Working Paper 117

Young Lives

An International Study of Childhood Poverty

Intergenerational Transmission of Poverty and Inequality: Young Lives

Jere R. Behrman, Whitney Schott, Subha Mani, Benjamin T. Crookston, Kirk Dearden, Le Thuc Duc, Lia C. H. Fernald, Aryeh D. Stein and the Young Lives Determinants and Consequences of Child Growth Project Team

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The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (in Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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Abstract: There is considerable emphasis in academic and policy literatures on intergenerational transmissions of poverty and inequality. The perception is that improving schooling attainment and income/consumption for parents in poor households will result in important reductions in poverty and inequality for the next generation of adults. However, the extents of these intergenerational effects on poverty and inequality are empirical questions that have not been examined much if at all, particularly for developing countries. We use data on children born in the 21st century in four developing countries to estimate critical relations with which to simulate how changes in parents' schooling attainment and consumption would affect poverty headcounts and inequality in the children's generation when the children become adults. We find that reductions in poverty headcounts and inequalities in the parents' generation carry over to distributions of human capital and per capita adult consumption for the children's generation, but the effects are not very large for the distribution of per capita consumption. Therefore, while reductions in poverty and inequality in the parents' generation are likely to be desirable in themselves to improve welfare among current adults, they are not likely to have much impact on reducing per capita consumption poverty and inequality in the next generation of adults.

Keywords: Intergenerational transmission of poverty and inequality, human capital, developing countries

JEL Codes: I3 Welfare and Poverty, I24 Education and Inequality, O15 Human Resources; Human Development; Income Distribution; Migration

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1. Introduction:

The extent of intergenerational economic mobility in both developed and developing countries has long been of considerable interest to policy makers and academicians. A strong component of this interest is whether there is intergenerational transmission of income/consumption poverty and inequality: that is, how likely are children from poor families to end up as adults in poor households? A number of policy efforts are directed towards breaking the intergenerational transmission of poverty. For example, Santiago Levy, the "father" of the well-known Mexican PROGRESA/Opportunidades Conditional Cash Transfer program on which many other programs have been explicitly modeled worldwide, states that the program's overall objective was "to break the vicious cycle of poverty" in which children of poor families become the next generation of adults in poor families (Levy 2006, p. 21).

Policies thought to be promising to reduce poverty and inequality in the next generation of adults include ones that directly support greater investment in human capital of children of poor families in hopes that such interventions will increase their earnings capacities and reduce the probabilities of these children living in poverty when they become adults. There is also considerable emphasis on how improving the conditions of currently poor parents may not only improve their own welfare, but enhance the human capital of their children and, through this mechanism, reduce probabilities of their children living in poverty when they become adults. For example, a recent influential World Bank study on inequalities of opportunities for children includes, inter alia, "[lack of] schooling of the family head [and low] per capita family income" as important limitations on poor children's opportunities (Barros et al. 2009, p. 59). Reports on the intergenerational transmission of poverty in developing countries by other international organizations, such as the Inter-American Development Bank (IADB) (Castañeda and Aldaz-Carroll 1999) and the U.K. Overseas Development Institute (ODI) (Bird 2007), also emphasize the importance of family per capita income or consumption and parental schooling (particularly mothers' schooling) among the critical factors that affect the intergenerational transmission of poverty and inequality in developing countries.

The empirical literature underlying the assumption that changes in such parental family characteristics can have important impacts on reducing poverty and inequality when the children become adults can be categorized into two broad groups: *First*, intergenerational associations often indicate limited intergenerational mobility when schooling and long-run income are considered and, generally, less mobility in developing than in developed countries (e.g., Behrman et al. 2001; Black and Devereux 2010; Birdsall and Graham 2000; Corak 2006; Solon 1999, 2002). Concomitantly, children whose families start at the bottom of income and consumption distributions are more likely than children whose families start higher to be poor when they become adults. *Second*, there are many empirical micro studies that report significant associations between parental family background, particularly parental schooling and family income, and investments in the human capital of children in developing countries. The papers cited in the previous paragraph give references to a number of these studies, as do various surveys, for example, Behrman and Knowles (1999), Orazem and King (2008), Strauss and Thomas (2008) and Strauss and Thomas (1998). These studies are widely interpreted to mean that increased parental schooling and income for poor families lead to increased human capital outcomes in their children, and thus lower rates of poverty and inequality when the children become adults than otherwise would occur.

The literatures summarized in the previous paragraph provide a strong basis for the assumption in the World Bank, IADB and ODI reports noted above and elsewhere that higher parental schooling attainment and higher income/consumption for currently poor families are likely to reduce the probabilities that the children in such families end up as poor adults. An important implication is that when these children become adults, poverty and inequality would likely be reduced. However, a critical question is how large are these effects? How much would the incidence of poverty and inequality fall for the next generation if, for example, all parents had at least primary schooling? Or if all parents had at least nine completed grades of schooling? Or if the household per capita income of the bottom fifth of households was increased to $1 a day or that of the 20th percentile? To our knowledge, the answers to such questions for developing countries (or for developed countries) remain unknown.

Our contribution in this paper is to provide answers to such questions for children born in the 21st century. To do so we develop and implement a combined estimation/simulation approach that allows exploration of impacts of changes in parental schooling and consumption on poverty and inequality in the distribution of predicted adult per capita consumption for children when they become adults. We investigate these questions for four quite different low- and middle-income countries – Ethiopia, India (Andhra Pradesh), Peru and Vietnam.

In particular, we are interested in (a) characterizing poverty and inequality in the parents' generation using per capita consumption and human capital, (b) presenting associations between key parental measures (consumption, height and schooling) and children's human capital outcomes (height and cognitive outcomes), (c) simulating the distribution of per capita consumption for these children when they become adults under assumptions about stability in associations between their human capital in childhood and in adulthood and about the relations between human capital and per capita consumption across generations,[1] (d) characterizing

[1] Rather than make these assumptions about stability over time, there are two alternatives. (1) We could wait 30 years or so to collect and analyze data on children born in the 21st century when they are in prime adult ages. (2) We could investigate data that has the necessary information for current adults and their parents. There are a few, though not many, data sets from developing countries with the necessary information at least for special samples (e.g., the Guatemalan INCAP longitudinal study of four villages with 2392 children born in 1962-1977 who have been followed up as adults in the 21st century). However such a strategy would focus on children born in the 1960s-1980s, probably in much different

poverty and inequality in the children's generation both in terms of human capital among children and in predicted per capita consumption as adults, and (e) simulating to what extent poverty rates and inequality would be reduced when the children become adults if it were possible to increase substantially parental schooling attainment and per capita consumption of poor parental families in the left tails of these distributions. For both parents and children, to characterize poverty we consider poverty head counts (*i.e.* proportions of individuals below some threshold) and to characterize inequalities we use Gini coefficients.[2] The poverty head counts are of particular interest because we are particularly interested in those in the left tails of the various distributions.

We begin with a simple human capital investment framework to help structure our investigation. We then summarize our data, methods, results and conclusions. A number of findings emerge from our analysis. *First*, consistent with much existing literature, there are strong positive associations between parental resources (consumption, schooling and height) and children's human capital (height and cognitive outcomes). *Second*, increasing parental schooling to a minimum of primary schooling, that is, levels currently targeted by the Minimum Development Goals, does little to decrease incidence of poverty and inequality in that generation. Whereas, increasing parental schooling to nine completed grades and/or increasing per capita consumption to $1 a day does result in substantial reductions in both the incidence of poverty and inequality in the parents' generation. *Third*, fairly substantial increases in parental schooling (nine completed grades) for parents with limited schooling and in per capita consumption ($1 a day) for parents in the left tail of the distributions are predicted to reduce the incidence of poverty in cognitive skills and height for their children with the effects being smaller for inequality in cognitive skills and height, though not insignificant at least for Ethiopia and India. *Fourth*, reductions in poverty headcounts and inequalities in the parents' generation carry over to distributions of human capital and per capita adult consumption for the children's generation, but the effects are not very large compared to the large changes we estimate for the parents' generation. Therefore, while reducing poverty and inequality in the parents' generation may be desirable in and of itself in terms of improving welfare among current adults, substantial increases in parental schooling for parents with limited schooling and in per capita consumption for parents in the left tail of the

circumstances than children born in the 21st century given the considerable changes in most developing countries since then. The advantage of our strategy, at the cost of making additional assumptions, is that the focus is on children born in the conditions of the 21st century.

[2] There are a number of alternative measures of poverty and inequality that are used in the literature (e.g., the Foster, Greer and Thorbecke (1984) class of poverty measures), but we limit our presentation to the poverty headcount and Gini inequality measures because we are presenting such measures for a number of simulations and these are the most common and best-known measures.

distributions are not likely to have large impacts on reducing per capita consumption poverty and inequality in the next generation.

2. Human Capital Investment Framework

A standard human capital investment framework, as in the well-known Becker (1967) Woytinksy Lecture, suffices for the purpose of this study. Consider Figure 1 in which the expected private marginal benefits and expected private marginal costs are measured on the vertical axis and schooling investments in children are measured on the horizontal axis (though the same points hold for any human capital investments, including those in health and nutrition). The expected private marginal benefits are downward-sloping[3] as schooling increases in the relevant range due to diminishing marginal returns to fixed abilities and pre-schooling investments. The expected private marginal costs are increasing due to increasing private opportunity costs of more schooling in terms of other time-use options (e.g. working on family farms, caring for younger siblings) and possibly increasing marginal costs of financing current schooling investments given imperfect or missing capital markets for such investments. The equilibrium private investment in schooling S* is given by the intersection of the expected private marginal benefits and expected private marginal costs curves in Figure 1, with the equilibrium expected private marginal benefits and expected private marginal costs equal to r*.

How do increased parental financial resources or income affect the equilibrium human capital investments in children? If capital markets for human capital investments were perfect, then increasing parental financial resources would do little to change the equilibrium investment made in children's schooling. However, in developing country contexts such as those under investigation in this study, capital markets for human capital are thought to be often quite imperfect and the private components of the marginal costs of such investments are generally thought to be primarily self-financed (Foster, 1995). As a result, if credit constraints are

[3] There is some evidence suggesting that, at least over a range, the marginal benefit curve may be upward-sloping. For instance, Johannes and Noula (2011) estimate that the marginal benefit in primary and secondary schooling is increasing for the middle-income group. However, this and other such studies do not control for unobserved abilities, motivations and family connections. If, as is suggested by the models of familial human capital investment in children in Becker and Tomes (1976) and Behrman, et al (1982, 1995) and seems plausible, students with greater abilities, higher motivation and better family connections both have greater schooling and higher post-schooling incomes because of their abilities, motivations and family connections, then these estimates are biased upward more for higher levels of schooling in a way that may obscure the declining returns to students with fixed abilities, motivations, and family connections. Finally we note that though presentations such as Figure 1 usually are drawn as if there are declining expected private marginal benefits with more schooling, there could be a stable equilibrium with increasing expected private marginal benefits as long as the slope of the increasing expected private marginal benefits curve is less than the slope of the increasing expected private marginal cost curve in the neighborhood of the equilibrium.

alleviated, the private marginal cost curve is likely to shift down, and the equilibrium investment in child schooling is likely to increase.

How does increased parental human capital affect the equilibrium human capital investments in children? Underlying the expected private marginal benefit curve in Figure 1 is a production function for earnings (or whatever outcomes are of interest) that includes as an input child schooling. As the private returns (measured in earnings) to investment in schooling increases, the private marginal benefit curve will shift to the right increasing equilibrium investment in children's schooling. Familial inputs play an important role in this process, including *inter alia* the quality of parental time spent in child stimulation particularly in early life and in help with homework when the children are of school age.[4] If these familial inputs are complementary with time in school as generally is thought to be the case, then greater parental human capital in the form say greater parental schooling attainment is likely to shift the expected private marginal benefit curve to the right, thus increasing the equilibrium investment in children's schooling.

Thus this simple framework predicts that increased parental financial and human capital resources in the contexts under consideration lead to increased investment in children's human capital.

Further, of course, decisions to invest in the children's human capital are made in a particular community context, where the population size and the availability of related educational and health services may affect the equilibrium human capital investment in children. More accessible public schools and health services, for example, are likely to shift the expected private marginal cost curves down, and induce higher equilibrium investments in children. Higher quality public schools and health services are likely to enter the production function underlying the expected private marginal benefit curves and to be complementary with time in school, thus shifting the expected marginal benefits curve upwards and induce greater human capital investments in children.

Finally, it is important to note that this simple framework also points to an estimation challenge in ascertaining the impact of increased parental financial and human capital resources on investments in children's human capital. Underlying the expected private marginal benefits curve are intrinsic child endowments. These endowments range from innate ability and innate health to family connections for job and marriage markets. They are likely to enter directly into the

[4] Time-use surveys in the United States suggest that both men and women spend about 14% of their time on "educational" child-care activities that include reading to children, helping with homework, teaching children and attending activities in school (Guryan et. al 2008). To our knowledge, such detailed time-use surveys on child care activities are unavailable for our study countries.

production function determining the expected private marginal benefits. This means that the estimated relations between both parental financial and human capital resources on one hand and investments in children's human capital on the other hand are likely to be upward-biased as estimates of causality unless these endowments can be controlled in the estimation.[5]

3. Data

We use data on children from Young Lives, a cross-national cohort panel study on poverty and child well-being conducted in Ethiopia, India (Andhra Pradesh), Peru and Vietnam. Our analysis sample uses data on the younger cohort from round 3 (2009-10), who were first surveyed in 2002 at ages 6-17.9 months (round 1) and subsequently followed through rounds 2 (2006-07) at about age 5 years and 3 at about age 8 years.[6] Sampling details are at http://www.younglives.org.uk. Comparisons with representative data suggest that the samples represent a variety of contexts in each of the countries studied, but do not include the highest parts of the income distributions. We include all children for whom there are data available on two cognitive scores (PPVT and math, described below) in round 3.[7] Attrition rates are fairly low in the young lives panel study, less than 2% per annum (see Schott et. al 2013). Our final sample size is 6,915, consisting of 1,669 in

[5] There is likely to be an upward bias if there are positive intergenerational correlations in such endowments (so that such endowments in the parental generation are likely to be positively correlated with parental income and human capital and in the children's generation with their human capital) and if such endowments are complementary with schooling in producing expected child marginal benefits.

[6] The Young Lives study also follows an older cohort of children initially surveyed at age 8 years in 2002 and followed through the 2006/07 and 2009/10 waves of the panel study. However, the sample size for the older cohort is 50% smaller than the younger cohort and hence we include only the younger cohort. Because the intergenerational associations between parental schooling attainment and income on one hand and indicators of child human capital on the other hand tend to be larger for the younger cohort than for the older cohort (Georgiadis, 2013), our use of the younger cohort probably leads to higher estimates of the impacts of improving schooling and consumption of poor parents than would result from similar analysis of the older cohort.

[7] Data are missing for some variables used in samples for the analysis. Per capita consumption is missing for 0.1% in Peru and 1% in India; mothers' schooling is missing for 0.8% (Ethiopia), 0.2% (India), 0.9% (Peru), and 0.8% (Vietnam); father's schooling is missing for 4.3% (Ethiopia), 0.2% (India), 3.1% (Peru), and 2.6% (Vietnam); mother's age is missing for 2.5% (Ethiopia), 0.4% (India), 0.6% (Peru), and 0.2% (Vietnam); and hospital in community and secondary school in community are missing for 5.3% in Ethiopia and 2.2% in India. For the individual-level variables, we use the variable median at the community level to impute data for missing values, and include dummies for each human capital measure missing in the regressions. For missing data on language, we use the community mode and make cross-reference to native language and language of previous exams when there is discordance among these three measures. For the missing community variables, we code them to zero and include a dummy for missing data on the presence of a hospital and secondary school in the community. Most of these dummies are statistically insignificant.

Ethiopia, 1,787 in India, 1,748 in Peru, and 1,711 in Vietnam. The main outcome variables of interest in the children's regressions are measures of human capital; the main outcome variable of interest in the parents' generation is per capita consumption expenditure.

Children's Measures: We represent children's human capital at age 8 years (round 3) by nutritional status (height) and two cognitive scores obtained at age 8. We use raw height at round 3 to represent nutritional status (as opposed to height for age z-scores, HAZ) for the inequality analysis because Gini coefficients are not defined for negative values and for these poor populations many children have negative HAZ values.[8] The two cognitive exams at age 8 years are:[9]

1. The Peabody Picture Vocabulary Test (PPVT) uses items consisting of a stimulus word and a set of pictures and is a test of receptive language that has been widely used in low- and middle-income countries (Walker et al. 2000, Walker et al. 2005). The Spanish PPVT (*Test de Vocabulario Imagenes Peabody, TVIP* 125 items) was used in Peru while the PPVT III (204 items) was used in Ethiopia, India, and Vietnam. The PPVT (and TVIP) was adapted and standardized by Young Lives researchers in each country using consistent techniques. Psychometric characteristics of the test were examined by Young Lives researchers with results indicating a high degree of test reliability and validity (Cueto and Leon 2012).
2. A mathematics achievement test was administered. The test had 29 items relating to counting, number discrimination, knowledge of numbers, and basic operations with numbers in which interviewers read the questions aloud to avoid bias resulting from poor reading skills. These scores were evaluated for psychometric properties by the Young Lives study team. Scores were corrected for items with indicators of low reliability and validity resulting in corrected data that exhibits strong psychometric characteristics (Cueto and Leon 2012).

[8] Because the age range for the children is relatively small (12 months) and we control for child age in the estimates, the use of height rather than HAZ is not likely to make much difference in the relevant estimates.

[9] A third test is also available: The Early Grade Reading Assessment (EGRA) from the World Bank Living Standards Measurement Study to assess verbal achievement (Glewwe 1991). This test is typically administered orally and is used to evaluate the most basic skills for literacy acquisition in early grades, including pre-reading skills such as listening comprehension. The Young Lives adaptation of the EGRA explored the child's ability to identify familiar words, read and comprehend a small text, and to understand a small text read to them. We do not include this test because scores are missing for a large proportion of the children, particularly in Ethiopia (20.1%).

We also control for the language in which the exam was conducted and for whether the exam was in the child's native language.[10] In addition, we control for age in months and the sex of each child to control for age-gender specific differences in performance on tests.

Table 1 shows descriptive statistics for the sample. It is worth noting that there is substantial variation in within-country performance on these scores, especially for children in Ethiopia and India.

Parental Measures: We use per capita daily household consumption expenditure, averaged over rounds 2 and 3 (the two rounds for which consumption data were collected), to characterize the parental household financial resource position. Consumption is generally considered to be a better indicator of the longer-run resource constraints than income for the same time periods because of the substantial transitory components of income, particularly for poorer households in rural environments that are subject to considerable shocks from weather, markets and other sources (Deaton, 1997; Behrman and Knowles, 1999). Household consumption per capita is calculated using adult respondents' estimation of food and non-food items with a recall period ranging from 15 days for food to 12 months for clothing. The total expenditures were first converted to real monthly expenditures in 2006 local currency and divided by household size (adult equivalent in Ethiopia).[11] We then convert the total monthly expenditures to daily consumption in 2006 USD. For parental human capital, we use continuous measures of maternal and paternal schooling attainment in grades and mothers' height (data on fathers' height were not collected). We also control for mothers' age to capture lifecycle patterns.

Average per capita consumption per day in USD is reported in Table 1 and is highest for Peru (US$2.05) and lowest for Ethiopia (US$0.56).[12] Sample averages for parental schooling mimic this pattern: mothers' schooling (7.8 grades for Peru and 3.1 grades for Ethiopia) and fathers' schooling (9.1 grades for Peru and 5.0 grades for Ethiopia) are also highest in Peru and lowest for Ethiopia. Mothers' age is lowest in India (23.6 years) and highest in Ethiopia (27.4 years) and mother's height is highest in Ethiopia (158.7 cm) and lowest in Peru (150 cm).

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[10] There are missing data on the language of the exam. We coded missing data to the mode of the community, and then checked these values with language of exam in round 2 (when two other exams were given) as well as their native language in both rounds 2 and round 3. In the few cases where there was discordance between the imputed value and these other values, we recoded the missing data to the language of exam in the previous year (in these cases they were the same as the native language).

[11] Young Lives country teams calculated consumption independently, resulting in this slight methodological difference for Ethiopia.

[12] Since per capita consumption in Ethiopia is per adult equivalent, this value slightly over-represents consumption compared to values for the other three countries in this table.

Community Characteristics: The community variables we use include an indicator for whether communities in which children lived have hospitals,[13] an indicator for urban residence, community wealth (constructed separately by country across three rounds as an asset-based index of the first principal component of 19 indicators of household durables, housing quality, and available services (e.g., safe water sources and electricity) (Filmer and Scott 2012), the presence of a secondary school facility in the community, and an indicator for whether children moved to different communities after round 1 (to control for unmeasured changes in these variables over time for those who moved).

The percentage of children living in an urban residence in round one varies from 18.1 (Vietnam) to 66.4 (Peru), the percentage who had moved over the time of the study ranges from 11.4 in India to 48.6 in Peru, the percentage of communities with a hospital ranges from 30.3 in Ethiopia to 89.5 in Vietnam, the percentage of communities with a secondary school present is also highest in Vietnam (98.1) and lowest in Ethiopia (34.7). The presence of substantial heterogeneity in community resources across countries points to the possible importance for controlling for these factors in the regression models, which we do in the sections to follow.

4. Empirical Specification

We are interested in (1) characterizing poverty and inequality in per capita consumption and human capital among the parents' generation, (2) examining the associations between key parental variables and children's human capital outcomes, and (3) documenting poverty and inequality in the children's generation both in terms of human capital among children and in predicted per capita consumption as adults. We then use these relations to simulate how changing the distribution of per capita consumption and schooling attainment of the parents would affect the distribution of the children's human capital and their predicted per capita consumption when they become adults under assumptions that we discuss below.

We begin with the following relation for the per capita consumption (C_P) in the parents' generation (subscript P) as dependent (presumably through their income) on father's and mother's schooling attainment (FS_P and MS_P), maternal age (MA_P), maternal height (MH_P) and

[13] An alternative to this measure would be the presence of primary care facilities; however, we did not use this measure because there is no variation in Vietnam in the presence of primary care facilities.

an unobserved family factor (u_P) related to unobserved income-generating factors that are assumed to be uncorrelated with the right-side variables[14]:

$$lnC_P = \beta_0 + \beta_1 MS_P + \beta_2 FS_P + \beta_3 MH_P + \beta_4 MA_P + \beta_5 MA^2{}_P + u_P \text{------------ (1)}$$

We estimate this relation with ordinary least squares (OLS) to obtain coefficient estimates for mother's schooling, father's schooling, mother's age and maternal height, and compute the predicted residual, all of which we assume carry over to the children's generation when they become adults.[15]

We next estimate how children's human capital (H_C) at age 8 years is determined by parental financial resources as represented by (C_P), parental schooling attainment MS_P and FS_P, other individual child and family characteristics (X) and community/village characteristics (Z), as well as uncorrelated child-specific factors (u_C)[16]:

$$H_C = \gamma_0 + \gamma_1 C_P + \gamma_2 MS_P + \gamma_3 FS_P + \gamma_4 X + \gamma_5 Z + u_C \text{------------(2)}$$

Measures of child human capital H_C are scores on the PPVT and math exams, as well as height in cm at age 8 years. Other individual demographic and family characteristics (X) include sex and age (in months) of the child at the time of the survey, mother's height, mother's age, and, for the cognitive exams, whether the child took the exam in his or her native language and dichotomous variables for the language of the exam.[17] Community characteristics (Z) include

[14] We are limited in the variables that we may include in this relation to those that are available for the parents' generation and possible within the data that we use to estimate for the children's generation.

[15] The assumption that the residuals in relation (1) carry over to the children's generation implies limited intergenerational mobility. Another extreme possibility would be that the for the children's generation each child had a random draw from the distribution of residuals for the parents' generation. In between would be the possibility that there is some fixed and some random component. All of these assumptions will result in the distribution of per capita consumption in the children's generation being similar to that in the parents' generation (except for the rightward shift in the distributions due to the assumed intergenerational secular trends in schooling attainment and height). But the basic point for our simulations is that all of these assumptions affect the baseline simulation for per capita consumption in the children's generation, but not the shift in the distribution due to the hypothetical scenarios in which parental schooling attainment and per capita consumption are changed because these variables are orthogonal to the residuals in relation (1).

[16] Both X and Z may be vectors, but for simplicity are written as scalars here.

[17] Examination of the psychometric qualities of the tests suggests that test performance varied by language, so scores should be compared within languages only (Cueto and Leon 2012). Hence we include language dummies for each language. The dummy for whether a child was tested in a language

urban residence, community wealth, whether there is a hospital in the community, whether there is a secondary school in the community, and—to control for changes for households who no longer live in the community in which these data were collected—whether the family moved after round 1. We include splines in mother's and father's schooling, as well as consumption, to allow the coefficients to vary by whether schooling attainment was less than or more than nine grades, and whether the family consumed less than or more than the 20th percentile of per capita consumption.

We use the estimates of equation (2) (including the predicted residual[18]) to simulate the impact on the distribution of child human capital at age 8 years of changes in parental financial resources and human capital. We use seemingly unrelated regression (SUR) methods to obtain these estimates in order to allow the errors to be correlated across the child cognitive exams (PPVT, math) and thereby increase efficiency. To simulate the impact on height, we use OLS with standard errors clustered by community. We analyze inequality in the distributions of these scores with Gini coefficients and poverty headcounts.

We then use the estimates from equation (1) and the predicted test scores and height from equation (2) to simulate the distribution of per capita consumption when the child becomes an adult. To do so we make the additional assumptions that (a) the consumption relation in (1) is stable across the generations (including the unobserved family factor u_P), (b) the human capital distribution for the children when they become adults is the same as for their parents (except that the schooling attainment distribution is shifted up by two grades to reflect a secular intergenerational change in schooling[19]) and (c) the child's percentile position in the human capital distribution at age 8 persists and determines that child's place in the percentile distribution in the adult schooling attainment distribution for the child's generation. Furthermore, we assume that (d) children's height when they are adults will follow the same distribution as maternal height (except shifted up by 3 cm to reflect a secular intergenerational increase in height), and that (e) the child's percentile position in height at age 8 persists to adulthood and

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other than his or her native tongue controls for a possible deficiency resulting from being tested in a second language.

[18] A comment parallel to that above for the residual in equation (1) also holds here. This assumption that the residual is a fixed child characteristics that carries over to adulthood affects the baseline simulation for per capita consumption in the children's generation through their simulated human capital values, but not the simulated shifts in the distributions due to the hypothetical scenarios in which parental schooling attainment and per capita consumption are changed because these variables are orthogonal to the residuals in relation (2).

[19] Estimates for recent decades and projections for the first half of the 21st century of changes in schooling attainment are of this rough magnitude (Lutz et al. 2007; Samir et al. 2010).

determines his or her place in the percentile distribution in adult height for the child's generation. We estimate the child's future consumption at age 40 years, which is during prime adulthood. We note that assumptions regarding the secular trend in schooling of two grades per generation, the secular trend in height of 3 cm per generation, and the age in adulthood being 40 years affect our base simulation, but do not affect how any of the other simulations differ from the base simulation – and those differences with the base simulations are what are of interest for this study.

To estimate the child's predicted schooling as an adult, we first map the average (by country) percentile position in the distribution of the two cognitive scores to adult schooling levels at that same percentile in the parents' schooling distribution. For example, a child who scored in the 48th percentile on the PPVT exam and 52nd percentile the math exam would have an average percentile placing of 50, and would be assigned the 50th percentile of schooling attainment from the mothers' and fathers' distributions (separately) in the sample.[20] We then added two years of schooling to allow for a secular increase in schooling.

To estimate the predicted maternal height for the child's household as an adult, we map the percentile placing in child height at age 8 to the maternal distribution of height. That is, a child who is 20th percentile in child height at age 8 would be assigned the maternal height at the 20th percentile from the original parental distribution of height. We then added 3 cm to allow for secular increase in height.

To obtain the estimated baseline consumption in the child's future household, we insert the estimated parental schooling and maternal height of the child's future household into equation (1) (using the coefficient estimates obtained from the parents' generation) to predict children's future household consumption at (maternal) age 40 years, during what normally is considered prime adulthood.

To characterize inequality in household per capita consumption and human capital for both the parents' and the children's generations, we calculate the Gini coefficients, by country. We also calculate the poverty headcount for both generations, with the poverty threshold defined by households at the 20th percentile of per capita consumption in the original data for the parents' generation and by 5 grades of schooling attainment.

Next, using the coefficients and residuals estimated in equation (2), we insert hypothetical values

[20] This assumption implies perfect assortative mating in the sense that increases in the child's completed schooling attainment are presumed to result in proportional increases in the child's eventual spouse's completed schooling, which gives an upper-bound estimate of the impacts on the expected household income for the child when the child becomes an adult, all else equal.

for maternal and paternal schooling and per capita consumption in order to simulate what the child's cognitive scores and height at age 8 years would be under a number of scenarios, with the assumption that our estimates in relation (2) represent a causal relationship.[21] We calculate the resulting Gini coefficients and poverty headcounts. The differences between the Gini coefficients and poverty headcounts for the baseline simulations and the Gini coefficients and poverty headcounts for the hypothetical scenarios thus reflect the effects on the children's human capital of hypothetical changes in schooling attainment and per capita consumption in the parental generation. The scenarios that we consider are:[22]

1. Increased parental schooling attainment to completion of primary schooling (6 grades in Peru, 5 grades in India and Vietnam, and 4 grades in Ethiopia) for all parents who did not complete primary schooling.
2. Increased parental schooling attainment to 9 grades for all parents who did not complete 9 grades of schooling.
3. Increased per capita household consumption to the 20th percentile of per capita household consumption for all households below the 20th percentile in the parental generation.
4. Increased per capita household consumption to \$1 US per day for all households with per capita daily consumption below \$1US.
5. Increased parental schooling to 9 grades for all parents with less than 9 grades of schooling, **and** increased per capita household consumption to \$1 US per day for all households with per capita daily consumption below \$1 US.

Finally, in order to examine how these scenarios might impact future adult household per capita consumption for the children's generation when they become adults, we map their simulated cognitive scores to new levels of schooling using the percentage change in the two cognitive scores under these scenarios and the standard deviation of parental schooling (and analogously map simulated height to new levels of maternal height using the percentage change in height compared to baseline and the standard deviation of maternal height). Specifically, we use the following formula to obtain predicted parental schooling and maternal height levels:

$S_i = S_b + C_i/100 * SD_{Sa}$

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[21] In these simulations we assume that the effects of parental schooling are the direct effects as estimated for relation (2) but that there are not in addition indirect effects through per capita household consumption.

[22] Note that households with parental human capital values above the thresholds listed below remain unaltered in the simulations. We are primarily concerned with improving the conditions for those in the lower tails of the distributions.

Where S_i is the simulated schooling under scenario i, C_i is the average of the percent change in the PPVT and math scores (change from actual performance to the simulated performance under scenario i), S_b is the baseline level of predicted adult schooling and SD_{Sa} is the standard deviation of adult schooling, conducted separately by country and mothers/fathers.

That is, a child who increased his or her PPVT score by 14 percent and the math score by 10 percent (average = 12 percent increase) under the scenario is assigned an increase of 0.12 times the standard deviation in father's schooling for that country over the originally predicted baseline adult schooling level (and likewise for mother's schooling).[23] For mother's height, the formula is similar, except that rather than C_i representing the average percentage change of two scores, it is simply the percentage change in height.

These predicted schooling (and height) levels based on the simulated changes in the cognitive scores (and height) and the standard deviation in parental schooling (and maternal height) were then inserted into equation (1) in order to obtain predicted consumption per capita under these scenarios. Finally, we analyze inequality in these simulated distributions by calculating Gini coefficients and poverty headcounts by country.

We think that this approach probably leads to upper-bound estimates of the impacts of the hypothetical changes in the parental generation on reductions in the poverty headcount rates and in inequality in the children's generation when they become adults because:

1. Our OLS estimates of relation (1) probably give upward-biased estimates of the impacts of schooling and height on per capita consumption, even though measurement error tends to work in the opposite direction, because of omitted variable bias due to unobserved abilities and motivations.[24] Therefore, using this

[23] We also considered two alternative increases, (1) mapping the percentile placing of the simulated score to the levels of parental schooling at that percentile (plus 2 years for secular increase), so that a child who obtained a simulated score which placed him or her in the 50th percentile in the original cognitive index score distribution would be assigned the level of parental schooling at the 50th percentile in the parental distribution (plus 2 years), and (2) predicted schooling = $(100+ I_i)/100*S_b$. Neither of these alternatives produced changes in the Gini coefficients that were greater in magnitude. Thus, the results presented here are those that produced the greatest change and therefore may arguably be considered upper-bound estimates.

[24] For example, Behrman and Rosenzweig (1999) survey results for earnings functions using identical twins to control for unobserved endowments and report only one exception that finds the measurement error bias greater than the omitted variable bias (Ashenfelter and Krueger 1994) and in that case, subsequent estimates with an added round of the same data find, as in other cases, the omitted variable bias is greater than the measurement error bias (Ashenfelter and Rouse 1998).

relation to simulate the impact of the children's human capital on their per capita consumption probably overestimates these effects.

2. Our OLS estimates of relation (2) probably give upward-biased estimates of the impacts of parental schooling on children's human capital, even though measurement error tends to work in the opposite direction, because of omitted variable bias due to unobserved intergenerationally-correlated abilities and motivations.[25] However measurement error is more likely to be a larger problem for per capita consumption on the right side of this relation than for parental schooling, so it is more likely that in this case the effects are underestimated (though we use per capita consumption rather than income to lessen this possibility). Therefore, the simulations are likely to overestimate the impact of hypothetical changes in parental schooling on child human capital, but this probably is less likely for parental household per capita consumption.

3. In our simulations we assume that changes in parental characteristics that affect child human capital at age 8 remain equally strong until the child is an adult. That is, we assume that there is not subsequent fading of these effects as children age due to experiences after age 8, such as the quality of secondary schooling or shocks experienced in adolescence that affect secondary schooling. If there are such effects after age 8 years, again our procedure probably results in upper-bound estimates.[26]

4. In our simulations we assume perfect assortative mating on schooling for the child when s/he becomes an adult. Even though most estimates in the literature indicate significantly positive assortative mating, they are substantially less than one.[27] Therefore our assumption that any increase in the child's schooling is matched perfectly by proportional increases in the child's eventual spouse's schooling probably leads to upper-bound estimates of the impacts on per capita consumption when the children become adults.

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[25] This is the result, particularly for maternal schooling, from a series of studies that control for the endogenous determination of parental schooling (Behrman and Rosenzweig 2002; Black et al. 2005; Plug 2004; de Haan and Plug 2006).

[26] And again, the estimates in Georgiadis (2013) suggest that intergenerational associations of parental schooling and income with child human capital are smaller for the older cohort than for the younger cohort that we use.

[27] If there are controls for endowments in assortative schooling mating relations, Behrman et al. (1994) find that spouse's schooling increases by about 0.3 grades for every additional grade of own schooling.

5. Results: Regression Estimates and Simulation

5.1 Predicted Per Capita Consumption

Table 2 gives the estimated coefficients from equation (1). The R^2s for these regressions range from 0.16 in India to 0.35 in Ethiopia, indicating better explanatory power for some countries. Mother's and father's schooling are significant in all countries, and mother's height is significant in all but India. Mother's age is significant only in Ethiopia. Given that we are limited in what variables we may include here by what is possible to estimate for the children's generation, the model performs fairly well in predicting per capita consumption. However the majority of the variance in the natural log of per capita consumption, from 65% for Ethiopia to 84% in India, is due to unobserved family factors that are not correlated with parental schooling, maternal height or maternal age.

5.2 Poverty Headcounts and Gini Coefficients for Parents' Generation

Table 3 gives the poverty headcounts and Gini coefficients in the distributions for per capita consumption, parental schooling, and mother's height for the parents' generation. Parental resources are most unequally distributed in Ethiopia, with Gini coefficients of 0.320 for per capita consumption, 0.302 for mothers' schooling attainment, and 0.307 for fathers' schooling attainment. Fathers' schooling is most equally distributed in Peru, with a Gini coefficient of 0.226, and mother's schooling is most equally distributed in Vietnam with a Gini coefficient of 0.241. With the "poverty" threshold for schooling set at 5 grades of schooling attainment, there is little variation in the incidence of consumption poverty across countries; however, there is substantial heterogeneity in deprivations in parental schooling with Ethiopia performing the worst and Vietnam the best. For instance, the majority of both mothers (72.1%) and fathers (58.8%) in Ethiopia, and the majority of mothers (60.7%) in India fall below this threshold. Vietnam has the lowest percentage of mothers (22.7%) below this threshold, and Peru has the lowest percentage of fathers below this threshold (11.7%). On the other hand, mothers' height is distributed remarkably equally among all four samples.

5.3 Estimates of the Associations of Child Human Capital Outcomes with Parental Family and Characteristics

Table 4 gives the full set of estimated coefficients from the regressions of child outcomes at age 8 years as related to parental characteristics in equation (2) above. These results suggest that the lower end of the schooling distributions for both mothers and fathers and the lower tails of consumption per capita all tend to be significantly associated with children's cognitive scores and, to some extent, their height. The R^2s indicate that these relations are consistent, with 16%

(India) to 50% (Ethiopia) of the variance in PPVT, 22% (India) to 49% (Ethiopia) of the variance in math scores, and 17% (Ethiopia) to 37% (Peru) of the variance in child height. Thus, while parental schooling and per capita consumption are significantly associated with child human capital, half or more of the variance in child human capital is due to the residual and is orthogonal to parental schooling and per capita consumption. (Appendix A gives more detail, including how the estimates differ across the four countries.)

5.4. Baseline Simulations of Child per Capita Consumption as Adults

After replacing the estimated schooling and height levels for the children (and the predicted residuals from the parents' generation) into equation (1), we obtain the predicted future adult per capita consumption for the children presented in Table 5 at age 40 years for the mothers. The values shift upwards due to the assumption of secular increases in schooling attainment and height. Under these assumptions, the next generation in Peru is expected to consume 27% more than the previous generation. Similarly, children from Vietnam and India are also expected to consume 21-23% more than their parents' generation. However, in Ethiopia, children in the next generation are predicted to consume only 10% more than the current generation. These estimates, of course, are conditional on the assumed secular trends in human capital. However, it is important to note again that these assumptions only affect the baseline simulations and what is of real interest for this paper is how the hypothetical scenarios differ from the baseline values, which is not affected by these assumptions.

In Table 6, we see that the distributions of the predicted human capital levels for children depict similar Gini coefficients to those in the parents' generation reported in Table 3, reflecting substantial inequality across countries that are consistent between two generations, suggesting limited intergenerational mobility.

5.5 Simulations of Five Scenarios Regarding Improving the Left Tails of the Distributions of Parental Per Capita Consumption and Schooling Attainment

To provide some perspective about the variation in poverty head counts and Gini coefficients for consumption per capita over time and across countries, Figure 2 gives poverty head counts based on World Bank estimates and a poverty threshold of $1.25 per day in purchasing-power-parity (PPP) terms for 1982-1986 and 2008-2012 for our four study countries (data are not available for Vietnam for 1982-1986 and are not available using $ 1 US per day values). Figure 3 gives similar information for Gini coefficients. Figure 2 indicates considerable variation across countries, with much higher poverty headcount rates in Ethiopia and India than in Peru and Vietnam, but with substantial declines between 1982-1986 and 2008-2012 particularly for Ethiopia (over 30 percent) and India (over 20 percent). Figure 3 indicates about the same levels of inequality in 2008-2012 for three of the countries, but much higher inequality in Peru. It also suggests some increase in inequality between 1982-1986 and 2008-2012 for the three countries for which the estimates are available for 1982-1986. For these three countries the two figures suggest substantial drops in the poverty head count rates so that the absolute levels of consumption of the poorer members of the society in the left tail of the distribution increased at the same time that inequality increased.

We now turn to the five simulations described in section 4. In order to capture the changes implied by these simulations, we show the Gini coefficients and poverty headcounts for parental schooling and per capita consumption under these scenarios in Table 7. Comparing the Gini coefficients in Tables 3 (no simulations) and Table 7 (with simulations) for both maternal schooling and paternal schooling shows that inequality in schooling would not be substantially reduced by increasing the minimum grades of schooling to primary schooling as currently targeted by the Millennium Development Goals. However, inequality in schooling would be reduced substantially by instead increasing the minimum grades of schooling completed to nine in these countries. For instance, increasing mothers' schooling to a minimum of 9 grades would reduce the Gini coefficients for mothers' schooling in Ethiopia from 0.302 to 0.026, in India from 0.248 to 0.036, in Peru from 0.260 to 0.089 and in Vietnam from 0.241 to 0.063. Similar effects are observed for father's schooling as well. Of course, in all but two cases (for schooling in Ethiopia, where primary schooling is 4 grades), the percentage of individuals below the "poverty threshold" of 5 grades of schooling is zero. We also find that changing minimum consumption to $1 US per day decreases consumption inequality substantially in all countries except Peru (where the mean per capita daily consumption in USD is much higher in comparison to the other three countries). Increasing the minimum consumption to $1 US per day also decreases the incidence of poverty in all countries except Peru.

Table 8 gives the percent increase in the PPVT and math scores as well as height at age 8 years under the simulated scenarios. For the children's generation, increasing mother's schooling to a minimum of nine grades and/or minimum consumption to $1 US per day substantially increases predicted math scores and PPVT scores (and to some extent, height).

Table 9 gives the Gini coefficients for the predicted values of the age 8 outcomes under the various scenarios.[28] Under each of these scenarios in which parental schooling and per capita consumption are increased for the left sides of the distribution, inequality is reduced. For example, the Gini coefficient for the PPVT in Ethiopia falls from 0.296 to 0.282 in the first hypothetical scenario, when all parents with less than primary schooling are assigned primary

[28] Since the Gini coefficient may only be calculated using nonzero values, we coded any scores of 0 (possible for the Math scores) to 0.4. While this is an arbitrary value, it rounds to zero and allows for the Gini coefficient to be calculated for the full sample of scores.

schooling, and falls to 0.232 in the last hypothetical scenario, when all parents with less than nine grades of schooling are assigned nine grades of schooling and households with consumption of less than $1 US per day are assigned $1 US consumption per day. Similarly, in India, the Gini coefficient for PPVT falls from 0.280 in the original distribution to 0.252 in the primary schooling scenario and to 0.219 in the last scenario. While reductions in inequality occur across the board for the cognitive outcomes, the reductions are not large in magnitude. Declines in the Gini coefficients are a bit larger for math in Ethiopia, where for the primary schooling scenario, the Gini coefficient falls from 0.447 to 0.414 and then to 0.323 under the last scenario.

Table 10 gives the poverty headcount, or measure of children performing below a certain threshold. Under these hypothetical scenarios, the lower end of the distribution performs better, as expected, given positive intergenerational associations in human capital. For example, for Ethiopia those below the threshold of the 20th percentile in the original distribution of PPVT scores [29] would fall to 16.1% if all parents had at least primary school and to 8.8 % if all parents had at least nine grades of schooling. It would fall to 9.6% if parental per capita consumption were increased to $1 US per day for all households below that level. In the most generous hypothetical scenario, where schooling and consumption are assumed to be at their highest levels, only 2.1% remains below this threshold. These numbers are similar in general terms, though the degree of simulated change varies for the other three countries.

Finally, Table 11 gives the implications of the greater child human capital under the five different scenarios for future household per capita consumption when the children become adults. The changes in the Gini coefficients are quite small, even under the most generous scenarios. In fact, only for the most generous scenario does the Gini coefficient drop by as much as 0.03 points for even one country. Thus, fairly substantial changes in inequality in the parents' generation are simulated to have fairly small impacts on inequality in per capita consumption in the children's generation when they become adults. The small R^2s for the estimates for equations (1) and (2) suggest that unobserved determinants that are orthogonal to the included parental characteristics account for substantial shares of the variation in both the natural log of per capita consumption and child human capital relations – and these components are not changed between the base and the hypothetical scenarios.

On the other hand, the decreases in the poverty headcount for the children's per capita consumption as adults are in some cases simulated to be greater in magnitude. For example, if the lower bound on parental schooling of completing nine grades of schooling is imposed, the poverty headcounts are simulated to drop from 18.0% to 11.6% for Ethiopia, 11.0% to 8.8% in

[29] The poverty headcount is less than 0.20 in some cases since only those performing lower than the 20th percentile are measured as being below the "poverty line."

India, 12.5% to 10.6% in Peru and 10.6% to 8.6% in Vietnam. Similarly if the lower bound on parental per capita consumption at $1 US per day is imposed, the poverty headcounts for the children's per capita consumption as adults are simulated to drop from 18.0% to 13.3% for Ethiopia, from 11.0% to 10.3% for India, 12.5% to 12.2% in Peru, and 10.6% to 10.1% in Vietnam. And, of course, there are larger drops in the most generous scenario (9 grades of parental schooling and $1 US of minimum consumption)-- from 18.0% to 7.6% in Ethiopia, from 11.0% to 7.9% in India, from 12.5% to 10.2% in Peru and from 10.6% to 8.1% in Vietnam. However, to obtain these more notable drops, quite considerable improvements in the parental generations' schooling attainment and per capita consumption need to be assumed.

6. Conclusions

Theoretical models, empirical estimates, and policy prescriptions place considerable emphasis on the importance of the family and its role in improving life chances of children. With this comes a widely-held perception that improving schooling attainment and income/consumption for parents in poor households will result in important reductions in poverty and inequality for the next generation of adults. However, the extent to which these improvements facilitate reductions in per capita consumption poverty and inequality for the children when they become adults is an empirical question that has not been examined much, if at all, particularly for developing countries.

This paper uses data on children born in the 21st century collected in four low- and middle-income countries (Ethiopia, India, Peru and Vietnam) to estimate the returns to human capital for the parents' generation and the determinants of human capital for the children's generation. We then use the coefficient estimates from these relationships, under assumptions about relations between child human capital and their human capital when they become adults and about the stability of the income/consumption-generating relation across generations, to simulate how changes in parents' schooling attainment (primary schooling vs. grades of schooling) and consumption (1$ US or 20 percentile) would affect the incidence of income poverty and income inequality in the children's generation when the children become adults.

We explore the impacts of assumed changes in parental human capital and per capita consumption that lead to substantial reductions in per capita consumption inequality and poverty in the parents' generation. Simulations suggest that these substantial changes in the parents' generation carry over somewhat to the distributions of human capital of their children, but lead to relatively small changes to per capita adult consumption for the children's generation when they become adults. Fairly large changes in parental schooling attainment and per capita consumption would be needed to have much impact on per capita consumption poverty heads counts for the children when they become adults, and even these changes have very limited impact on Gini coefficients for the distribution of per capita consumption when the children become adults.

Therefore, while plausible increases in parental schooling attainment and per capita consumption for poor households in the parents' generation are likely to be desirable in themselves to improve welfare among current poor households, they are not likely to have large impacts on reducing per capita consumption poverty and inequality in the next generation of adults.

Appendix A. More Detailed Discussion of the Estimates of the Associations of Child Human Capital Outcomes with Parental Family and Community Characteristics in Table 6

Table 4 lists the full set of estimated coefficients from the regressions of outcomes at age 8 years. The R-squared for the cognitive regressions ranges from 0.16 for PPVT in India to 0.50 for PPVT in Ethiopia. The R-squared for the math regressions is also highest for Ethiopia (0.49) and lowest for India (0.22). The R-squared for the regressions of height at age 8 years is highest in Peru (0.37) and lowest in Ethiopia (0.17).

Consumption per capita is associated with higher PPVT scores in all four countries, with differing coefficients based on whether the household is above or below the 20^{th} percentile. Consumption per capita per day in USD for households in the lowest income quintile is associated with significant increases of 59.0 points in Ethiopia and 12.6 points in Peru for PPVT score, while beyond the 20^{th} percentile of consumption, it is associated with significant increases of 12.0 points in Ethiopia, 6.7 points in India, 0.6 points in Peru, and 2.3 points in Vietnam. For Math, greater gains also appear in the lowest quintiles for all four countries, India, Peru and Vietnam, with significant increases of 12.5, 5.0, and 7.5 points, respectively in Math scores (in India the pattern is the same but the coefficient on consumption for the higher quintiles is not significant). Similarly, for height, there is a higher association with consumption in the lowest quintile, where an additional USD in consumption per capita is associated with 35.9 cm increase in height in Ethiopia, 3.4 cm increase in height in Peru, and 11.2 cm increase in height in Vietnam, compared to increases of 1.4 in Ethiopia, 1.8 in India, 0.2 in Peru, and 0.5 Vietnam, for increases in consumption at the higher income quintiles. These numbers are quite large in magnitude in some cases because an increase of 1USD is large in magnitude, considering average levels of per capita consumption per day for these countries.

We also include a spline in mothers' schooling, so that coefficients may be determined separately by whether the mother has greater or less than 9 years of schooling. Here, we find differences in associations with earlier years of schooling which vary by exam and country. For Ethiopia, India, and Peru, earlier years of schooling are associated with smaller increases to PPVT scores (0.6, 1.0, and 0.4) compared to schooling after grade 9 (1.2, 1.3, 1.0, respectively, though not significant for Ethiopia after grade 9). For Vietnam, the reverse is true, where increases in schooling at earlier years is associated with a greater change in PPVT (1.6) compared to increases at higher levels of schooling (1.5). For math, this pattern holds somewhat for Ethiopia, India and Peru (an additional year of schooling in the early years of schooling is associated with increases of 0.1, 0.3, and 0.2 in Ethiopia, India, and Peru, while in later years of schooling an additional year of schooling is associated with increases of 0.2, 0.4, and 0.4 in Ethiopia, India, and Peru, though not significant in for Ethiopia at higher levels; Vietnam shows significant increases only at earlier years of schooling, with coefficient 2.4). For height in cm, an additional year of schooling at lower levels of schooling is again associated with significant increases that are smaller in magnitude in India, Peru, and Vietnam (0.2, 0.2, 0.1) compared to an additional year of schooling at higher levels of schooling (0.3, 0.3, 0.3).

Fathers' schooling at the earlier years is significant for both exams in all countries, while additional schooling at greater than 9 years is significant in five (PPVT in India and Peru, Math in India, and EGRA in India) of the eight possible cases. Fathers' schooling is significant for height only in Ethiopia and Peru for lower levels of schooling, and significant at higher levels of schooling in Vietnam.

Community wealth is significant in all countries for both exams in all four countries. Its magnitude for PPVT ranges from 1.1 in Peru to 5.7 in Ethiopia, and for math, from 0.2 in Peru to 0.9 in India. For height, community wealth is significant in Ethiopia, India and Peru (coefficients of 0.3, 0.4 and 0.3, respectively).

These results suggest that increases in the lower end of the schooling distribution for both mothers and fathers, and in the lower tails of consumption per capita may all have significant implications for children's cognitive scores and, to some extent, their height.

Figure 1: Expected Private Marginal Benefits and Costs for Investment in Children's Schooling from Becker's (1967) Woytinsky Lecture

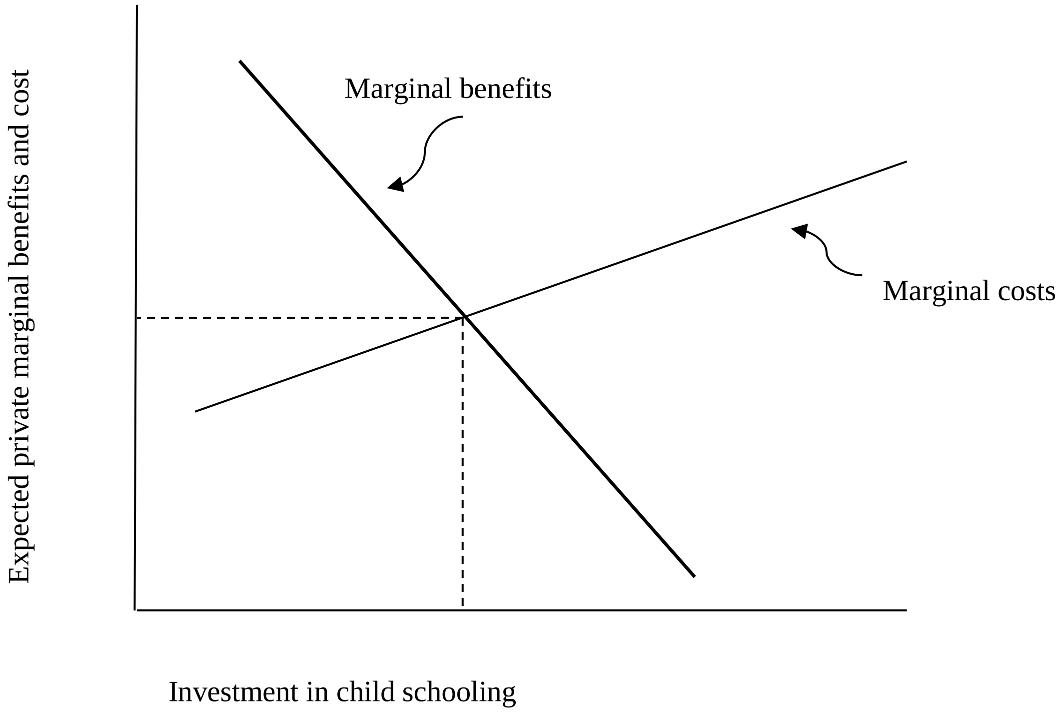
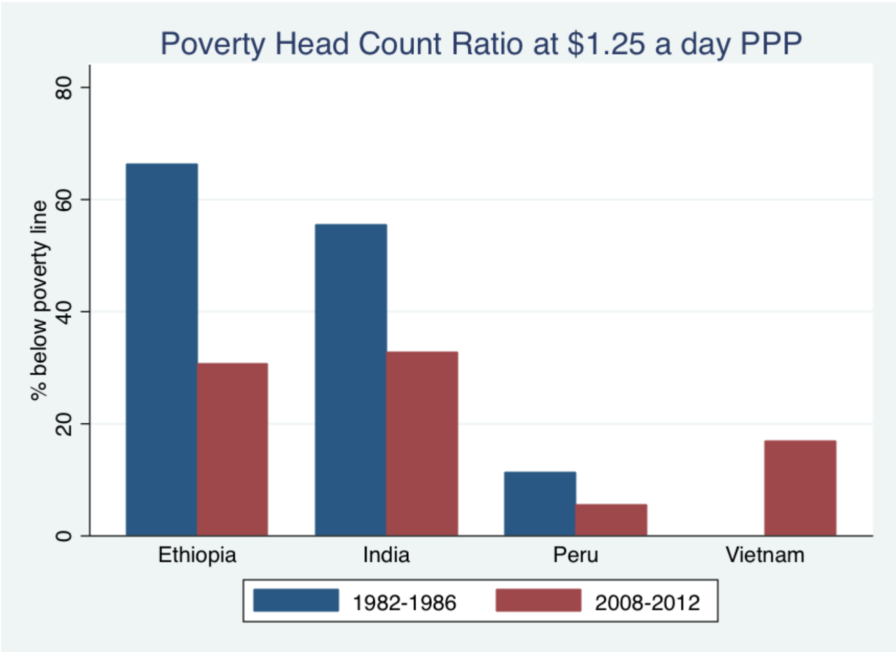
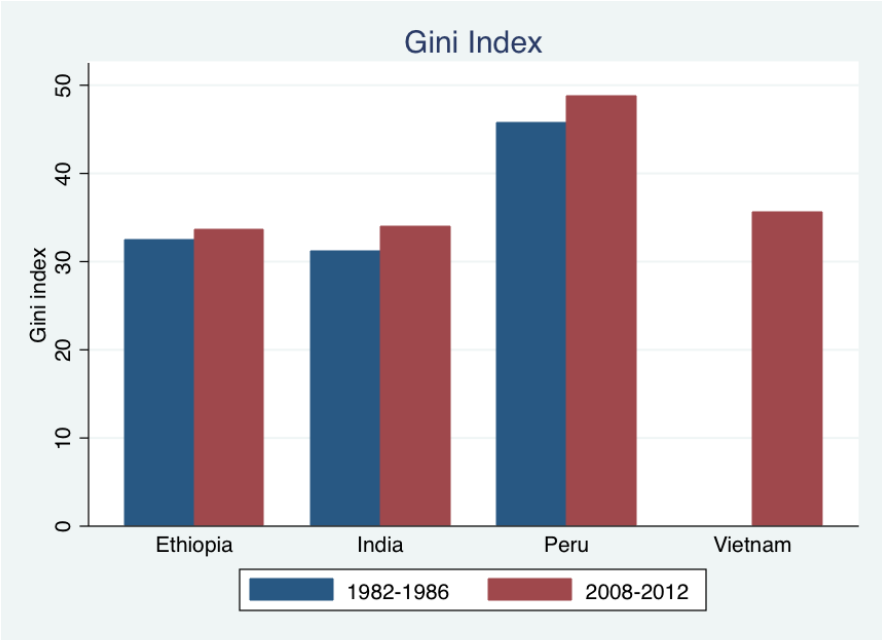


Figure 2: % Below Poverty Line defined at $1.25 a day PPP



Notes: Author calculations based on World Bank Data. The World Bank poverty incidence is computed using the $1.25 per day per person value. Data for Vietnam 1982-1986 are not available.

Figure 3: Gini Index



Notes: Author calculations based on World Bank Data. A Gini index of 0 implies perfect equality and 100 inequality (i.e., all resources are consumed by one individual). Data for Vietnam 1982-1986 are not available.

Table 1. Descriptive Statistics

	Ethiopia (n=1,669)		India (n=1,787)		Peru (n=1,748)		Vietnam (n=1,711)	
	Mean/percent	**SD**	**Mean/percent**	**SD**	**Mean/percent**	**SD**	**Mean/percent**	**SD**
Child Measures								
PPVT	68.6	36.8	49.1	26.7	47.1	13.4	77.8	23.4
Math	6.6	5.4	12.0	6.4	14.3	5.8	18.5	5.7
HAZ (height-for-age z score)	-1.21	1.05	-1.45	1.00	-1.14	1.02	-1.09	1.01
Height	120.66	6.95	118.61	5.93	120.11	5.99	121.10	6.03
Female	46.7		46.3		50.1		48.9	
Age in (months)	97.1	3.7	95.4	3.9	95.0	3.6	96.6	3.4
Parental Measures								
Per capita consumption per day (USD)	0.56	0.38	0.60	0.30	2.05	1.37	0.99	0.76
Mother's schooling	3.1	3.9	3.7	4.4	7.8	4.4	7.1	3.9
Father's schooling	5.0	4.3	5.6	5.0	9.1	3.8	7.7	3.9
Percent mothers <5 yrs schooling	72.4		60.6		24.2		22.7	
Percent fathers <5 yrs schooling	59.7		44.5		11.9		18.9	
Mother's age in round 1	27.4	6.4	23.6	4.3	26.8	6.7	27.0	5.7
Mother's height	158.7	5.9	151.5	6.0	150.0	5.4	152.2	5.8
Community Measures								
Community wealth (PCA index)	0.11	2.73	-0.01	2.38	-0.05	2.61	-0.02	2.42
Moved after round 1	21.1		11.4		48.6		15.0	
Urban	36.5		24.7		66.4		18.1	
Hospital in community	30.3		46.3		34.3		89.5	
Secondary school in community	34.7		43.8		78.1		98.1	

Table 2. Regressions of the natural log of per Capita Consumption, Parents' Generation

	Ethiopia	India	Peru	Vietnam
Mother's schooling	0.053*	0.015*	0.045*	0.048*
	[0.004]	[0.003]	[0.003]	[0.004]
Father's schooling	0.027*	0.027*	0.042*	0.037*
	[0.003]	[0.003]	[0.004]	[0.004]
Mother's height	0.008*	0.001	0.008*	0.010*
	[0.002]	[0.002]	[0.002]	[0.002]
Mother's age	-0.072*	-0.006	-0.017	-0.001
	[0.012]	[0.018]	[0.013]	[0.015]
Mother's age squared	0.001*	0.00	0.00	0.00
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-1.156*	-0.989*	-1.167*	-2.248*
	[0.335]	[0.335]	[0.362]	[0.359]
Observations	1,669	1,787	1,748	1,711
R-squared	0.352	0.156	0.336	0.335

Notes: *Indicates significance at p<0.05. Standard errors in brackets.

Table 3. Gini Coefficient and Poverty Headcount (PH), Parents' Generation

	Ethiopia		India		Peru		Vietnam	
	Gini	**PH**	**Gini**	**PH**	**Gini**	**PH**	**Gini**	**PH**
Consumption	0.320	0.198	0.246	0.168	0.322	0.200	0.319	0.190
	0.006	0.010	0.246	0.009	0.006	0.010	0.009	0.009
Mother's schooling	0.302	0.721	0.248	0.607	0.260	0.241	0.241	0.227
	0.006	0.011	0.005	0.012	0.005	0.010	0.005	0.010
Father's schooling	0.307	0.588	0.257	0.445	0.226	0.117	0.237	0.185
	0.004	0.012	0.005	0.012	0.004	0.008	0.004	0.009
Mother's height	0.020		0.021		0.020		0.021	
	0.000		0.001		0.000		0.000	

Notes: Poverty line is 20th percentile of original distribution for consumption per capita, and is 5 years of schooling for mother's and father's schooling; standard deviations below coefficients.

Table 4. Coefficients from Seemingly Unrelated Regression for PPVT and Math and from Ordinary Least Squares for Height

	PPVT				Math				Height			
	Ethiopia	India	Peru	Vietnam	Ethiopia	India	Peru	Vietnam	Ethiopia	India	Peru	Vietnam
HH per capita consumption (<=20p)	59.02*	7.7	12.66*	12.03	4.13	12.49*	4.93*	7.52*	35.90*	-0.2	3.44*	11.20*
	[24.49]	[15.41]	[1.92]	[10.30]	[3.64]	[3.55]	[0.90]	[2.42]	[7.49]	[2.86]	[1.05]	[3.09]
HH per capita consumption (>20p)	12.01*	6.71*	0.57*	2.27*	1.05*	0.3	0.37*	0.50*	1.40*	1.81*	0.20*	0.45*
	[2.16]	[2.37]	[0.22]	[0.82]	[0.32]	[0.55]	[0.10]	[0.19]	[0.52]	[0.48]	[0.10]	[0.24]
Child female	0.1	-4.54*	-0.79*	-0.23	-0.09	-0.21	-0.65*	0.42*	0.4	-0.4	-0.75*	-0.38
	[1.29]	[1.17]	[0.48]	[0.95]	[0.19]	[0.27]	[0.23]	[0.22]	[0.28]	[0.25]	[0.23]	[0.23]
Age in months	2.08*	0.57*	0.54*	1.26*	0.17*	0.27*	0.37*	0.49*	0.39*	0.37*	0.40*	0.43*
	[0.17]	[0.15]	[0.07]	[0.14]	[0.03]	[0.04]	[0.03]	[0.03]	[0.04]	[0.03]	[0.04]	[0.04]
Mother's height	0.02	0.03	-0.06	0.03	0	0.05*	-0.01	0.05*	0.21*	0.26*	0.33*	0.32*
	[0.11]	[0.10]	[0.05]	[0.09]	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.02]	[0.03]
Mother's schooling (<=9)	0.63*	1.00*	0.38*	1.62*	0.11*	0.32*	0.24*	0.24*	0.13*	0.17*	0.21*	0.13*
	[0.29]	[0.22]	[0.13]	[0.23]	[0.04]	[0.05]	[0.06]	[0.05]	[0.06]	[0.04]	[0.06]	[0.06]
Mother's schooling (>9)	1.18	1.32*	1.01*	1.51*	0.17	0.35*	0.39*	0.09	-0.13	0.32*	0.26*	0.25*
	[0.80]	[0.67]	[0.19]	[0.37]	[0.12]	[0.15]	[0.09]	[0.09]	[0.12]	[0.13]	[0.11]	[0.11]
Father's schooling (<=9)	0.71*	0.66*	0.77*	0.63*	0.17*	0.13*	0.32*	0.28*	0.15*	0.05	0.22*	0.09
	[0.28]	[0.20]	[0.15]	[0.23]	[0.04]	[0.05]	[0.07]	[0.05]	[0.05]	[0.04]	[0.08]	[0.07]
Father's schooling (>9)	0.6	1.13*	0.40*	0.27	0.19*	0.34*	0.1	0.14*	0.00	0.00	-0.02	0.18*
	[0.55]	[0.48]	[0.17]	[0.35]	[0.08]	[0.11]	[0.08]	[0.08]	[0.12]	[0.10]	[0.09]	[0.09]
Mother's age	0.33*	0.17	0.05	-0.07	0.03*	0.01	0.01	0	0.07*	0.05*	0.04*	-0.05*
	[0.10]	[0.14]	[0.04]	[0.09]	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]	[0.03]	[0.02]	[0.02]
Moved after R1	-2.01	-1.4	1.37*	-8.58*	0.07	-1.08*	0.55*	0.53	-1.03*	0.25	-0.07	-0.63
	[1.83]	[2.07]	[0.52]	[1.68]	[0.27]	[0.48]	[0.25]	[0.39]	[0.51]	[0.50]	[0.41]	[0.62]
Urban residence	-10.36*	-7.19*	0.74	-3.14	0.44	-5.80*	0.55	-1.23*	-1.27	-0.14	0.62	1.89*
	[3.50]	[3.30]	[0.87]	[2.45]	[0.52]	[0.76]	[0.41]	[0.58]	[0.77]	[0.73]	[0.49]	[1.03]
Exam in native language	6.06	-2.66	3.67*	-0.26	0.1	-1.23*	0.08	-1.18*				
	[7.92]	[2.66]	[1.19]	[1.46]	[0.80]	[0.63]	[0.51]	[0.34]				

Table 4. Coefficients from Seemingly Unrelated Regression for PPVT and Math and from Ordinary Least Squares for Height

	PPVT				Math				Height			
	Ethiopia	**India**	**Peru**	**Vietnam**	**Ethiopia**	**India**	**Peru**	**Vietnam**	**Ethiopia**	**India**	**Peru**	**Vietnam**
Language 1	14.24*	-11.52*	-8.62*	0.29	2.24*	-1.32*	-2.87*	-8.00*				
	[2.26]	[3.12]	[1.50]	[13.80]	[0.34]	[0.71]	[0.77]	[1.68]				
Language 2	-12.31*	6.03	2.13	-3.98	-2.01*	-0.27	-1.02	0.78				
	[2.24]	[3.68]	[1.55]	[5.74]	[0.33]	[0.93]	[0.76]	[1.34]				
Language 3	-2.23				-0.85*							
	[2.19]				[0.33]							
Community wealth	5.66*	2.11*	1.09*	2.11*	0.74*	0.91*	0.17*	0.48*	0.29*	0.37*	0.28*	0.13
	[0.68]	[0.63]	[0.18]	[0.40]	[0.10]	[0.15]	[0.08]	[0.09]	[0.15]	[0.15]	[0.12]	[0.15]
Hospital presence in community	13.50*	-5.38*	-1.63*	-1.67	0.39	-0.23	-0.44	1.56*	0.78	1.53*	0.2	0.97*
	[2.12]	[1.39]	[0.68]	[1.87]	[0.32]	[0.32]	[0.32]	[0.44]	[0.74]	[0.33]	[0.64]	[0.41]
Secondary school presence in community	6.23*	5.09*	1.22*	4.96	-0.42*	1.27*	-0.33	1.22	-0.36	-0.31	-0.69*	-0.89*
	[1.53]	[1.34]	[0.67]	[3.53]	[0.23]	[0.31]	[0.31]	[0.82]	[0.60]	[0.31]	[0.37]	[0.39]
Constant	-181.64*	-18.65	-24.22*	-71.39*	-13.95*	-26.12*	-29.96*	-44.69*	35.75*	41.36*	23.98*	24.42*
	[26.24]	[21.99]	[10.01]	[20.47]	[3.81]	[5.09]	[4.68]	[4.78]	[6.18]	[4.88]	[4.68]	[5.35]
Observations	1,669	1,787	1,748	1,711	1,669	1,787	1,748	1,711	1,669	1,787	1,748	1,711
R-squared	0.501	0.158	0.438	0.295	0.487	0.224	0.34	0.363	0.174	0.274	0.374	0.328

Notes: Robust standard errors in brackets; *Indicates significance at p<0.05; coefficient estimates on the dummy variables for the missing values are included but suppressed here.

Table 5. Consumption per Capita per Day, 2006 USD (Average over Rounds 2 and 3)

Country	Generation	Mean	SD
Ethiopia	Parents (actual)	0.56	0.38
	Children (expected)*	0.62	0.45
India	Parents (actual)	0.60	0.30
	Children (expected)*	0.73	0.37
Peru	Parents (actual)	2.05	1.37
	Children (expected)*	2.61	1.79
Vietnam	Parents (actual)	0.99	0.76
	Children (expected)*	1.22	0.91

Notes:*Indicates statistically significant difference ($p<0.05$) between children's and parents' generation. Sample size: Ethiopia -1,669; India – 1,787; Peru – 1,748; Vietnam – 1,711.

Table 6. Gini coefficient and poverty headcount (PH), next generation

	Ethiopia		India		Peru		Vietnam	
	Gini	**PH**	**Gini**	**PH**	**Gini**	**PH**	**Gini**	**PH**
Estimated consumption	0.339	0.180	0.259	0.110	0.337	0.125	0.326	0.106
	0.007	0.009	0.006	0.007	0.006	0.008	0.008	0.007
Estimated mother's schooling	0.365	0.612	0.366	0.528	0.238	0.138	0.213	0.117
	0.003	0.012	0.004	0.012	0.004	0.008	0.004	0.008
Estimated father's schooling	0.324	0.366	0.331	0.351	0.180	0.045	0.195	0.081
	0.004	0.012	0.004	0.011	0.003	0.005	0.004	0.007
Estimated mother's height	0.020		0.020		0.020		0.020	
	0.000		0.000		0.000		0.000	

Notes: Poverty line is 20th percentile of parents' distribution for consumption per capita, and is 5 years of schooling for mother's and father's schooling; standard errors below estimates.

Table 7. Estimated inequality in distribution of hypothetical scenarios for schooling and consumption, parents' generation

	Mothers' schooling			
	Gini Coefficient		**Poverty Headcount**	
	MS=P	***MS=9y***	***MS=P***	***MS=9y***
Ethiopia	0.194	0.026	0.721	0.000
	0.006	0.002	0.011	0.000
India	0.172	0.036	0.000	0.000
	0.004	0.002	0.000	0.000
Peru	0.188	0.089	0.000	0.000
	0.002	0.002	0.000	0.000
Vietnam	0.204	0.063	0.000	0.000
	0.003	0.003	0.000	0.000
	Fathers' schooling			
	Gini Coefficient		**Poverty Headcount**	
	MS=P	***MS=9y***	***MS=P***	***MS=9y***
Ethiopia	0.257	0.057	0.588	0.000
	0.004	0.003	0.012	0.000
India	0.219	0.069	0.000	0.000
	0.002	0.003	0.000	0.000
Peru	0.183	0.098	0.000	0.000
	0.002	0.002	0.000	0.000
Vietnam	0.205	0.076	0.000	0.000
	0.003	0.003	0.000	0.000
	Per Capita Consumption			
	Gini Coefficient		**Poverty Headcount**	
	MC=20p	***MC=$1d***	***MC=20p***	***MC=$1d***
Ethiopia	0.297	0.040	0.198	0.000
	0.007	0.005	0.010	0.000
India	0.228	0.026	0.000	0.000
	0.004	0.003	0.000	0.000
Peru	0.292	0.299	0.000	0.200
	0.007	0.007	0.000	0.010
Vietnam	0.296	0.155	0.000	0.000
	0.008	0.008	0.000	0.000

Notes: Poverty line is 20th percentile of parents' distribution for consumption per capita, and is 5 years of schooling for mother's and father's schooling; MS= minimum schooling, MC=minimum consumption, P=primary, 9y=9 years, 20p= 20th percentile, $1d=$1 per day.

Table 8. Percentage increases in children's human capital, simulated scenarios

	MS=P	*MS=9y*	*MC=20p*	*MC=$1d*	*MS=9 &MC=$1d*
			PPVT		
Ethiopia	4.8	15.4	1.5	13.4	28.8
India	11.2	23.6	0.3	7.6	31.2
Peru	3.1	7.8	2.9	2.2	10.1
Vietnam	2.6	9.1	0.4	1.1	10.2
			Math		
Ethiopia	16.0	50.9	1.7	18.2	69.1
India	19.6	39.6	4.1	5.8	45.4
Peru	6.1	15.1	4.0	3.0	18.1
Vietnam	3.0	9.9	1.3	2.1	12.0
			Height		
Ethiopia	0.4	1.3	0.3	0.9	2.1
India	0.5	1.0	0.0	0.6	1.6
Peru	0.3	0.7	0.2	0.1	0.9
Vietnam	0.1	0.5	0.2	0.3	0.7

Notes: MS= minimum schooling, MC=minimum consumption, P=primary, 9y=9 years, 20p=20th percentile, $1d=$1US per day.

Table 9. Gini Coefficients, Simulated Scenarios

		none	*MS=P*	*MS=9y*	*MC=20p*	*MC=$1d*	*MS=9 &MC=$1*
PPVT	Ethiopia	0.296	0.282	0.258	0.291	0.262	0.232
		0.003	0.003	0.003	0.003	0.003	0.003
Math	Ethiopia	0.447	0.414	0.350	0.443	0.409	0.323
		0.005	0.006	0.004	0.005	0.005	0.004
Height	Ethiopia	0.031	0.030	0.029	0.030	0.029	0.029
		0.001	0.001	0.001	0.001	0.001	0.001
PPVT	India	0.280	0.252	0.230	0.280	0.263	0.219
		0.004	0.004	0.004	0.004	0.004	0.003
Math	India	0.304	0.266	0.238	0.297	0.293	0.231
		0.005	0.004	0.003	0.005	0.005	0.003
Height	India	0.028	0.027	0.027	0.028	0.028	0.026
		0.001	0.001	0.000	0.000	0.000	0.000
PPVT	Peru	0.156	0.147	0.136	0.148	0.150	0.131
		0.003	0.003	0.003	0.004	0.004	0.003
Math	Peru	0.229	0.214	0.195	0.220	0.222	0.190
		0.005	0.004	0.004	0.004	0.004	0.003
Height	Peru	0.028	0.027	0.026	0.028	0.028	0.026
		0.000	0.000	0.000	0.000	0.000	0.000
PPVT	Vietnam	0.161	0.152	0.138	0.160	0.158	0.136
		0.003	0.003	0.003	0.003	0.003	0.003
Math	Vietnam	0.176	0.167	0.152	0.172	0.170	0.148
		0.004	0.003	0.003	0.003	0.003	0.002
Height	Vietnam	0.028	0.028	0.027	0.027	0.027	0.027
		0.000	0.000	0.000	0.000	0.001	0.000

Notes: Zeros coded to 0.4; MS=minimum schooling, MC=minimum consumption, P=primary, 9y=9 years, 20p=20th percentile, $1d=$1 per day; standard errors below coefficients.

Table 10. Poverty Headcounts, Simulated Scenarios

		none	*MS=P*	*MS=9y*	*MC=20p*	*MC=$1d*	*MS=9 &MC=$1*
PPVT	Ethiopia	0.200	0.161	0.088	0.187	0.096	0.021
		0.010	0.009	0.007	0.010	0.007	0.004
Math	Ethiopia	0.141	0.110	0.036	0.141	0.131	0.016
		0.009	0.008	0.005	0.009	0.008	0.003
PPVT	India	0.175	0.071	0.035	0.175	0.100	0.019
		0.009	0.006	0.004	0.009	0.007	0.003
Math	India	0.167	0.119	0.061	0.164	0.163	0.049
		0.009	0.008	0.006	0.009	0.009	0.005
PPVT	Peru	0.193	0.177	0.146	0.180	0.185	0.137
		0.009	0.009	0.008	0.009	0.009	0.008
Math	Peru	0.172	0.156	0.126	0.161	0.164	0.111
		0.009	0.009	0.008	0.009	0.009	0.008
PPVT	Vietnam	0.189	0.150	0.069	0.185	0.177	0.060
		0.009	0.009	0.006	0.009	0.009	0.006
Math	Vietnam	0.157	0.146	0.103	0.155	0.152	0.092
		0.009	0.009	0.007	0.009	0.009	0.007

Notes: poverty threshold=20 percentile of actual scores; MS=minimum schooling, MC=minimum consumption, P=primary, 9y=9 years, 20p=20th percentile, $1d=$1 per day; standard errors below estimates.

Table 11. Gini coefficient and poverty headcount under simulated scenarios, estimated future household consumption, children's generation

Gini Coefficients

Country	*none*	*MS=P*	*MS=9y*	*MC=20p*	*MC=$1d*	*MS=9 &MC=$1d*
Ethiopia	0.339	0.333	0.322	0.337	0.323	0.308
	0.007	0.007	0.007	0.008	0.007	0.006
India	0.259	0.255	0.253	0.257	0.255	0.249
	0.006	0.004	0.005	0.005	0.005	0.005
Peru	0.337	0.332	0.328	0.333	0.334	0.325
	0.006	0.006	0.007	0.006	0.006	0.006
Vietnam	0.326	0.324	0.320	0.325	0.324	0.318
	0.008	0.008	0.008	0.010	0.008	0.007

Poverty Headcounts

Country	*none*	*MS=P*	*MS=9y*	*MC=20p*	*MC=$1d*	*MS=9 &MC=$1d*
Ethiopia	0.180	0.158	0.116	0.174	0.133	0.076
	0.009	0.009	0.008	0.009	0.008	0.006
India	0.110	0.097	0.088	0.107	0.103	0.079
	0.007	0.007	0.007	0.007	0.007	0.006
Peru	0.125	0.117	0.106	0.120	0.122	0.102
	0.008	0.008	0.007	0.008	0.008	0.007
Vietnam	0.106	0.096	0.086	0.102	0.101	0.081
	0.007	0.007	0.007	0.007	0.007	0.007

Notes: Poverty threshold=20th percentile of consumption in the parents' generation; MS=minimum schooling, MC=minimum consumption, P=primary, 9y=9 years, 20p=20th percentile, $1d=$1 per day; standard errors below estimates.

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Intergenerational Transmission of Poverty and Inequality: Young Lives

There is considerable emphasis in academic and policy literatures on intergenerational transmissions of poverty and inequality. The perception is that improving schooling attainment and income/consumption for parents in poor households will result in important reductions in poverty and inequality for the next generation of adults. However, the extents of these intergenerational effects on poverty and inequality are empirical questions that have not been examined much if at all, particularly for developing countries. We use data on children born in the 21st century in four developing countries to estimate critical relations with which to simulate how changes in parents' schooling attainment and consumption would affect poverty headcounts and inequality in the children's generation when the children become adults. We find that reductions in poverty headcounts and inequalities in the parents' generation carry over to distributions of human capital and per capita adult consumption for the children's generation, but the effects are not very large for the distribution of per capita consumption. Therefore, while reductions in poverty and inequality in the parents' generation are likely to be desirable in themselves to improve welfare among current adults, they are not likely to have much impact on reducing per capita consumption poverty and inequality in the next generation of adults.

Young Lives
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About Young Lives

Young Lives is an international study of childhood poverty, involving 12,000 children in 4 countries over 15 years. It is led by a team in the Department of International Development at the University of Oxford in association with research and policy partners in the 4 study countries: Ethiopia, India, Peru and Vietnam.

Through researching different aspects of children's lives, we seek to improve policies and programmes for children.

Young Lives Partners

Young Lives is coordinated by a small team based at the University of Oxford, led by Professor Jo Boyden.

- *Ethiopian Development Research Institute, Ethiopia*
- *Pankhurst Development Research and Consulting plc*
- *Save the Children (Ethiopia programme)*
- *Centre for Economic and Social Sciences, Andhra Pradesh, India*
- *Save the Children India*
- *Sri Padmavathi Mahila Visvavidyalayam (Women's University), Andhra Pradesh, India*
- *Grupo de Análisis para el Desarollo (GRADE), Peru*
- *Instituto de Investigación Nutricional, Peru*
- *Centre for Analysis and Forecasting, Vietnamese Academy of Social Sciences, Vietnam*
- *General Statistics Office, Vietnam*
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