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"Height and Cognitive Achievement among Indian Children"

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Abstract

Taller children perform better on average on tests of cognitive achievement, in part because of differences in early-life health and net nutrition. Recent research documenting this height-achievement slope has primarily focused on rich countries. Using the India Human Development Survey, a representative sample of 40,000 households which matches anthropometric data to learning tests, this paper documents a height-achievement slope among Indian children. The height-achievement slope in India is more than twice as steep as in the U.S. An earlier survey interviewed some IHDS children's households eleven years before. Including matched early-life control variables reduces the apparent effect of height, but does not eliminate it; water, sanitation, and hygiene may be particularly important. Being one standard deviation taller is associated with being 5 percentage points more likely to be able to write, a slope that falls only to 3.4 percentage points controlling for a long list of contemporary and early-life conditions.

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1 Introduction

Economists, demographers, and medical researchers are accumulating persuasive evidence of lasting consequences of early-life health and net nutrition for life-long economic, cognitive, and health outcomes (Currie, 2009; Almond and Currie, 2011). Much of this literature uses height as a marker of health: as Deaton (2007) explains, "height is determined by genetic potential and by net nutrition, most crucially by net nutrition in early childhood." Net nutrition "is the difference between food intake and the losses to activities and to disease." People who suffer net nutritional deficits early in life are shorter, on average, because they tend not to reach their genetic potential heights. These same nutritional deficits matter for cognitive development. Case and Paxson (2008) documented that the positive association between height and earnings emerges because "height is positively associated with cognitive ability, which is rewarded in the labor market:" people who fulfill their genetic height potential are also more likely to fulfill their genetic cognitive potential.

The recent literature in economics documenting the association between height and cognitive development has focused on richer countries. Generally, this literature requires large survey datasets, and few are available in poor countries that match anthropometric data with cognitive tests. Grantham-McGregor et al. (2007) review studies from developing countries documenting a link between childhood stunting and low cognitive achievement; these range in sample size from 72 to 2489 and typically focus on a binary indicator of stunting. Victora et al. (2008) review studies in poor countries that find an association between height-for-age and schooling attainment, but do not address tested cognitive achievement. In a randomized, controlled trial in Guatemala that began with 2,392 participants, Stein et al. (2008) found that children "exposed to *atole* (a protein-rich enhanced nutrition supplement) at birth through age 24 months" scored higher in adulthood on tests of intellectual functioning than "those exposed to the supplement at other ages or to *fresco*, a sugar-sweetened beverage."[1]

[1]Because it targeted such young children, this program worked partially by improving the nutrition of

In a longitudinal study primarily of the intergenerational transmission of social-economic status among 2,600 children in the Phillippines, Carvalho (2010) notes that taller children score higher on cognitive tests at ages 8 and 11.

The recent work most complementary to this paper is Kingdon and Monk's (2010) analysis of 4,000 students living in rural areas in 11 districts of India. They, too, find a high correlation between height for age — scaled using CDC standards — and cognitive achievement, also using a test related to Pratham's ASER survey, described below in section 2.1. Kingdon and Monk studied children from 6 to 14 years old, with two observations for each child during this period, but cannot match their panel to early life data. Instead, they instrument for health using rainfall data from early in a child's life.

This paper documents and describes an association between child height and cognitive achievement in India using the India Human Development Survey, a large, nationally-representative dataset. In particular, section 2 first estimates the Indian height-achievement slope and compares it across subsamples of children. Next, section 3 compares this Indian slope to the slope in the U.S. Case and Paxson (2010) have investigated the association between height and test scores among U.S. children using the NLSY Child and Young Adult Survey. We will compare our results to their paper (henceforth CP10) and make similar use of NLSY79 data. Finally, section 4 attempts to explain the association between height and achievement by controlling for omitted indicators of early life health. In particular, the Human Development Profile of India surveyed many of the rural IHDS households 11 years earlier. Matching these data provides information about children's initial environments.

There are several reasons to add a detailed study of the height-cognitive achievement slope in a poor country to the literature. First, the effects of health on cognitive achievement could be different where the average person is extremely deprived. Second, Indian children could face different barriers to learning and achievement, such as gender and caste

pregnant and lactating mothers (Martorell, 1995).

discrimination and extremely low-quality schools. Third, Indian children may exhibit wider variation than U.S. children in early-life health status. Finally, this study of Indian anthropometric data may contribute to understanding, or at least clarifying, the puzzle of especially high malnutrition in South Asia: this evidence suggests that short Indian children are, indeed, unhealthy.

2 Height and cognitive achievement in India

2.1 Data: India Human Development Survey

Do taller Indian children score higher, on average, on cognitive achievement and learning tests? This section investigates the height-achievement slope using data on eight- to eleven-year olds in the India Human Development Survey.[2]

The IHDS interviewed a representative national sample of over 40,000 Indian households. Interviews were carried out in 2004 and 2005. Surveyors asked a broad range of economic, social, political, and health-related questions. In particular, surveyors made anthropometric measurements, including children's height. Using WHO reference tables based on an international reference population of wealthy and healthy children (World Health Organization, 2006), we transformed heights into height-for-age z-scores.

Table 1 reports summary statistics, separately by age and rural or urban location. Indian children are, on average, much shorter than the reference population (which would, by construction, have a mean of zero) even at the 75th percentile. Averaging over ages 8

[2] "The India Human Development Survey (IHDS) is a nationally representative, multi-topic survey of 41,554 households in 1503 villages and 971 urban neighborhoods across India. Two one-hour interviews in each household covered health, education, employment, economic status, marriage, fertility, gender relations, and social capital. Children aged 8-11 completed short reading, writing and arithmetic tests. Village, school, and medical facility interviews are also available. Fieldwork began in November 2004 and was mostly completed by October 2005. IHDS was jointly organized by researchers from the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi. Funding for the survey was provided by the National Institutes of Health, grants R01HD041455 and R01HD046166" (Desai et al., 2007). Available online at: ihds.umd.edu

to 11, these statistics represent an average height deficit of about 13 centimeters. These results are consistent with findings using other data sources that about 50 percent of Indian children are stunted ($z < -2$) and about 25 percent are severely stunted ($z < -3$) (Deaton, 2007; Klasen, 2008). At each age, in each statistic, rural children are shorter than urban children. There are many more reported ten-year-olds than in the other categories, and, on average, they have lower height-for-age z-scores than the other ages, despite the built-in age adjustments of these scores; this could reflect age heaping in poorer households.

Children age 8 to 11 in the IHDS were given cognitive achievement tests; therefore, only children in this age range are studied in this paper. The three tests – in reading, math, and writing – were developed by Pratham, an Indian NGO, and are annually implemented in Pratham's Annual Status of Education Report (ASER) survey.[3] ASER reports have documented low and heterogenous levels of learning among Indian children (ASER Centre, 2011).

These tests offer a coarse measure of achievement. The reading test divides children into five categories: unable to read, reads letters, reads words, reads paragraphs, and reads stories. Math reports four levels: unable to do math, understands numbers, subtracts, and divides. Writing offers only two levels: unable to write, and writes a sentence with two mistakes or fewer. While a finer measure of learning could be more useful, the ASER tests must be consistently implemented by field surveyors in rural villages and urban slums. Slightly more than 2 percent of the children did not take each test.

Table 1 also presents the fraction of children in each group scoring at or above certain levels on the ASER tests. For example, 68.8 percent of rural eight-year-olds read words or better. For each age, on each test, urban children perform better than rural children, and on each test, in each location, older children score higher than younger children, on

[3]Hindi and English versions of the tests are publicly available online at the IHDS website; the ASER survey is described online at: www.asercentre.org.

average. Performance is low: less than 70 percent of rural eleven-year-olds can read a simple paragraph, and less than 60 percent of rural eleven-year-olds can do a simple subtraction problem.

The table also reports the fraction of each group that is female: as in other Indian data, this is notably below 50 percent. Mean household consumption per capital — as already computed from survey questions and available in the public IHDS data — is reported in rupees per month. Urban households consume about 50 percent more than rural households.

2.2 Results

Figure 1, plotting non-parametric local polynomial regressions, displays the main result of this paper: on average, taller Indian children score higher on the cognitive achievement tests. Panel (a) plots the fraction of children at each height scoring at or above each reading level. The line for each level slopes up throughout the height distribution. One simple summary of the magnitude of the slope and the depth of Indian malnutrition is that children at the mean reference z-score of 0 are about 10 percentage points more likely to be able to read a simple paragraph than children at the observed mean.

Panel (b) focuses on reading words or better, an easy-to-measure threshold, and one with clear quality-of-life consequences. The slope is plotted separately for urban and rural girls and boys. While clearly important, health reflected in height-for-age is not the only determinant of cognitive achievement. The urban averages are above the rural lines everywhere except the very top: at almost all heights, urban boys and girls are more likely to be able to read words than rural boys and girls. Further, although the urban lines cross, rural girls are less likely to be able to read than rural boys at every height.

Panel (c) again focuses on reading words or better, separating children by age. Because reading words is a skill level that many children will learn towards as they grow, it is unsurprising that the curve pivots: while at all ages about 90 percent of the tallest children read words, less than 60 percent of the shortest eight-year-olds do, compared with about 80 percent of the shortest eleven-year-olds.

Table 2 confirms the statistical significance of these results. Each estimated coefficient is $\hat{\beta}$ from one of 48 separate ordered logit regressions,

$$achievement^*_{ij} = \alpha_k + \beta z^{hfa}_{ij} + \theta X_{ij} + \varepsilon_{ij}.$$

The dependent variable, $achievement^*_{ij}$ is the unobserved latent achievement level, α_k are the cut-points of the k test levels, and z^{hfa}_{ij} is the height-for-age z-score. Individual children i belong to villages and urban sampling units j, according to which standard errors are clustered. Recommended sampling weights are used. All regressions in this paper omit observations with z scores below -6 (which the WHO guidelines describe as unreliable) or outside the 1st to 99th percentiles. The second and fourth columns include child and household economic, demographic, and educational control variables X_{ij}, detailed below in section 4.

The coefficients on height-for-age are always positive and almost always statistically significant. Coefficients are, in general, larger for younger children than for older children, and for rural children than for urban children, although not always; section 4 will discuss in more detail the difficulty comparing ordered logit coefficients across models. In general, the control variables reduce the coefficient estimates, but do not eliminate their statistical significance.

While it is possible that the relationship between height and achievement could change at extremely low values, in figure 1 the height-achievement slope appears approximately linear. This linearity can be tested. A height-for-age quadratic term is not statistically significant in pooled ordered logits for the reading ($t = 1.29$), math ($t = 1.38$), or writing tests ($t = 0.46$). More formally, writing is most suitable for linear regression because it is binary and a linear probability model can be used. A Box-Cox transformation of height-for-age ($\frac{z^\lambda - 1}{\lambda}$) in this linear model with the control variables maximizes likelihood at $\lambda = 1.26$ with a standard error of 0.38; the hypothesis that $\lambda = 1$ and no transformation is necessary is unambiguously not rejected.

3 Comparing India and the U.S.

The recent literature documenting the economic consequences of early-life health with large, survey datasets – including CP10 – has focused on richer countries, especially the U.S. and the U.K. As figure 2 plots, the distribution of Indian children's heights is far to the left of the distribution of U.S. heights. How does the Indian slope compare to that in the U.S., a richer country with a different health environment?

Comparing these slopes requires a comparable achievement test. CP10 use the National Longitudinal Study of Youth 1979 (NLSY79) child and young adult data – data about the children of the 1979 longitudinal cohort. There data report children's scores on the Peabody Individual Achievement Test, including reading recognition and comprehension scores. PIAT scores offer a much finer measure of achievement than ASER tests, with 84 categories. Moreover, the PIAT tests do not test the exact same skills, requiring, for example, matching a sentence to a picture it describes in the comprehension test.

In unreported results, we approximately replicate CP10's Table 4 results (an exact replication would require knowing the cutoffs CP10 use to exclude z-score outliers), which use standardized, continuous PIAT scores. PIAT tests are proprietary, and the NLSY79 documentation offers no guidance in interpreting them to indicate reading levels (letters, words, paragraphs) that are comparable to the ASER levels. We matched the ASER "reads letters" and "reads words" levels to points on the PIAT reading recognition test and the "reads paragraphs" level to a point on the PIAT reading comprehension test. After examining the recognition test materials used in the NLSY,[4] we selected PIAT reading recognition test raw scores of at least 18 and 23 as "reading letters" and "reading words" comparable to those in the ASER tests, respectively: after level 18 the recognition test advances from letters to words, and after 23 the test advances from simple words similar to those in the ASER test to more complicated words. The NLSY PIAT reading comprehension test materials are not similarly available; based on a break point in the raw score distributions for children of each age, we selected PIAT reading comprehension test scores of 34 as corresponding to the ASER "reads paragraphs" threshold. While these selections are probably imperfect matches, results below will demonstrate robustness to selecting *any* PIAT level as the corresponding cut-point.

Figure 3 plots the U.S. and Indian height-achievement patterns for reading words or better, separately for eight- or nine-year olds and ten- or eleven-year olds. As CP10 and previous studies of richer countries have documented, the lines for U.S. children slope upwards: taller children are more likely to read words. However, the slope is much steeper for Indian children: among Indian children, a given increase in their height-for-age z-score is associated with a much greater average increase in the likelihood of being able to read.

To confirm that this difference is statistically significant, we stack the U.S. and Indian surveys into one large dataset. Then, separately for the various reading levels, at each age we estimate the linear probability interactive model:

$$reads_i = \beta_0 + \beta_1 z_i^{hfa} + \beta_2 India_i \times z_i^{hfa} + \beta_3 India_i + \beta_4 female_i + \beta_5 India_i \times female_i + \varepsilon_i,$$

where $India_i$ is an indicator for the observation coming from the Indian IHDS rather than the U.S. NLSY79 data, and $female_i$ is an indicator for being female. The estimate of β_1 will document the U.S. slope; a positive β_2 coefficient reflects a steeper Indian slope. Because

[4] Available online as of April 2011 at http://www.nlsinfo.org/usersvc/Child-Young-Adult/childya2006/Child%202006%20questionnaires/AssessmentPIATReadingRecognition.htm

the surveys have different sampling structures, only heteroscedasticity-robust standard errors can be used.

Table 3 reports the results. For both reading words and reading paragraphs, the interaction between India and height-for-age is positive and statistically significant, implying that the Indian slope is steeper. One might worry that this difference in slopes is partially driven by the upper bound of 100 percent in the U.S. However, the Indian slope remains steeper even in cases where both the U.S. and the Indian averages are far from 100 pecent. For example, for reading paragrpahs among eight- and nine-year olds, the overall means are only 13 and 15 percentage points apart, respectively, and the $India_i$ indicator is not statistically significant, but in both cases the height-achievement slope is more than twice as steep in India. Additionally, the interaction remains in logistic regression, where a one standard-deviation increase in height increases the odds of reading paragraphs by 10 percent in the U.S., but by 25 percent in India (interaction $t = 5.72$).

Could these results be an artifact of the chosen PIAT thresholds? Might the height-achievement slope be steeper in the U.S. for a different PIAT cut-point? Figure 4 investigates this possibility. To construct it, we used the U.S. data only to run 84 regressions of the form

$$\mathbf{1}[\text{PIAT reading comprehension} \geq s] = \beta_0 + \beta_1 z_i^{hfa} + \varepsilon_i,$$

where $\mathbf{1}[\cdot]$ is an indicator function and s, the PIAT score cut-point determining the dependent variable, ranged from 1 to 84, the entire range of possible cut-points.

The bar graph plots $\hat{\beta}_1$, the coefficient on height for age, for the regression with each dependent variable. The horizontal lines at the top of the graph represent the estimates using IHDS data predicting "reading paragraphs" and "reading stories." Because each of the U.S. coefficients is far below the Indian coefficients, the conclusion that the Indian slope is steeper would hold no matter which PIAT reading comprehension score is deemed comparable to the ASER "reads paragraphs" level. The same finding emerges from comparing all PIAT reading recognition cut-points to the ASER "reads letters" and "reads words" levels.

3.1 Why is the Indian slope steeper?

As CP10 and other researchers have argued, the correlation between cognitive achievement and height may reflect imitted variables. What can be learned about early life health and human capital from the fact that the Indian slope is steeper?

Most generically, we might imagine that cognitive achievement, c, and height, z (for z-score), both depend on a genetic potential g and early-life health and net nutrition h that may cause later outcomes to fall short of the genetic potential:

$$c = g_c - f_c(h); \qquad z = g_z - f_z(h).$$

The functions f_c and f_z map health levels into outcome deficits that are deducted from genetic potentials. We will assume that g_c and g_z are uncorrelated with one another and with h (which may be less likely to be the case in India if mortality selection is important — for example, if large babies are only born alive if their parents can afford a Caesarian or delivery in a hospital).

Simplifying the model in light of the linearity results of section 2.2, let f be linear in both cases, so that

$$c = \beta_c h + \varepsilon_c; \qquad z = \beta_z h + \varepsilon_z.$$

Assuming that the conditional expectations of c and z given h are indeed linear, then ε_c and ε_z (into which g_c and g_z are now included) will be uncorrelated with h. Finally, assume that the determinants of cognitive achievement and height that have nothing to do with early-life human capital are, themselves, unrelated, so ε_c and ε_z are uncorrelated.

This list of assumptions allows us to write a simple expression for the OLS coefficient obtained from regressing cognitive achievement on height:

$$\beta^{OLS} = \frac{\beta_c \beta_z \sigma_h^2}{\beta_z^2 \sigma_h^2 + \sigma_z^2},$$

where σ_h^2 is the variance of h and σ_z^2, in a slight abuse of notation, is the variance of ε_z.

This simple formulation allows us to consider three categories of reasons why β^{OLS} might be greater in India than in the U.S.:

- $\frac{\beta_c^{\text{India}}}{\beta_z^{\text{India}}} > \frac{\beta_c^{\text{U.S.}}}{\beta_z^{\text{U.S.}}}$: Relative to its effect on height, health is much more important for cognitive achievement in India than in the U.S.

- $\beta_c^{\text{India}} > \beta_c^{\text{U.S.}}$ and $\beta_z^{\text{India}} > \beta_z^{\text{U.S.}}$: The effects of health are greater in India for both height and cognition, diluting the noise from ε_z. This could be because remedial health and education opportunities are less available to vulnerable children in India than in the U.S.

- $\sigma_{h\text{ India}}^2 > \sigma_{h\text{ U.S.}}^2$, relative to σ_z^2: The variation in early-life health is greater in India, swamping the noise from ε_z. This would suggest that the relatively less healthy children in India are much less healthy than the relatively less healthy children in the U.S.

If instead of regressing cognitive achievement on height we regress height on cognitive achievement, we find that the Indian slope is again steeper: U.S. children who read paragraphs are 0.15 standard deviations taller, on average, than those who do not, but this difference is 0.36 standard deviations wider in India (interaction $t = 8.99$). This makes the first candidate unlikely to be the only explanation: in these flipped regressions, β_c would only be in the deonominator of β^{OLS}, but the Indian coefficient remains greater.

The bottom rows of table 3 provide further evidence. In simple linear regressions of cognitive achievement on height, computed separately for the U.S. and Indian samples, the R^2 is approximately an order of magnitude greater in India than in the U.S. for every age, for both achievement indicators. This is consistent with either of the second and third candidate explanations: early-life health is more important for subsequent outcomes in India than in the U.S. relative to unrelated sources of variance in ε, including differences in genetic potential.

This discussion, following other analyses of height outside of Africa, has focused on scarring effects of early life health and net nutrition, rather than mortality selection (Deaton, 2007). If selection is quantitatively important – such that healthier babies are more likely to survive – then ε_c and ε_z will indeed be correlated, and the numerator of β^{OLS} would include the positive term σ_{cz}, almost surely greater in India than in the U.S.

4 Explaining the slope: Early life environment

If the correlation between height and cognitive achievement reflects unobserved differences across children in early-life health and net nutrition, then controlling for these omitted variables may reduce the coefficient on height, predicting cognitive achievement. CP10 find in NLSY79 data that controlling first for properties of a child's mother and then for mother fixed effects both reduce the height-achievement slope, but do not eliminate it.

Stepwise addition of control variables could clarify the important sources of variation in h, early-life health, by revealing which covariates importantly reduce the coefficient on height-for-age. This is possible for some children in the IHDS data. In 1993 and 1994 the National Council of Applied Economic Research (NCAER) conducted a similar survey of rural households, the Human Development Profile of India (HDPI). To permit longitudinal analysis, the IHDS revisited some of these households when it conducted its survey in 2004 and 2005. For IHDS eleven-year-olds, the HDPI recorded conditions approximately when they were born; ten-year olds would have been *in utero*; and while eight- and nine-year-olds would not yet have been alive, their household conditions a few years before their birth are probably highly correlated with conditions at their birth. Because the HDPI only surveyed rural households, urban children cannot be included in this analysis. Additionally, as the last row of table 1 demonstrates, not all rural IHDS children can be matched to HDPI households.

As figure 5 summarizes graphically, the early life data reduces the height-achievement slope, but not by very much. These regressions present the dummy coefficients β_k in the linear probability regression:

$$reads\ words_{ij} = \sum_{k=-4}^{0} \beta_k \mathbf{1}[k \leq z_{ij}^{hfa} < k+1] + \theta X_{ij}^{IHDS} + \vartheta X_{ij}^{HDPI} + \varepsilon_{ij},$$

where $\mathbf{1}[\cdot]$ are indicator functions such that height for age z-scores are sorted into five categories, where the categories are chosen to be standard deviations above or below a z-score of zero, and are connected by splines. The graph connects the point estimates of β_k as estimated first with no controls, then with a set of 2004-2005 IHDS controls, and finally with the IHDS controls and a set of 1993-1994 HDPI controls, discussed below. These controls flatten the slope only a little.

Table 4 presents these results in more detail. Each column, for each achievement test, presents the coefficient on height for age from a restricted step of the model

$$achievement_{ij}^{*} = \alpha_{age} + \beta z_{ij}^{hfa} + \theta_1 X_{ij}^{IHDS} + \theta_2 X_{ij}^{94hh} + \theta_3 X_{ij}^{94food} + \theta_4 X_{ij}^{94air} + \theta_5 X_{ij}^{94water} + \varepsilon_{ij},$$

where α_{age} are age indicators, a linear probability model is fit to the binary writing test (to avoid the difficulty of comparing logit coefficients across models), and reading and math are modeled as ordered logits. Although CP10 show that in the U.S. data controlling for mother fixed effects reduces the coefficient on height-for-age, in the IHDS data few households have multiple children in the 8 to 11 age range. Below the estimated coefficients, the table reports predicted effects.[5] These were computed by predicting the probabilities of each outcome with

[5]Ordered logit coefficients cannot be directly compared across models because only β/σ is identifiable,

each z-score set first to -2 and then to -1, summing to find the probability of a high test score at each z-score, and subtracting to find the predicted effect of increasing the z-score from -2 to -1.

Covariates are added step by step in order to separate any effects of different dimensions of the early-life environment. The full model controls for:

- *04-05 controls*: male; ever school; government school; son or daughter of household head; consumption per capita (cubic); income; an asset index (quadratic); highest education of any household adult, of a male, and of a female; the household's count of people, children, and teenagers; and indicators for caste status and religion, states, and taking the tests in English or Hindi.

- *93-94 household*: income per capita (quadratic); household size (quadratic); whether the house was at least semi-pucca; productive and unproductive asset indices; highest household male and female education; and indicators for household adult occupational and literacy groups.

- *93-94 food & nutrition*: consumption of cereals and pulses for the last 30 days per capita (quadratic); per capita expenditure on fruits and on vegetables; and an indicator for being non-vegetarian (buying a positive amount of meat or fish).

- *93-94 respiratory environment*: indicators for using clean fuel, having a modified stove, having a kitchen in a separate room, having electricity, and having a chimney or smoke outlet.

- *93-94 water, sanitation, & hygiene*: indicators for reporting adequate water supply, for having a water source at home, for the water source being very far, for having a

the ratio of the coefficient predicting the latent dependent variable to the dispersion of the error term in this space. Adding coefficients could both change the estimates of β and absorb residual variation in σ, and these two effects cannot be reliably separated.

toilet, and for the surveyed woman knowing about oral rehydration salts; a set of eight hand-washing indicators constructed from the adult surveys for the household average and minimum of hand-washing, both at all and with soap, and both after defecating and before eating.

As in the figure, adding these covariates reduces the height-achivement slope, but not by much. There is little further reduction after adding the 93-94 household controls, although the handwashing and water controls do appear to have a slightly larger impact than the nutrition and respiratory controls. Even in the fully controlled model, the apparent effects on the three cognitive achievement tests of a one standard deviation increase in height are 65, 68, and 75 percent as large as in the model with no controls at all.

Concentrating on the easier-to-interpret linear probability model for writing, while the χ^2 statistics verify that the groups of added variables are collectively significant and improve the fit of the model, none of the food or respiratory environment variables are individually significant. However, several of the water, sanitation, and hygiene variables are. Controlling for all of the covariates including height, in 1993 or 1994 having a toilet in the household is associated with being 9 percentage points more likely to write in 2004 or 2005 ($t = 2.93$), facing a long walk to the water source is associated with being 8 percentage points less likely to write ($t = 2.15$), and the 19 percent of children who grew up in households where no adult reported washing hands before eating were 41 percentage points less likely to write ($t = 2.09$). Some of these controls are coarse measures, and questions about health knowledge, food consumption, and hygiene behavior probably include measurement error.

These results confirm that early-life health and nutrition environments are important determinants of the omitted health variable shaping subsequent height and cognitive achievement. However, these variables clearly have not fully accounted for the height-achievement slope. Better measures of household health behavior, exactly what babies and pregnant and lactating mothers ate, and environmental pollution might further account for the remaining slope.

5 Discussion

Because of heterogeneity in early-life health and net nutrition, taller children perform better on average on tests of cognitive achievement. Recent research documenting this height-achievement slope has primarily focused on rich countries. Using the India Human Development Survey, a representative sample of 40,000 households which matches anthropometric data to learning tests, this paper documents a height-achievement slope among Indian children. Among the age groups and cognitive tests studied here, the Indian slope ranges from 2.4 times to 25 times as steep as the U.S. slope. An earlier survey interviewed some IHDS children's households eleven years before. Including matched early-life control variables reduces the apparent effect of height, but does not eliminate it; water, sanitation, and hygiene may be particularly important. Being one standard deviation taller is associated with being 5 percentage points more likely to be able to write, a slope that falls only to 3.4 percentage points controlling for a long list of contemporary and early-life conditions.

According to anthropometric indicators, Indians are among the most malnourished people in the world (Deaton, 2007). Yet, Deaton and Drèze (2007) puzzlingly document that calorie consumption has been falling in India, despite rapid and sustained economic growth. This paper's findings are evidence against the "small but healthy" resolution of the paradox: perhaps, some have suggested, Indians are short on average, but this does not represent a health deficit. To the contrary, short Indian children face deep developmental disadvantages.

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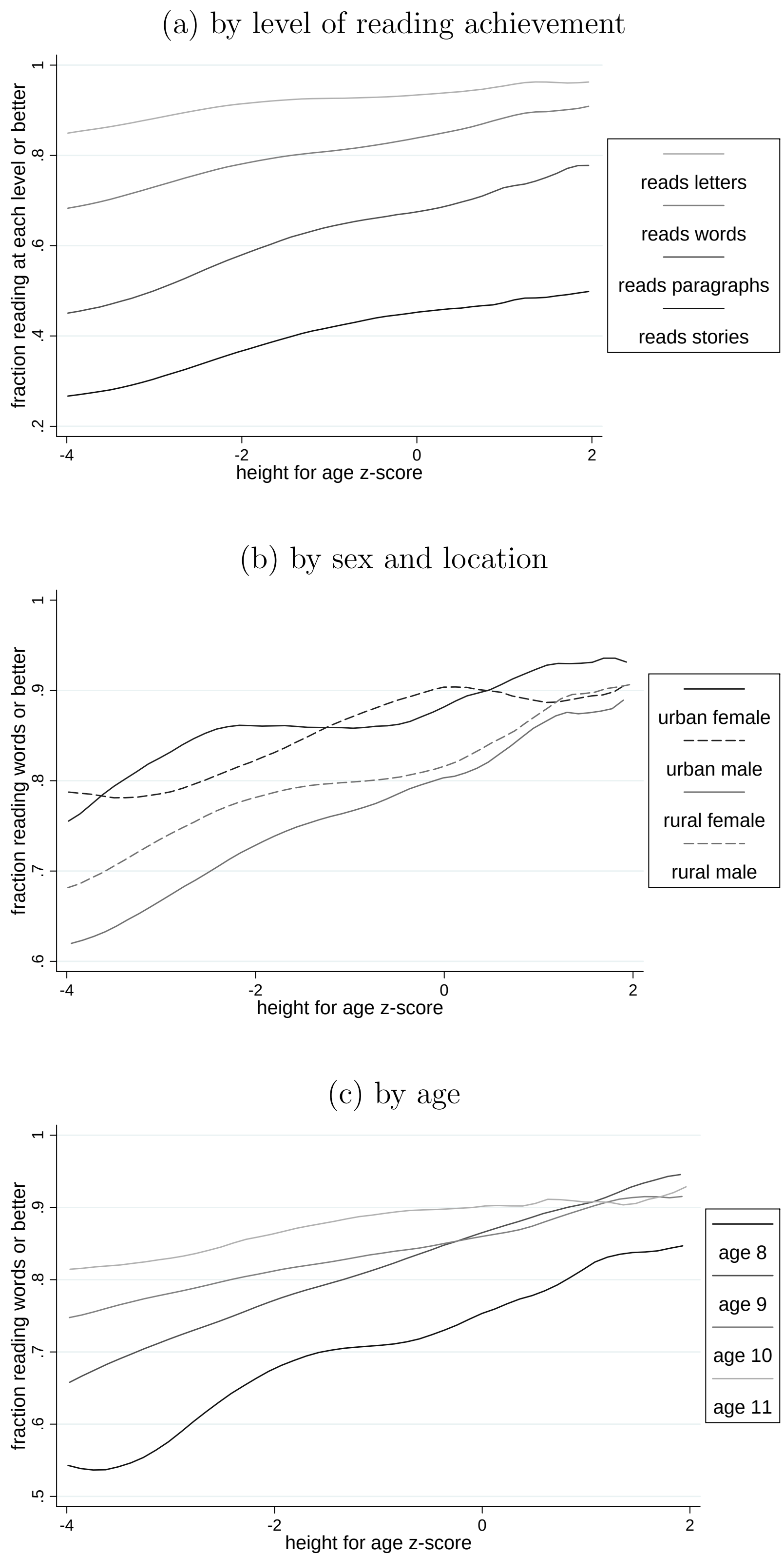


Figure 1: Height and cognitive achievement among Indian children

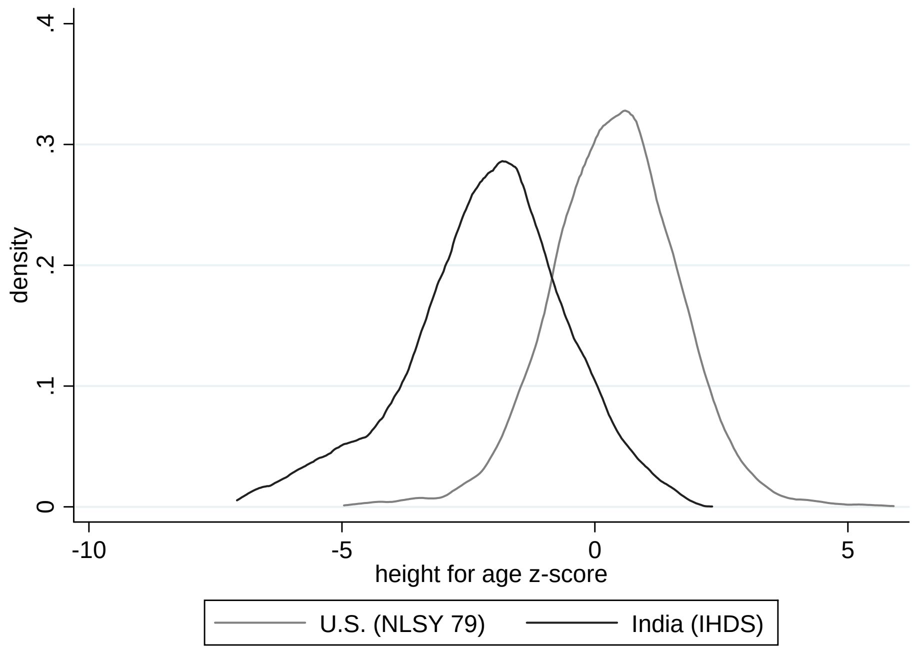


Figure 2: Density of height for age, India and U.S.

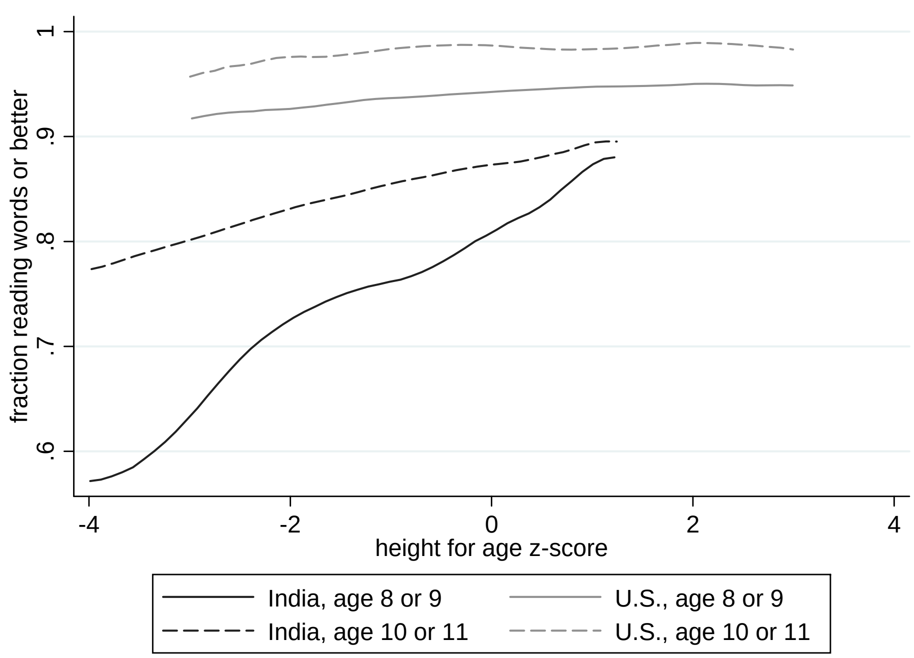


Figure 3: Height and reading by age, India and U.S.

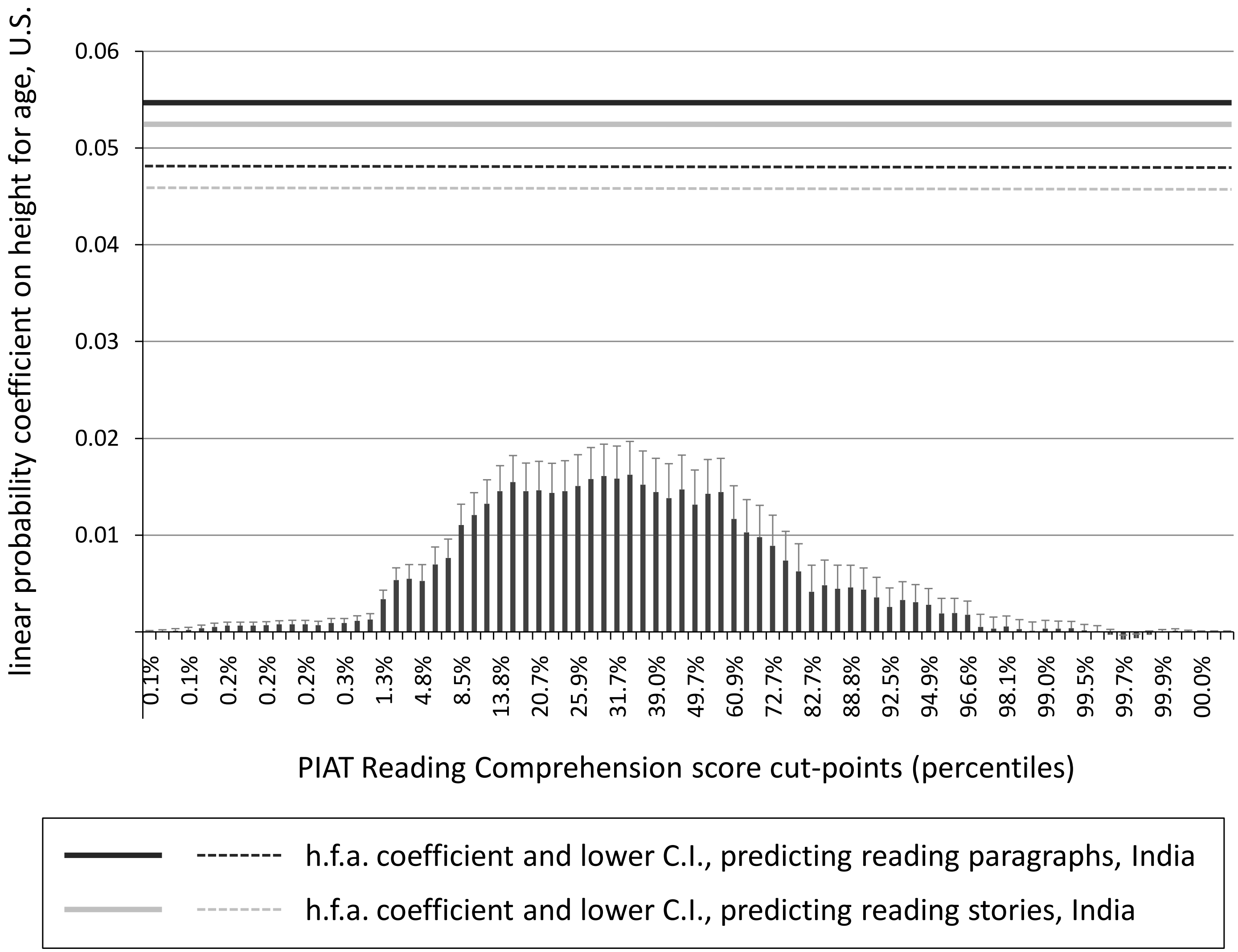
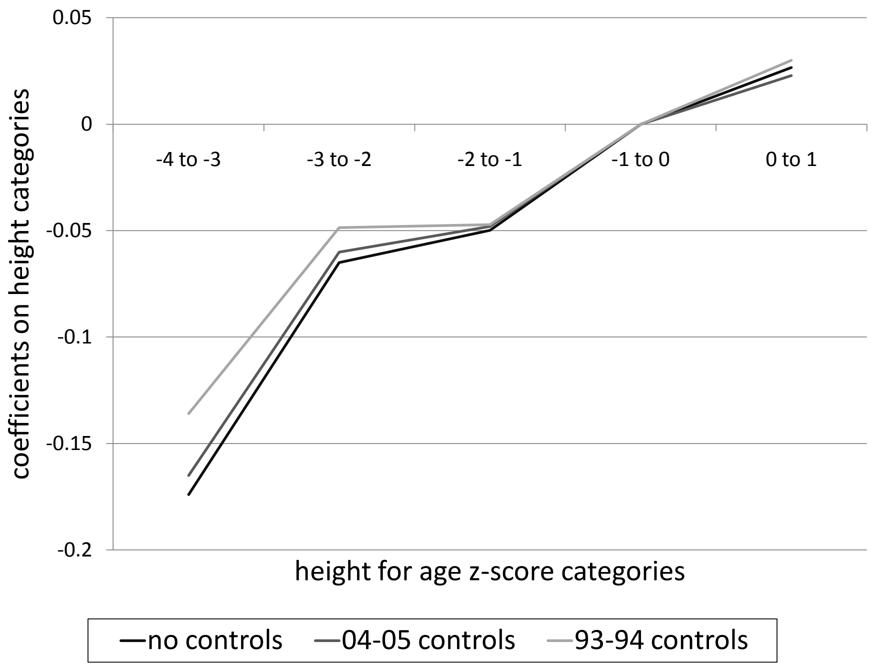


Figure 4: Comparing coefficients on height for age: All possible U.S. cut-points



Coefficients are from linear probability regressions predicting reading words or better.
Height for age z-scores from -1 to 0 are the reference category.

Figure 5: Explaining the slope by adding omitted variables

Table 1: Summary of independent and dependent variables, by age and location

	age 8		age 9		age 10		age 11	
	rural	urban	rural	urban	rural	urban	rural	urban
height for age z								
mean	-1.98	-1.85	-2.08	-1.81	-2.20	-1.99	-2.17	-2.00
25th percentile	-3.00	-2.89	-2.94	-2.61	-3.11	-2.91	-3.04	-2.86
50th percentile	-1.87	-1.70	-2.05	-1.68	-2.19	-1.89	-2.10	-1.88
75th percentile	-0.95	-0.76	-1.16	-0.87	-1.28	-0.96	-1.21	-0.94
cognitive achievement								
reads words	0.638	0.748	0.748	0.849	0.781	0.879	0.839	0.911
reads paragraphs	0.363	0.520	0.518	0.685	0.578	0.732	0.694	0.822
uses numbers	0.724	0.829	0.804	0.903	0.828	0.909	0.863	0.932
subtracts	0.297	0.478	0.443	0.633	0.500	0.693	0.598	0.776
writes	0.534	0.685	0.661	0.769	0.693	0.811	0.754	0.846
female	0.468	0.479	0.472	0.500	0.488	0.469	0.481	0.494
consumption per capita	604	912	620	948	608	943	652	1016
n	2329	998	1969	887	3004	1225	1788	643
n matched to HDPI	1044	0	862	0	1492	0	971	0

Consumption per capita is measured in rupees per month.

Table 2: Predicting achievement: Ordered logit coefficients on height for age, by test

	rural		urban			
	no controls	controls	no controls	controls	n	
reading						
age 8	0.299***	0.286***	0.271***	0.252***	rural:	1964
	(0.0401)	(0.0446)	(0.0447)	(0.0497)	urban:	860
age 9	0.320***	0.246***	0.246***	0.197***	rural:	1704
	(0.0388)	(0.0448)	(0.0480)	(0.0531)	urban:	798
age 10	0.251***	0.212***	0.207***	0.229***	rural:	2646
	(0.0345)	(0.0357)	(0.0392)	(0.0475)	urban:	1096
age 11	0.196***	0.207***	0.158**	0.140*	rural:	1573
	(0.0454)	(0.0471)	(0.0579)	(0.0703)	urban:	587
math						
age 8	0.276***	0.238***	0.211***	0.171**	rural:	1959
	(0.0406)	(0.0424)	(0.0514)	(0.0552)	urban:	856
age 9	0.277***	0.196***	0.305***	0.266***	rural:	1701
	(0.0416)	(0.0451)	(0.0520)	(0.0612)	urban:	796
age 10	0.195***	0.147***	0.191***	0.219***	rural:	2641
	(0.0357)	(0.0391)	(0.0451)	(0.0517)	urban:	1090
age 11	0.153**	0.0935	0.239***	0.249**	rural:	1562
	(0.0471)	(0.0516)	(0.0643)	(0.0816)	urban:	581
writing						
age 8	0.309***	0.289***	0.282***	0.333***	rural:	1943
	(0.0449)	(0.0484)	(0.0520)	(0.0656)	urban:	852
age 9	0.234***	0.151**	0.266***	0.274***	rural:	1695
	(0.0516)	(0.0556)	(0.0652)	(0.0793)	urban:	795
age 10	0.214***	0.145**	0.151**	0.183*	rural:	2626
	(0.0469)	(0.0498)	(0.0538)	(0.0714)	urban:	1088
age 11	0.150**	0.108	0.128	0.105	rural:	1557
	(0.0532)	(0.0614)	(0.0820)	(0.113)	urban:	579

Standard errors clustered by village or urban sampling unit in parentheses.

Each estimate reports the coefficient on the height-for-age z-score from a separate model.

Table 3: Comparing the height-reading achievement slope, India and the U.S.

	reads words				reads paragraphs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	age 8	age 9	age 10	age 11	age 8	age 9	age 10	age 11
height for age	0.0131**	0.00938**	0.000818	0.00176	0.0205**	0.0253***	0.00698	0.0133**
z score	(0.00429)	(0.00301)	(0.00228)	(0.00161)	(0.00678)	(0.00614)	(0.00541)	(0.00487)
India × h.f.a.	0.0245***	0.0316***	0.0195***	0.0180***	0.0337***	0.0355***	0.0383***	0.0267**
	(0.00690)	(0.00601)	(0.00454)	(0.00532)	(0.00886)	(0.00889)	(0.00735)	(0.00820)
India	-0.117***	-0.0820***	-0.0964***	-0.0572***	0.0389	-0.00429	-0.0479**	-0.0322
	(0.0170)	(0.0151)	(0.0119)	(0.0134)	(0.0210)	(0.0213)	(0.0177)	(0.0194)
female	0.0639***	0.0346***	0.0212***	0.0155***	0.0803***	0.0665***	0.0607***	0.0372***
	(0.00929)	(0.00637)	(0.00480)	(0.00385)	(0.0172)	(0.0154)	(0.0132)	(0.0113)
India × female	-0.101***	-0.0307	-0.0586***	-0.0601***	-0.103***	-0.0306	-0.107***	-0.0682**
	(0.0198)	(0.0175)	(0.0136)	(0.0156)	(0.0250)	(0.0247)	(0.0204)	(0.0222)
c	0.880***	0.943***	0.969***	0.979***	0.488***	0.681***	0.792***	0.860***
	(0.00798)	(0.00567)	(0.00431)	(0.00363)	(0.0126)	(0.0116)	(0.0104)	(0.00894)
n	6322	5929	7143	5395	6216	5878	7113	5377
U. S. mean	0.92	0.96	0.98	0.99	0.54	0.72	0.83	0.88
India mean	0.67	0.78	0.81	0.86	0.41	0.57	0.62	0.73
U.S. only R^2	0.0033	0.0038	0.0000	0.0004	0.0025	0.0049	0.0005	0.0026
India only R^2	0.0163	0.0222	0.0071	0.0082	0.0307	0.0336	0.0221	0.0184

Heteroscedasticity robust standard errors in parentheses. For U.S. children, "reads words" represents a PIAT Reading Recognition score of at least 23 and "reads paragraphs" represents a PIAT Reading Comprehension score of at least 34. R^2 statistics reflect simple linear probability regressions restricted to only U.S. or India data.

Table 4: Explaining the slope: contemporary and early life controls

	(1)	(2)	(3)	(4)	(5)	(6)
addition:		04-05	93-94 h.h.	93-94 food	93-94 air	93-94 water
writing (linear probability)						
height for age	0.0519***	0.0351***	0.0348***	0.0348***	0.0348***	0.0339***
	(0.00845)	(0.00819)	(0.00810)	(0.00807)	(0.00806)	(0.00777)
χ^2		644	44	13.82	1.45	71
p		0.0000	0.0001	0.0168	0.9191	0.0000
n	3789	3789	3789	3789	3789	3789
reading (ordered logit)						
height for age	0.262***	0.239***	0.237***	0.238***	0.238***	0.235***
	(0.0327)	(0.0347)	(0.0347)	(0.0346)	(0.0348)	(0.0339)
predicted effect	0.0447	0.0318	0.0310	0.0310	0.0309	0.0302
χ^2		5.7×10^6	3.9×10^5	48625	43162	2.7×10^6
p		0.0000	0.0000	0.0000	0.0000	0.0000
n	3815	3815	3815	3815	3815	3815
math (ordered logit)						
height for age	0.241***	0.188***	0.183***	0.183***	0.183***	0.181***
	(0.0339)	(0.0370)	(0.0364)	(0.0364)	(0.0369)	(0.0349)
predicted effect	0.0602	0.0470	0.0455	0.0457	0.0457	0.0451
χ^2		5.8×10^6	2.9×10^5	42825	45529	4.9×10^5
p		0.0000	0.0000	0.0000	0.0000	0.0000
n	3803	3803	3803	3803	3803	3803
age dummies	✓	✓	✓	✓	✓	✓
state dummies		✓	✓	✓	✓	✓
04-05 variables		✓	✓	✓	✓	✓
93-94 household			✓	✓	✓	✓
93-94 food				✓	✓	✓
93-94 respiratory					✓	✓
93-94 sanitation						✓
deg. of freedom		39	15	4	5	13

Standard errors clustered by village or urban sampling unit in parentheses. χ^2 statistics test the null hypothesis that added variables do not improve the fit. Predicted effects are the differences between the probability of a high achievement test score predicted at z-scores of -2 and -1, with all controls at their means. High test scores are reading words and doing subtraction.