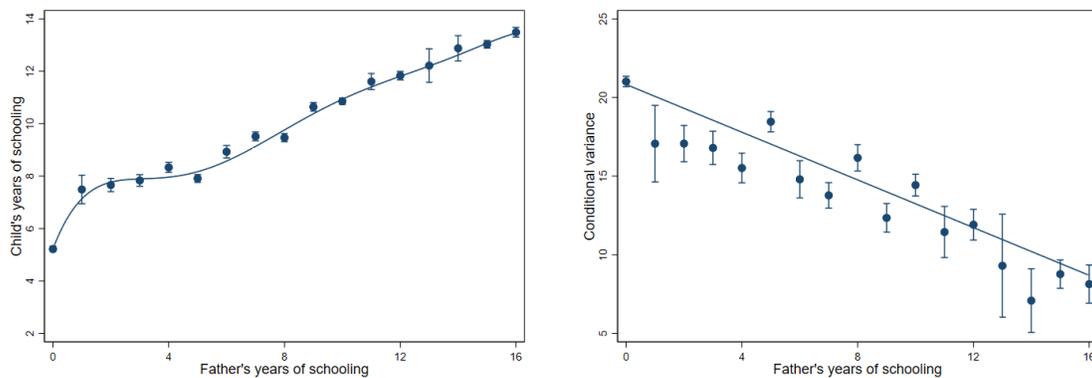
Panel C. Indonesia
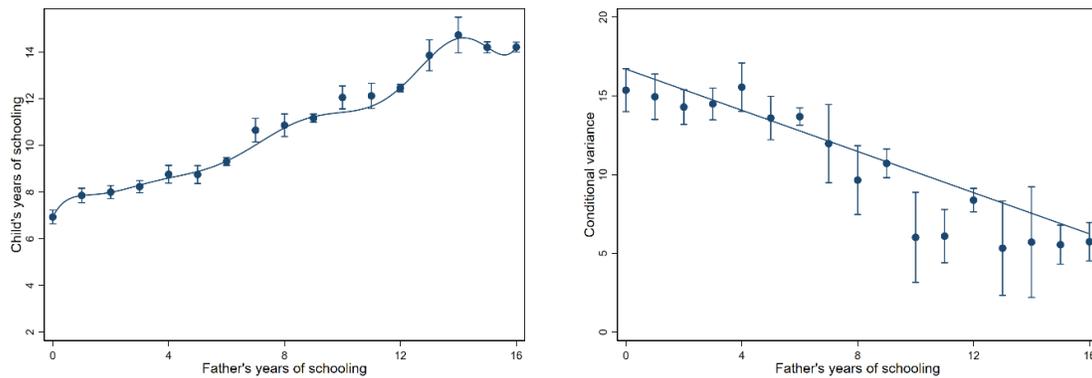
Notes: (1) Each panel presents the conditional mean and conditional variance function based on the binscatter method in each specified country. (2) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia. (3) The sample sizes are 45,100 in China, 70,101 in India, and 15,466 in Indonesia, respectively.

Section AIII. The Role of Children's Cognitive Ability Heterogeneity: Evidence from Indonesia

Table A8. Conditional Variance and Conditional Mean Functions in Indonesia
Adding Ability Controls, Children of Age 18-40 Years

	Yrs. Sch.	Cond. Var.
Full Sample		
Father's Edu	0.406***	-0.455***
	(0.010)	(0.034)
Constant	7.743***	11.242***
	(0.124)	(0.367)
Observations	15,466	15,466
Mean of Y	10.48	9.357
Urban		
Father's Edu	0.370***	-0.504***
	(0.013)	(0.038)
Constant	8.385***	11.418***
	(0.148)	(0.439)
Observations	9,486	9,486
Mean of Y	11.17	8.372
Rural		
Father's Edu	0.390***	-0.256***
	(0.014)	(0.062)
Constant	7.239***	10.178***
	(0.156)	(0.572)
Observations	5,980	5,980
Mean of Y	9.374	10.31
Sons		
Father's Edu	0.386***	-0.482***
	(0.012)	(0.042)
Constant	7.880***	11.327***
	(0.138)	(0.410)
Observations	7,058	7,058
Mean of Y	10.48	9.298
Daughters		
Father's Edu	0.423***	-0.433***
	(0.012)	(0.045)
Constant	7.622***	11.180***
	(0.135)	(0.468)
Observations	8,408	8,408
Mean of Y	10.47	9.395

Notes: (1) The regressions include 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. (2) The data include children aged between 18 and 40 years, obtained from the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A9. Conditional Variance and Conditional Mean Functions in Indonesia
Adding Ability Controls, Children of Age 18-35 Years

	Yrs. Sch.	Cond. Var.
	Full Sample	
Father's Edu	0.384***	-0.487***
	(0.011)	(0.035)
Constant	8.017***	11.159***
	(0.135)	(0.399)
Observations	12,419	12,419
Mean of Y	10.66	8.976
	Urban	
Father's Edu	0.351***	-0.527***
	(0.013)	(0.041)
Constant	8.620***	11.204***
	(0.156)	(0.492)
Observations	7,583	7,583
Mean of Y	11.31	7.968
	Rural	
Father's Edu	0.371***	-0.300***
	(0.015)	(0.066)
Constant	7.548***	10.264***
	(0.175)	(0.623)
Observations	4,836	4,836
Mean of Y	9.625	10.04
	Sons	
Father's Edu	0.367***	-0.517***
	(0.013)	(0.045)
Constant	8.112***	11.267***
	(0.150)	(0.461)
Observations	5,593	5,593
Mean of Y	10.64	8.976
	Daughters	
Father's Edu	0.400***	-0.466***
	(0.013)	(0.047)
Constant	7.933***	11.086***
	(0.149)	(0.510)
Observations	6,826	6,826
Mean of Y	10.67	8.966

Notes: (1) The regressions include 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. (2) The data include children aged between 18 and 35 years, obtained from the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table A10. Conditional Variance and Conditional Mean Functions in Indonesia
Adding Ability Controls, Children of Age 22-40 Years

|	Yrs. Sch.	Cond. Var.
	Full Sample	
Father's Edu	0.435***	-0.404***
	(0.011)	(0.040)
Constant	7.550***	11.478***
	(0.126)	(0.402)
Observations	13,192	13,192
Mean of Y	10.39	9.979
	Urban	
Father's Edu	0.404***	-0.469***
	(0.014)	(0.046)
Constant	8.169***	11.688***
	(0.156)	(0.493)
Observations	8,002	8,002
Mean of Y	11.11	8.953
	Rural	
Father's Edu	0.408***	-0.185***
	(0.016)	(0.071)
Constant	7.082***	10.382***
	(0.158)	(0.623)
Observations	5,190	5,190
Mean of Y	9.278	10.91
	Sons	
Father's Edu	0.414***	-0.423***
	(0.014)	(0.052)
Constant	7.717***	11.459***
	(0.141)	(0.470)
Observations	6,031	6,031
Mean of Y	10.42	9.899
	Daughters	
Father's Edu	0.453***	-0.388***
	(0.013)	(0.053)
Constant	7.405***	11.496***
	(0.141)	(0.512)
Observations	7,161	7,161
Mean of Y	10.37	10.03

Notes: (1) The regressions include 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. (2) The data include children aged between 22 and 40 years, obtained from the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Appendix Section B. Place, Time, and Risk: Robustness Checks

Table B1. Place, Time, and Risk: Conditional Variance Function with Location and Time Fixed Effects
Children of Age 18-35 Years

	(1)	(2)	(3)
Panel A. China			
Father's Edu	-0.729***	-0.443***	-0.352***
	(0.086)	(0.063)	(0.070)
Constant	18.789***	17.030***	16.479***
	(0.946)	(0.388)	(0.431)
Observations	29,548	29,548	29,548
Panel B. India			
Father's Edu	-0.812***	-0.621***	-0.501***
	(0.024)	(0.033)	(0.045)
Constant	20.666***	19.727***	19.225***
	(0.179)	(0.164)	(0.215)
Observations	56,994	56,994	56,994
Panel C. Indonesia			
Father's Edu	-0.553***	-0.418***	-0.356***
	(0.0379)	(0.0391)	(0.0466)
Constant	12.77***	11.85***	11.48***
	(0.473)	(0.269)	(0.315)
Observations	12,419	12,419	12,419
Location FE	No	Yes	No
Birth Year FE	No	No	No
Location * Birth Year FE	No	No	Yes

Notes: (1) The dependent variable is conditional variance of children's schooling from estimates in Table 2. (2) The conditional variance function is jointly estimated with the conditional mean function by maximum likelihood estimator of Western and Bloome (2009). (3) Column 1 reproduces the results in Table 2 without any fixed effects. Column 2 includes the location fixed effects (FE) at the Primary Sample Unit (PSU) level. Column 3 includes the fixed effects (FE) for the PSU location interacted with birth year. (4) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table B2. Place, Time, and Risk: Conditional Variance Function with Location and Time Fixed Effects
Children of Age 22-40 Years

	(1)	(2)	(3)
Panel A. China			
Father's Edu	-0.528***	-0.310***	-0.260***
	(0.056)	(0.060)	(0.071)
Constant	18.440***	17.268***	17.001***
	(0.678)	(0.324)	(0.378)
Observations	40,292	40,292	40,292
Panel B. India			
Father's Edu	-0.585***	-0.454***	-0.342***
	(0.029)	(0.040)	(0.053)
Constant	20.943***	20.368***	20.008***
	(0.168)	(0.174)	(0.225)
Observations	55,007	55,007	55,007
Panel C. Indonesia			
Father's Edu	-0.476***	-0.340***	-0.344***
	(0.0416)	(0.0447)	(0.0564)
Constant	13.09***	12.20***	12.29***
	(0.462)	(0.292)	(0.363)
Observations	13,192	13,192	13,192
Location FE	No	Yes	No
Birth Year FE	No	No	No
Location * Birth Year FE	No	No	Yes

Notes: (1) The dependent variable is conditional variance of children's schooling from estimates in Table 2. (2) The conditional variance function is jointly estimated with the conditional mean function by maximum likelihood estimator of Western and Bloome (2009). (3) Column 1 reproduces the results in Table 2 without any fixed effects. Column 2 includes the location fixed effects (FE) at the Primary Sample Unit (PSU) level. Column 3 includes the fixed effects (FE) for the PSU location interacted with birth year. (4) The data include children aged between 22 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

ONLINE APPENDIX SECTION C:
DERIVATION OF THE RISK PREMIUM FORMULA

$$EW\left(\hat{\alpha} + \hat{\beta}S_i^p + \hat{\epsilon}_i\right) = W\left(\hat{\alpha} + \hat{\beta}S_i^p - \Pi_i\right) \tag{1}$$

Taking second order Taylor series expansion around the conditional mean, we get the following for the LHS:

$$EW\left(\hat{\alpha} + \hat{\beta}S_i^p + \hat{\epsilon}_i\right) \simeq W\left(\hat{\alpha} + \hat{\beta}S_i^p\right) + W'\left(\hat{\alpha} + \hat{\beta}S_i^p\right)E\left(\hat{\epsilon}_i\right) + \frac{1}{2}W''\left(\hat{\alpha} + \hat{\beta}S_i^p\right)E\left(\hat{\epsilon}_i^2\right)$$
$$\simeq W\left(\hat{\alpha} + \hat{\beta}S_i^p\right) + \frac{1}{2}W''\left(\hat{\alpha} + \hat{\beta}S_i^p\right)E\left(\hat{\epsilon}_i^2\right) \tag{2}$$

The second line in equation (2) follows from the fact that $E\left(\hat{\epsilon}_i\right) = 0$.

Taking first order Taylor series expansion, the RHS is:

$$W\left(\hat{\alpha} + \hat{\beta}S_i^p - \Pi_i\right) \simeq W\left(\hat{\alpha} + \hat{\beta}S_i^p\right) - \Pi_i W'\left(\hat{\alpha} + \hat{\beta}S_i^p\right) \tag{3}$$

Using equations (2) and (3) in equation 1, we get:

$$\Pi_i \simeq -\frac{1}{2}\frac{W''\left(\hat{\alpha} + \hat{\beta}S_i^p\right)}{W'\left(\hat{\alpha} + \hat{\beta}S_i^p\right)}E\left(\hat{\epsilon}_i^2\right) = \frac{1}{2}\left(\frac{\sigma_i^2}{\hat{\alpha} + \hat{\beta}S_i^p}\right)\left[\left(\hat{\alpha} + \hat{\beta}S_i^p\right)\frac{-W''\left(\hat{\alpha} + \hat{\beta}S_i^p\right)}{W'\left(\hat{\alpha} + \hat{\beta}S_i^p\right)}\right] \tag{4}$$

Now note that the term in bracket is the coefficient of constant relative risk aversion (CRRA). We denote the coefficient of CRRA by R, then we have:

$$\Pi_i \simeq \frac{1}{2}\left(\frac{\hat{\sigma}_i^2}{\hat{\alpha} + \hat{\beta}S_i^p}\right)R \tag{5}$$

Using the conditional variance equation:

$$\hat{\sigma}_i^2 = \hat{\theta}_0 + \hat{\theta}_1 S_i^p \tag{6}$$

Combining equations (5) and (6):

$$\Pi_i\left(S_i^p\right) \simeq \frac{1}{2}\left(\frac{\hat{\theta}_0 + \hat{\theta}_1 S_i^p}{\hat{\alpha} + \hat{\beta}S_i^p}\right)R \tag{7}$$

Appendix Section D. Risk-Adjusted Relative Mobility: Robustness and Heterogeneity

Table D1. Relative Mobility among Children of Age 18-35 Years
Risk-Adjusted Intergenerational Regression Coefficient (RIGRC) versus Intergenerational Regression Coefficient (IGRC)

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
No School	0.563	0.419	0.736	0.519	0.465	0.384
	(0.035)	(0.030)	(0.008)	(0.006)	(0.012)	(0.011)
Primary School	0.494	0.419	0.619	0.519	0.435	0.384
	(0.030)	(0.030)	(0.006)	(0.006)	(0.011)	(0.011)
Junior High	0.477	0.419	0.573	0.519	0.427	0.384
	(0.029)	(0.030)	(0.006)	(0.006)	(0.011)	(0.011)
Senior High	0.466	0.419	0.563	0.519	0.421	0.384
	(0.028)	(0.030)	(0.005)	(0.006)	(0.011)	(0.011)
College	0.455	0.419	0.551	0.519	0.415	0.384
	(0.028)	(0.030)	(0.005)	(0.006)	(0.010)	(0.011)

Notes: (1) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) The RIGRC estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D2. Relative Mobility among Children of Age 22-40 Years
Risk-Adjusted Intergenerational Regression Coefficient (RIGRC) versus Intergenerational Regression Coefficient (IGRC)

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
No School	0.574	0.424	0.863	0.570	0.530	0.435
	(0.028)	(0.022)	(0.010)	(0.006)	(0.012)	(0.011)
Primary School	0.500	0.424	0.687	0.570	0.490	0.435
	(0.023)	(0.022)	(0.006)	(0.006)	(0.011)	(0.011)
Junior High	0.482	0.424	0.631	0.570	0.480	0.435
	(0.023)	(0.022)	(0.006)	(0.006)	(0.011)	(0.011)
Senior High	0.470	0.424	0.619	0.570	0.473	0.435
	(0.022)	(0.022)	(0.006)	(0.006)	(0.011)	(0.011)
College	0.460	0.424	0.607	0.570	0.466	0.435
	(0.022)	(0.022)	(0.006)	(0.006)	(0.011)	(0.011)

Notes: (1) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) The RIGRC estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D3. Alternative Values for the Coefficient of Constant Relative Risk Aversion
Relative Mobility among Children of Age 18-40 Years, R=1.5

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
No School	0.644	0.421	0.923	0.541	0.530	0.406
	(0.032)	(0.022)	(0.010)	(0.005)	(0.012)	(0.010)
Primary School	0.533	0.421	0.708	0.541	0.480	0.406
	(0.025)	(0.022)	(0.006)	(0.005)	(0.011)	(0.010)
Junior High	0.507	0.421	0.632	0.541	0.466	0.406
	(0.023)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)
Senior High	0.489	0.421	0.614	0.541	0.456	0.406
	(0.023)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)
College	0.473	0.421	0.596	0.541	0.446	0.406
	(0.022)	(0.022)	(0.005)	(0.005)	(0.010)	(0.010)

Notes: (1) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text with R=1.5. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D4. Relative Mobility across Urban vs. Rural Areas
Children of Age 18-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
Urban						
No School	0.441	0.357	0.690	0.509	0.442	0.370
	(0.020)	(0.018)	(0.010)	(0.007)	(0.013)	(0.013)
Primary School	0.411	0.357	0.596	0.509	0.417	0.370
	(0.019)	(0.018)	(0.008)	(0.007)	(0.012)	(0.013)
Junior High	0.402	0.357	0.556	0.509	0.409	0.370
	(0.018)	(0.018)	(0.007)	(0.007)	(0.012)	(0.013)
Senior High	0.395	0.357	0.547	0.509	0.404	0.370
	(0.018)	(0.018)	(0.007)	(0.007)	(0.012)	(0.013)
College	0.389	0.357	0.536	0.509	0.398	0.370
	(0.018)	(0.018)	(0.007)	(0.007)	(0.012)	(0.013)
Rural						
No School	0.500	0.362	0.760	0.513	0.467	0.390
	(0.032)	(0.024)	(0.011)	(0.007)	(0.016)	(0.014)
Primary School	0.432	0.362	0.620	0.513	0.437	0.390
	(0.026)	(0.024)	(0.008)	(0.007)	(0.015)	(0.014)
Junior High	0.415	0.362	0.570	0.513	0.429	0.390
	(0.025)	(0.024)	(0.007)	(0.007)	(0.014)	(0.014)
Senior High	0.403	0.362	0.559	0.513	0.423	0.390
	(0.025)	(0.024)	(0.007)	(0.007)	(0.014)	(0.014)
College	0.394	0.362	0.547	0.513	0.418	0.390
	(0.024)	(0.024)	(0.007)	(0.007)	(0.014)	(0.014)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D5. Relative Mobility across Urban vs. Rural Areas
Children of Age 18-35 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
Urban						
No School	0.423	0.339	0.651	0.494	0.420	0.351
	(0.024)	(0.024)	(0.011)	(0.008)	(0.013)	(0.013)
Primary School	0.396	0.339	0.571	0.494	0.398	0.351
	(0.022)	(0.024)	(0.009)	(0.008)	(0.012)	(0.013)
Junior High	0.388	0.339	0.536	0.494	0.391	0.351
	(0.022)	(0.024)	(0.008)	(0.008)	(0.012)	(0.013)
Senior High	0.382	0.339	0.527	0.494	0.386	0.351
	(0.022)	(0.024)	(0.008)	(0.008)	(0.012)	(0.013)
College	0.375	0.339	0.517	0.494	0.381	0.351
	(0.022)	(0.024)	(0.008)	(0.008)	(0.012)	(0.013)
Rural						
No School	0.492	0.364	0.701	0.490	0.445	0.371
	(0.040)	(0.033)	(0.011)	(0.007)	(0.017)	(0.015)
Primary School	0.429	0.364	0.588	0.490	0.419	0.371
	(0.034)	(0.033)	(0.008)	(0.007)	(0.016)	(0.015)
Junior High	0.413	0.364	0.544	0.490	0.412	0.371
	(0.033)	(0.033)	(0.008)	(0.007)	(0.015)	(0.015)
Senior High	0.402	0.364	0.534	0.490	0.406	0.371
	(0.033)	(0.033)	(0.007)	(0.007)	(0.015)	(0.015)
College	0.394	0.364	0.523	0.490	0.401	0.371
	(0.032)	(0.033)	(0.007)	(0.007)	(0.015)	(0.015)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D6. Relative Mobility across Urban vs. Rural Areas
Children of Age 22-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
Urban						
No School	0.458	0.368	0.755	0.539	0.487	0.404
	(0.021)	(0.019)	(0.012)	(0.008)	(0.014)	(0.014)
Primary School	0.425	0.368	0.639	0.539	0.456	0.404
	(0.019)	(0.019)	(0.009)	(0.008)	(0.013)	(0.014)
Junior High	0.416	0.368	0.594	0.539	0.448	0.404
	(0.019)	(0.019)	(0.008)	(0.008)	(0.013)	(0.014)
Senior High	0.409	0.368	0.583	0.539	0.441	0.404
	(0.019)	(0.019)	(0.008)	(0.008)	(0.013)	(0.014)
College	0.402	0.368	0.572	0.539	0.435	0.404
	(0.019)	(0.019)	(0.008)	(0.008)	(0.013)	(0.014)
Rural						
No School	0.485	0.349	0.808	0.532	0.485	0.408
	(0.030)	(0.023)	(0.013)	(0.008)	(0.018)	(0.016)
Primary School	0.419	0.349	0.644	0.532	0.454	0.408
	(0.025)	(0.023)	(0.009)	(0.008)	(0.017)	(0.016)
Junior High	0.402	0.349	0.591	0.532	0.445	0.408
	(0.024)	(0.023)	(0.008)	(0.008)	(0.016)	(0.016)
Senior High	0.391	0.349	0.580	0.532	0.440	0.408
	(0.024)	(0.023)	(0.008)	(0.008)	(0.016)	(0.016)
College	0.382	0.349	0.568	0.532	0.434	0.408
	(0.023)	(0.023)	(0.008)	(0.008)	(0.016)	(0.016)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 22 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D7. Relative Mobility across Sons vs. Daughters
Children of Age 18-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
	Sons					
No School	0.491	0.379	0.647	0.485	0.464	0.386
	(0.026)	(0.023)	(0.007)	(0.006)	(0.013)	(0.012)
Primary School	0.443	0.379	0.567	0.485	0.434	0.386
	(0.023)	(0.023)	(0.006)	(0.006)	(0.012)	(0.012)
Junior High	0.430	0.379	0.532	0.485	0.426	0.386
	(0.023)	(0.023)	(0.006)	(0.006)	(0.012)	(0.012)
Senior High	0.421	0.379	0.523	0.485	0.419	0.386
	(0.022)	(0.023)	(0.006)	(0.006)	(0.012)	(0.012)
College	0.413	0.379	0.513	0.485	0.414	0.386
	(0.022)	(0.023)	(0.006)	(0.006)	(0.012)	(0.012)
	Daughters					
No School	0.655	0.463	0.957	0.590	0.516	0.423
	(0.034)	(0.024)	(0.014)	(0.006)	(0.013)	(0.012)
Primary School	0.548	0.463	0.717	0.590	0.478	0.423
	(0.025)	(0.024)	(0.008)	(0.006)	(0.012)	(0.012)
Junior High	0.525	0.463	0.653	0.590	0.468	0.423
	(0.024)	(0.024)	(0.007)	(0.006)	(0.012)	(0.012)
Senior High	0.511	0.463	0.640	0.590	0.461	0.423
	(0.024)	(0.024)	(0.007)	(0.006)	(0.011)	(0.012)
College	0.501	0.463	0.627	0.590	0.454	0.423
	(0.023)	(0.024)	(0.006)	(0.006)	(0.011)	(0.012)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D8. Relative Mobility across Sons vs. Daughters
Children of Age 18-35 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
	Sons					
No School	0.492	0.382	0.613	0.468	0.440	0.367
	(0.032)	(0.029)	(0.008)	(0.006)	(0.014)	(0.013)
Primary School	0.446	0.382	0.544	0.468	0.414	0.367
	(0.029)	(0.029)	(0.006)	(0.006)	(0.013)	(0.013)
Junior High	0.434	0.382	0.512	0.468	0.407	0.367
	(0.028)	(0.029)	(0.006)	(0.006)	(0.013)	(0.013)
Senior High	0.425	0.382	0.504	0.468	0.401	0.367
	(0.028)	(0.029)	(0.006)	(0.006)	(0.012)	(0.013)
College	0.416	0.382	0.495	0.468	0.395	0.367
	(0.027)	(0.029)	(0.006)	(0.006)	(0.012)	(0.013)
	Daughters					
No School	0.636	0.455	0.882	0.567	0.488	0.400
	(0.041)	(0.032)	(0.013)	(0.007)	(0.014)	(0.013)
Primary School	0.539	0.455	0.688	0.567	0.455	0.400
	(0.033)	(0.032)	(0.008)	(0.007)	(0.013)	(0.013)
Junior High	0.518	0.455	0.629	0.567	0.446	0.400
	(0.032)	(0.032)	(0.007)	(0.007)	(0.012)	(0.013)
Senior High	0.504	0.455	0.617	0.567	0.439	0.400
	(0.031)	(0.032)	(0.007)	(0.007)	(0.012)	(0.013)
College	0.494	0.455	0.604	0.567	0.433	0.400
	(0.030)	(0.032)	(0.007)	(0.007)	(0.012)	(0.013)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 35 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table D9. Relative Mobility across Sons vs. Daughters
Children of Age 22-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RIGRC	IGRC	RIGRC	IGRC	RIGRC	IGRC
Sons						
No School	0.495	0.388	0.714	0.520	0.501	0.414
	(0.026)	(0.021)	(0.009)	(0.006)	(0.015)	(0.014)
Primary School	0.447	0.388	0.614	0.520	0.467	0.414
	(0.023)	(0.021)	(0.007)	(0.006)	(0.014)	(0.014)
Junior High	0.434	0.388	0.573	0.520	0.457	0.414
	(0.023)	(0.021)	(0.006)	(0.006)	(0.013)	(0.014)
Senior High	0.425	0.388	0.564	0.520	0.451	0.414
	(0.022)	(0.021)	(0.006)	(0.006)	(0.013)	(0.014)
College	0.417	0.388	0.553	0.520	0.445	0.414
	(0.022)	(0.021)	(0.006)	(0.006)	(0.013)	(0.014)
Daughters						
No School	0.658	0.466	1.011	0.608	0.556	0.453
	(0.034)	(0.023)	(0.018)	(0.007)	(0.014)	(0.013)
Primary School	0.550	0.466	0.733	0.608	0.511	0.453
	(0.025)	(0.023)	(0.009)	(0.007)	(0.013)	(0.013)
Junior High	0.528	0.466	0.668	0.608	0.500	0.453
	(0.024)	(0.023)	(0.008)	(0.007)	(0.013)	(0.013)
Senior High	0.513	0.466	0.655	0.608	0.492	0.453
	(0.024)	(0.023)	(0.008)	(0.007)	(0.012)	(0.013)
College	0.504	0.466	0.643	0.608	0.485	0.453
	(0.023)	(0.023)	(0.007)	(0.007)	(0.012)	(0.013)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RIGRC" refers to the Risk-Adjusted Intergenerational Regression Coefficient, and "IGRC" is short for the Intergenerational Regression Coefficient from a linear conditional mean function. (2) RIGRC estimates are based on equation (8) in the main text. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 22 and 40 years, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Appendix Section E. Risk-Adjusted Absolute Mobility: Robustness and Heterogeneity

Table E1: Absolute Mobility among Children of Age 18-35 Years
Risk-Adjusted Expected Schooling (RES) versus Expected Schooling (ES)

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
No School	4.915	6.346	3.991	5.728	7.170	8.017
	(0.349)	(0.299)	(0.076)	(0.057)	(0.144)	(0.135)
Primary School	8.052	8.861	7.325	8.323	9.859	10.322
	(0.161)	(0.148)	(0.045)	(0.040)	(0.083)	(0.080)
Junior High	9.508	10.119	10.289	10.919	11.152	11.475
	(0.117)	(0.109)	(0.038)	(0.037)	(0.063)	(0.062)
Senior High	10.922	11.376	11.425	11.957	12.424	12.628
	(0.132)	(0.132)	(0.042)	(0.042)	(0.057)	(0.060)
College	12.763	13.053	13.095	13.514	14.095	14.165
	(0.210)	(0.221)	(0.050)	(0.053)	(0.074)	(0.083)

Notes: (1) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (2) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 35, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E2: Absolute Mobility among Children of Age 22-40 Years
Risk-Adjusted Expected Schooling (RES) versus Expected Schooling (ES)

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
No School	4.475	6.002	2.937	5.015	6.608	7.550
	(0.278)	(0.227)	(0.077)	(0.053)	(0.140)	(0.126)
Primary School	7.657	8.548	6.716	7.865	9.649	10.159
	(0.147)	(0.133)	(0.046)	(0.040)	(0.082)	(0.078)
Junior High	9.128	9.822	9.991	10.714	11.103	11.463
	(0.126)	(0.117)	(0.046)	(0.044)	(0.069)	(0.068)
Senior High	10.556	11.095	11.242	11.854	12.531	12.768
	(0.141)	(0.135)	(0.051)	(0.050)	(0.071)	(0.074)
College	12.415	12.793	13.079	13.563	14.407	14.507
	(0.196)	(0.195)	(0.062)	(0.062)	(0.093)	(0.100)

Notes: (1) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (2) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 22 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E3: Alternative Values for the Coefficient of Constant Relative Risk Aversion
Absolute Mobility among Children of Age 18-40 Years, R=1.5

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
No School	3.848	6.072	2.527	5.392	6.447	7.743
	(0.307)	(0.232)	(0.081)	(0.052)	(0.143)	(0.124)
Primary School	7.322	8.601	6.499	8.095	9.457	10.179
	(0.148)	(0.128)	(0.046)	(0.037)	(0.080)	(0.075)
Junior High	8.880	9.865	9.822	10.798	10.874	11.397
	(0.119)	(0.107)	(0.040)	(0.037)	(0.063)	(0.061)
Senior High	10.373	11.130	11.067	11.879	12.255	12.615
	(0.131)	(0.124)	(0.043)	(0.042)	(0.059)	(0.062)
College	12.297	12.815	12.880	13.501	14.058	14.239
	(0.187)	(0.187)	(0.051)	(0.052)	(0.077)	(0.083)

Notes: (1) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (2) Risk-adjusted absolute mobility estimates are based on equation 7 in the main text with R=1.5. (3) Standard errors are reported in parenthesis. (4) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E4. Absolute Mobility across Urban vs. Rural Areas
Children of Age 18-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
	Urban					
No School	7.135	8.178	4.767	6.287	7.599	8.385
	(0.225)	(0.206)	(0.112)	(0.088)	(0.156)	(0.148)
Primary School	9.682	10.319	7.942	8.831	10.165	10.607
	(0.127)	(0.120)	(0.066)	(0.059)	(0.087)	(0.084)
Junior High	10.901	11.389	10.810	11.376	11.403	11.718
	(0.103)	(0.099)	(0.045)	(0.044)	(0.065)	(0.063)
Senior High	12.097	12.459	11.912	12.394	12.622	12.829
	(0.107)	(0.105)	(0.045)	(0.046)	(0.058)	(0.062)
College	13.665	13.886	13.535	13.920	14.225	14.310
	(0.147)	(0.150)	(0.053)	(0.057)	(0.079)	(0.089)
	Rural					
No School	4.055	5.516	3.152	5.123	6.355	7.239
	(0.313)	(0.251)	(0.085)	(0.061)	(0.175)	(0.156)
Primary School	6.818	7.689	6.532	7.689	9.053	9.577
	(0.141)	(0.125)	(0.055)	(0.048)	(0.116)	(0.110)
Junior High	8.086	8.775	9.490	10.254	10.351	10.747
	(0.098)	(0.089)	(0.059)	(0.056)	(0.109)	(0.106)
Senior High	9.312	9.861	10.619	11.281	11.628	11.916
	(0.108)	(0.106)	(0.066)	(0.064)	(0.120)	(0.117)
College	10.507	10.948	12.277	12.820	13.308	13.475
	(0.155)	(0.159)	(0.080)	(0.079)	(0.151)	(0.151)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E5. Absolute Mobility across Urban vs. Rural Areas
Children of Age 18-35 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
Urban						
No School	7.617	8.644	5.163	6.546	7.849	8.620
	(0.278)	(0.268)	(0.122)	(0.099)	(0.161)	(0.156)
Primary School	10.068	10.676	8.187	9.014	10.296	10.724
	(0.150)	(0.145)	(0.071)	(0.064)	(0.090)	(0.087)
Junior High	11.244	11.692	10.943	11.483	11.480	11.775
	(0.109)	(0.105)	(0.046)	(0.045)	(0.065)	(0.064)
Senior High	12.399	12.708	12.006	12.470	12.645	12.827
	(0.104)	(0.107)	(0.045)	(0.046)	(0.057)	(0.060)
College	13.912	14.062	13.571	13.951	14.178	14.229
	(0.150)	(0.167)	(0.054)	(0.058)	(0.078)	(0.090)
Rural						
No School	4.470	5.837	3.697	5.499	6.693	7.548
	(0.393)	(0.326)	(0.091)	(0.067)	(0.193)	(0.175)
Primary School	7.204	8.020	6.869	7.949	9.275	9.777
	(0.164)	(0.147)	(0.058)	(0.050)	(0.127)	(0.121)
Junior High	8.467	9.111	9.685	10.399	10.520	10.891
	(0.103)	(0.094)	(0.059)	(0.056)	(0.116)	(0.113)
Senior High	9.689	10.203	10.762	11.379	11.747	12.006
	(0.124)	(0.125)	(0.066)	(0.065)	(0.124)	(0.123)
College	10.882	11.294	12.346	12.850	13.360	13.492
	(0.196)	(0.205)	(0.080)	(0.081)	(0.156)	(0.157)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 18 and 35, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E6. Absolute Mobility across Urban vs. Rural Areas
Children of Age 22-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
Urban						
No School	7.053	8.138	4.298	5.997	7.309	8.169
	(0.229)	(0.208)	(0.120)	(0.091)	(0.165)	(0.156)
Primary School	9.690	10.346	7.730	8.693	10.128	10.595
	(0.129)	(0.122)	(0.070)	(0.061)	(0.092)	(0.089)
Junior High	10.951	11.450	10.796	11.388	11.483	11.808
	(0.107)	(0.102)	(0.051)	(0.050)	(0.071)	(0.070)
Senior High	12.188	12.554	11.973	12.466	12.816	13.021
	(0.115)	(0.112)	(0.053)	(0.054)	(0.070)	(0.074)
College	13.809	14.027	13.704	14.083	14.569	14.639
	(0.158)	(0.159)	(0.064)	(0.066)	(0.097)	(0.107)
Rural						
No School	3.931	5.429	2.574	4.716	6.168	7.082
	(0.309)	(0.245)	(0.092)	(0.062)	(0.179)	(0.158)
Primary School	6.609	7.521	6.113	7.377	8.971	9.530
	(0.146)	(0.129)	(0.061)	(0.051)	(0.121)	(0.114)
Junior High	7.839	8.567	9.180	10.039	10.318	10.754
	(0.107)	(0.097)	(0.072)	(0.066)	(0.122)	(0.117)
Senior High	9.026	9.613	10.350	11.103	11.645	11.977
	(0.113)	(0.109)	(0.082)	(0.077)	(0.141)	(0.137)
College	10.185	10.660	12.070	12.700	13.392	13.609
	(0.155)	(0.155)	(0.099)	(0.096)	(0.182)	(0.180)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 22 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E7. Absolute Mobility across Sons vs. Daughters
Children of Age 18-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
Sons						
No School	5.494	6.740	5.065	6.475	7.038	7.880
	(0.253)	(0.222)	(0.070)	(0.057)	(0.150)	(0.138)
Primary School	8.275	9.015	8.069	8.901	9.721	10.198
	(0.125)	(0.115)	(0.041)	(0.037)	(0.085)	(0.081)
Junior High	9.585	10.152	10.805	11.326	11.010	11.357
	(0.101)	(0.094)	(0.034)	(0.034)	(0.068)	(0.066)
Senior High	10.862	11.290	11.860	12.297	12.277	12.515
	(0.120)	(0.118)	(0.038)	(0.039)	(0.070)	(0.070)
College	12.530	12.806	13.414	13.752	13.942	14.060
	(0.181)	(0.186)	(0.048)	(0.052)	(0.095)	(0.100)
Daughters						
No School	3.719	5.428	1.934	4.276	6.707	7.622
	(0.327)	(0.254)	(0.096)	(0.060)	(0.149)	(0.135)
Primary School	7.261	8.207	5.968	7.228	9.674	10.163
	(0.166)	(0.149)	(0.058)	(0.049)	(0.084)	(0.080)
Junior High	8.868	9.596	9.366	10.179	11.093	11.433
	(0.137)	(0.126)	(0.059)	(0.055)	(0.067)	(0.067)
Senior High	10.422	10.986	10.658	11.360	12.486	12.703
	(0.147)	(0.141)	(0.065)	(0.062)	(0.065)	(0.070)
College	11.939	12.375	12.557	13.131	14.315	14.397
	(0.186)	(0.183)	(0.077)	(0.074)	(0.087)	(0.098)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 18 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E8. Absolute Mobility across Sons vs. Daughters
Children of Age 18-35 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
Sons						
No School	5.713	6.925	5.350	6.665	7.295	8.112
	(0.314)	(0.282)	(0.075)	(0.062)	(0.158)	(0.150)
Primary School	8.508	9.218	8.215	9.006	9.850	10.311
	(0.143)	(0.134)	(0.043)	(0.039)	(0.090)	(0.087)
Junior High	9.827	10.364	10.846	11.347	11.081	11.411
	(0.103)	(0.096)	(0.035)	(0.035)	(0.072)	(0.069)
Senior High	11.113	11.511	11.862	12.283	12.291	12.510
	(0.124)	(0.124)	(0.039)	(0.041)	(0.072)	(0.073)
College	12.795	13.039	13.361	13.688	13.883	13.976
	(0.205)	(0.216)	(0.050)	(0.054)	(0.098)	(0.105)
Daughters						
No School	4.164	5.797	2.562	4.730	7.050	7.933
	(0.404)	(0.328)	(0.102)	(0.068)	(0.162)	(0.149)
Primary School	7.634	8.528	6.377	7.566	9.866	10.332
	(0.188)	(0.170)	(0.060)	(0.051)	(0.091)	(0.087)
Junior High	9.218	9.893	9.647	10.403	11.216	11.531
	(0.140)	(0.129)	(0.058)	(0.055)	(0.069)	(0.069)
Senior High	10.749	11.258	10.892	11.538	12.544	12.730
	(0.152)	(0.149)	(0.064)	(0.062)	(0.065)	(0.070)
College	12.245	12.624	12.721	13.240	14.288	14.330
	(0.208)	(0.214)	(0.076)	(0.075)	(0.088)	(0.100)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 18 and 35, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table E9. Absolute Mobility across Sons vs. Daughters
Children of Age 22-40 Years

Father's Edu	CHINA		INDIA		INDONESIA	
	RES	ES	RES	ES	RES	ES
Sons						
No School	5.425	6.700	4.658	6.221	6.815	7.717
	(0.253)	(0.218)	(0.076)	(0.060)	(0.155)	(0.141)
Primary School	8.227	8.999	7.934	8.823	9.702	10.204
	(0.129)	(0.118)	(0.044)	(0.039)	(0.088)	(0.084)
Junior High	9.547	10.149	10.888	11.425	11.087	11.447
	(0.110)	(0.103)	(0.040)	(0.040)	(0.077)	(0.075)
Senior High	10.834	11.298	12.024	12.466	12.449	12.690
	(0.131)	(0.127)	(0.046)	(0.047)	(0.086)	(0.086)
College	12.517	12.831	13.698	14.028	14.239	14.348
	(0.193)	(0.194)	(0.058)	(0.061)	(0.119)	(0.122)
Daughters						
No School	3.578	5.328	1.336	3.810	6.425	7.405
	(0.328)	(0.251)	(0.105)	(0.062)	(0.158)	(0.141)
Primary School	7.135	8.123	5.496	6.851	9.603	10.120
	(0.174)	(0.155)	(0.065)	(0.053)	(0.089)	(0.085)
Junior High	8.748	9.521	8.967	9.893	11.118	11.478
	(0.150)	(0.137)	(0.072)	(0.065)	(0.074)	(0.074)
Senior High	10.308	10.919	10.290	11.109	12.604	12.835
	(0.162)	(0.153)	(0.081)	(0.074)	(0.077)	(0.082)
College	11.832	12.317	12.236	12.934	14.556	14.646
	(0.200)	(0.194)	(0.096)	(0.090)	(0.104)	(0.115)

Notes: (1) Each panel reports estimates using the relevant subsample of data. (2) "RES" refers to the Risk-Adjusted Expected Schooling, and "ES" refers to the Expected Schooling from a linear conditional mean function. (3) Risk-adjusted absolute mobility estimates are based on the conditional mean and conditional variance function estimates in Table 2. (4) Standard errors are reported in parenthesis. (5) The data include children aged between 22 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Appendix Section F. Weighted Risk-Adjusted IGRC

Table F1: Summary Measures of Mobility:
Comparing Weighted Risk-Adjusted IGRC to IGRC
Children of Age 18-35 Years

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC
All	0.504	0.419	0.651	0.519	0.436	0.384
Urban	0.395	0.339	0.574	0.494	0.396	0.351
Rural	0.443	0.364	0.631	0.490	0.423	0.371
Sons	0.452	0.382	0.559	0.468	0.414	0.367
Daughters	0.554	0.455	0.751	0.567	0.455	0.400

Notes: (1) Weighted RIGRC estimates use the proportion of children at each level of father's schooling as the relevant weight. (2) The data include children aged between 18 and 35, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Table F2: Summary Measures of Mobility:
Comparing Weighted Risk-Adjusted IGRC to IGRC
Children of Age 22-40 Years

	CHINA		INDIA		INDONESIA	
	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC	Weighted RIGRC	IGRC
All	0.518	0.424	0.751	0.570	0.492	0.435
Urban	0.427	0.368	0.654	0.539	0.455	0.404
Rural	0.440	0.349	0.721	0.532	0.459	0.408
Sons	0.458	0.383	0.645	0.520	0.468	0.414
Daughters	0.577	0.466	0.850	0.608	0.513	0.453

Notes: (1) Weighted RIGRC estimates use the proportion of children at each level of father's schooling as the relevant weight. (2) The data include children aged between 22 and 40, obtained from the China Family Panel Survey (CFPS) 2010 round for China, the Indian Human Development Survey (IHDS) 2012 round for India, and the Indonesian Family Life Survey (IFLS) 2014 round for Indonesia.

Appendix Section G: Data Description and Sample Construction

Section GI. Data Appendix: China

The China Family Panel Survey (CFPS) is a nationally representative survey of launched in 2010 by the Institute of Social Science Survey of Peking University, China. This survey is designed to collect individual-, family-, and community-level data in contemporary China, focusing on the economic and non-economic, wellbeing of the Chinese population. In the 2010 baseline survey, the CFPS interviewed almost 15000 families and almost 30000 individuals within these families, covering 25 provinces (including municipalities and autonomous regions) and representing 95% of the entire population in China. For a more detailed discussion, please see Xie, Yu, Xiaobo Zhang, Ping Tu, Qiang Ren, Yan Sun, Ping Lv, Hua Ding, Jingwei Hu, and Qiong Wu, ``CFPS China Family Panel Studies User's Manual (3rd edition)," 2017.

The CFPS is well suitable for intergenerational mobility studies in China due to its unique T-tables design, which allows for identifying a complete family network and avoiding the co-residence bias.

Specifically, the T-tables design contains three tables: T1, T2, and T3, all of which appear at the beginning of the family roster questionnaire. The T1 table provides information about the co-resident family members, which is standard in most household surveys. The T3 table provides information on the immediate relatives who are not co-resident, which is a key feature of this T-tables design. The T2 table connects T1 and T3 tables, which identifies the relation of all the family members.

T1: The Table on Family Members Living Together

Personal Code	Name	DOB	Sex	Marital status	Highest degree	Main job	Admin/Managerial position	Info on people outside home

T2: The Table on the Relations of Parents, Spouse, and Children

Personal Code	Name	Father	Mother	Spouse	Child 1	Child 2	…	Child 10

T3: The Table on Parents, Spouse, and Children Not Living Together

Personal Code	Name	DOB	Sex	Marital status	Highest degree	Main job	Admin/Managerial position	Info on people outside home

Notes: reproduced from Figure 10 in Xie et al (2017)

Section GII. Data Appendix: India

The India Human Development Survey (IHDS) is a high quality nationally representative household panel survey of about 40000 households with two rounds in 2005 and 2012. This survey is a collaborative project between University of Maryland and National Council for Applied Economic Research (NCAER) in India. The second wave of IHDS - IHDS 2012 - has a number of important advantages that makes it unique for intergenerational mobility studies in India.

First, it includes a nonresident family members module, which is critical to avoid sample truncation bias due to coresidency criteria used in surveys to define family membership . The non-resident family members module provides information on both demographics and education of non-resident family members. In particular, this module includes children studying outside the household, and spouse who lives outside the household. Therefore, we are able to match non-resident children of a household head with his/her father, and match children with his/her non-resident father of female household heads. The only limitation of this module is the lack of information on the female household head's spouse who has passed away.

Second, it collected education information on the nonresident father of the household head based on the following question: Question 1.18c *And how many standards/years of education had he completed?* Such information is not available in many other Indian household surveys such as National Sample Survey (NSS) or National Family Health Survey (NFHS).

The first two features discussed above help us to generate matched son-father pairs for our mobility analysis based on a two-step procedure. In the first step, we follow Azam and Bhatt (2015) (cited in the main text) and obtain household head's father's education information directly from the household module, irrespective of a father's residency status. In the second step, we follow Emran, Jiang, and Shilpi (2021) (cited in the main text) and include non-resident children from the nonresident family members module.

In order to generate matched daughter-father pairs, we rely on another advantage of the IHDS 2012 and follow Azam (2016) closely. Specifically, the IHDS 2012 adds an ``eligible women'' module that collected parental education information on two ever married women of age 15-49, including daughters-in-laws in a household. This allows us to capture a random sample of women missing from their natal family because of marriage. In addition, we also add the daughters from the nonresident module, similar to what we do for the sons from the nonresident module.

Section GIII. Data Appendix: Indonesia

The Indonesian Family Life Survey (IFLS) is an ongoing longitudinal survey. So far five waves have been fielded. The first wave was fielded in 1993, and the second, third, fourth and fifth waves were fielded in 1997, 2000, 2007 and 2014, respectively. At the time of the first wave, 7224 households were interviewed and it represented 83% of the national population of Indonesia covering 13 out of the 27 provinces. In the subsequent waves, the sample size grew because others joined the sampled households either through marriage and births. An appealing feature of the IFLS is its low-attrition rate. For extended discussions on the IFLS survey, please see Frankenberg et al. (1995) and Strauss et al. (1996).

Below we provide detailed discussion the sample selection and how the data structure allows us to avoid co-residency issue: As noted in the data section of the manuscript, our primary mobility sample is based on children who are 18 to 40 years old in 2014. This is done to ensure comparability across the three countries. These individuals were in school at some point during 1990s and 2000s. An important advantage of the IFLS survey is that we can get the required information for children irrespective of whether a child was coresident at the household in the survey year (2014). We take advantage of two features of the data to find the schooling information

about the father-child pairs for the children who were nonresident in 2014. First, we can find a child from earlier rounds of the survey if he/she left the household in the last 21 years. Second, we can use the nonresident module to find nonresident parents and children in 2014. We obtain the information on children's years of schooling first from the individual education module (book 3A) in IFLS-5. If we are unable to locate the schooling information in book 3A, we use the household roster (book K) to obtain the schooling data of the remainder of the children.

Next, we obtain a respondent's father's years of schooling. We take advantage of three strands of data to extract father's schooling of these 18-40 year-old children. We explain the steps below:

First, we identify if any of the 18-40 year-old children reside in the same household as their parents in IFLS-5. These children are co-resident children in our sample. In each wave, the IFLS provides the identification link of co-resident parents. Using that identification link, we obtain the father's schooling from the household roster.

Second, if 18-40 year-old children are not residing in the same household as their parents in 2014, these children are non-resident in 2014. For these children, we obtain the father's schooling in the following steps:

1) We first check if the specific child co-resided with his/her father in any of the earlier waves (2007, 2000, 1997, 1993). If the child resided in the same household with the father in any of the earlier waves, we use the father's identification link in that wave to obtain the father's years of schooling from the household roster. If the child and his/her father co-resided in multiple previous waves, we obtain the schooling information from the latest wave in which the father has co-resided with the child.

2) If the child did not co-reside with the father in any of the previous wave, we take advantage of the non-resident parent module. In the non-resident parent module, the children are asked to report both father's and mother's schooling. Starting with the latest wave (2014), we identify in which wave a child has reported the father's schooling in the non-resident parent module.

Ideally, we should be able to find schooling information of all fathers using the above two sources. But in some cases, the father's schooling is missing because of non-response or the reported value

exceed any meaningful years of schooling value. In such cases, we check if the child co-resided with the mother in any of the IFLS waves starting with the latest wave (IFLS-5, 2014). This is useful if the father is away or dead, but mother was present in the household in any of IFLS waves. If we are able to identify mothers in any of the waves, we take advantage of mother's marriage module to collect data on her husband's years of schooling.

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