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The rise and fall of SES gradients in heights around the world

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ABSTRACT

We use data from a large sample of low- and middle-income countries to study the association (or "gradient") between child height and maternal education. We show that the gap in height between high- and low-SES children is small at birth, rises throughout childhood, and declines in adolescence as girls and boys go through puberty. This inverted U-shaped pattern is consistent with a degree of catch-up in linear height among children of low- relative to high-SES families, in partial contrast to the argument that height deficits cannot be overcome after the early years of life. This finding appears to be explained by the association between SES and the timing of puberty and therefore of the adolescent growth spurt: low-SES children start their adolescent growth spurt later and stop growing at later ages as well.

1. Introduction

A well-established literature documents the ubiquitous strong association (or "gradient") between different individual measures of health and socio-economic status (SES), both within and across countries (Strauss and Thomas 1998, 2008, Cutler et al. 2006). Richer and more educated individuals are on average healthier and live longer lives. Moreover, children of higher-SES parents enjoy better health and lower mortality rates in rich and poor countries alike. Several key questions in this literature remain unanswered. We do not fully understand when these gradients emerge, how they evolve over the lifetime, and whether they are malleable—i.e. the extent to which children that are born and/or grow up in disadvantaged conditions can catch-up in terms of their health outcomes (Case et al. 2002, Martorell et al. 1994). Most importantly, there is very little work investigating what happens in middle childhood and early adolescence compared to other life stages, especially with regards to the evolution of nutrition and health inequalities (Almond et al. 2018, Saavedra and Prentice 2022).

In this paper, we study the relationship between parental SES and child height, and how it evolves from birth into young adulthood, using high-quality individual-level data from a large number of low and middle income countries (LMICs). We focus on

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height–a summary measure of an individual's cumulative health and nutrition–as it is an objectively measured and widely-available health indicator. Height typically correlates both with other objective measures of health such as disease incidence and mortality, and with economic outcomes in adulthood and across generations (Fogel 1994, Steckel 1995, Strauss and Thomas 1998, see also Section 2.2 for additional references). We use maternal education as our preferred measure of SES: this indicator is available and consistently measured in household surveys across many LMICs and cohorts. We view maternal education as reflecting the broad long-term resources (informational, financial, social, and genetic) that are available to children while growing up. Consistent with this view, the patterns we document also hold for other measures of SES, such as paternal education or proxies for household wealth.

We offer the first evidence of an inverted U-shaped age profile of the height-SES association during childhood and adolescence. SES-based differences in height are small at birth, but they become progressively larger during childhood. However, while remaining positive, the gradient *decreases* during the adolescent years, highlighting a degree of height catch-up of low-SES children relative to high-SES peers. Using a novel empirical model of human growth from early childhood to adulthood, we show that the inverted U-shape can be explained by SES-based differences in the timing of puberty–which typically follows the adolescent growth spurt–as well as in the age at which adult height is achieved.

We start our investigation by using data from Demographic and Health Surveys (DHS) on about 1.6 million children under five years of age born in 1981–2018 in 73 LMICs. In these data, the cross-sectional association between child height and maternal schooling is small and insignificant at birth but increases steeply between birth and five years of age, similar to the findings in Aiyar and Cummins (2021) who document a growing association between country-level GDP at birth and height-for-age z-scores (that is, height normalized relative to a reference standard).[3] Although DHS data do not include height for children older than five, most surveys also record the height of women from the age of 15 onward. For adolescents who have not yet left their parent's home, it is possible to link their height to their mother's education. In this (potentially selected) sample of adolescents, the association between height and maternal education, while still substantively and statistically significant, is much smaller than for children around five years of age. This suggests that the gradient increases monotonically until a certain age but then declines.

To better evaluate the age-profile of the height-SES gradient and address potential selection concerns, we then use panel data from five LMICs where we can follow individuals from birth until young adulthood. We employ data from two cohorts in Ethiopia, India, Peru and Vietnam from the Young Lives study (YLS hereafter, Barnett et al. 2013), and from the Philippines' Cebu Longitudinal Health and Nutrition Survey (CLHNS, Adair et al. 2010). These data confirm the existence of a consistently positive relationship between height and maternal education. As in the DHS data, the strength of the association has an inverted U-shape, increasing first but then decreasing in adolescence, with the decline taking place earlier for girls and later for boys. The gap in girls' height between low and high-SES children increases from 1–1.7 cms at age one to 3.4–4.7 cms at age 12, but it declines to 2–2.3 cms at age 15 and to 1.4–1.7 cms at age 22, when adult height has presumably been attained. Among boys the pattern is similar, although the decline in the gradient takes place later, around age 15.

Next, we investigate whether the inverted U-shape of the gradient can be explained by the link between SES and the onset and duration of the adolescent growth spurt (AGS), by testing whether low SES children start their AGS later and keep growing for longer compared with high SES peers. This hypothesis is based on two documented patterns. First, a well-established secular decline in the age at menarche among girls has been observed in many countries, which is linked to overall improvements in socio-economic conditions and health (Wyshak and Frisch 1982, Hauspie et al. 1996, de Muinck Keizer-Shrama and Mul 2001, de La Rochebrochard 2000). The same considerations suggest the existence of a cross-sectional negative association between age at menarche and SES in low-income settings, an association that indeed has been documented in the Philippines (Adair, 2001) and is confirmed in our data. Low-SES children reach the peak of their AGS when high-SES are already past theirs, allowing them a degree of height catch-up. Second, it has been observed that children from malnourished populations achieve their adult height at older ages (Steckel 1986, Bozzoli et al. 2009). Based on these insights, we propose and estimate a growth model that rationalizes differential profiles of human growth based on SES. The results strongly support this hypothesis.

Like the previous literature on the emergence of the gradient, our evidence is correlational. We do not claim that the patterns we document are causal. Despite this, our results add to different literatures. First, many studies have investigated the emergence and evolution of the SES health gradient, especially in higher-income settings. In a seminal paper, Case et al. (2002) documented that, in the United States, the correlation between indicators of general health status and a measure of long-term income originates in childhood and becomes progressively stronger into adulthood. Similar results have been found for Canada (Currie and Stabile, 2003), Australia (Khanam et al., 2009), the Czech Republic (Borga et al., 2021), and in other US data sets (Murasko 2008, Fletcher and Wolfe 2014), but not in the UK (West, 1997) or Germany (Reinhold and Jürges, 2012) or in LMICs such as Indonesia and Vietnam (Cameron and Williams 2009, Park 2010, Sepehri and Guliani 2015). Most of this literature, however, has not focused on the evolution of *height* differences by SES over childhood, nor on the mechanisms underpinning such correlation. An exception is Li et al. (2004), who show that growth deficits among low-SES 7-year-old children from the 1958 British birth cohort were reduced in adulthood, although they did not disappear completely. By contrast, data from two more recent UK cohorts (with children born in 1992 and 2001) suggest that height inequalities remain unchanged or increase during childhood until age 15 (Howe et al. 2013, Bann et al. 2018). It is unclear why the results differ across cohorts. We are not aware of studies focusing on the evolution of the height gradient during early and late adolescence in LMICs.

Our second contribution is a novel methodology to estimate the shape of the growth curve with longitudinal data where height is only measured at infrequent intervals, such as in YLS or CLHNS. The model links (unobserved) growth velocity at high frequency

[3] Note that we estimate gradients at the individual level between a child and their mother, whereas Aiyar and Cummins (2021) look at associations with aggregate resources measured by country level GDP.

to (observed) height measured at low frequency, fitting the typical pattern of growth velocity in humans, which is highly non-linear, see Tanner et al. (1966, Fig. 8). We approximate this pattern with a piece-wise continuous linear function, where the kinks coincide with key transitions in growth velocity (such as the beginning of the AGS, or its peak), and may depend on SES. This model can be estimated using constrained ordinary least squares, with the location of the kinks determined by a simple algorithm in the spirit of Hansen (2017). Our method differs from alternative non-linear models that have been proposed in the literature, see Preece and Baines (1978), Sayers et al. (2013), Beath (2007), and Cole et al. (2010). These models typically approximate child growth using parameterized exponential functions, where the parameters describe features of the growth curves such as the start, peak, and duration of the adolescent growth spurt. We do not rely on these approaches because they are best suited to model individual growth patterns with longitudinal data that include height measurements taken with high frequency, which are rare and expensive to collect. In addition, such models have been validated for the description of height growth velocity around the timing of puberty, while we are interested in the whole age profile of growth velocity, including the early years and the time when adult height is achieved.

Our final contribution to the literature is to provide evidence of partial height catch-up between low- and high-SES children in adolescence. Previous literature has extensively debated whether or not catch-up in height (relative to a reference standard) is possible. The potential for catch-up in linear growth retardation after the first 1000 days is widely considered to be limited, although most studies do not follow children until adulthood (Martorell et al. 1994, Leroy et al. 2020). The evidence from longitudinal cohorts in LMICs regarding catch-up growth is mixed (see Campisi et al. 2018 for a review). We show that a degree of height catch-up of low-SES towards high-SES children appears to be present, and is associated with the differential timings of pubertal development and of achievement of adult height. This is consistent with Martorell et al. (1994)'s view that delayed maturation and a longer growth period allows for some catch-up. It is also consistent with recent work documenting that investments in adolescence can affect health, human capital, and economic well-being later in life (Akresh et al. 2012, van den Berg et al. 2014, Carneiro et al. 2019, Andersen et al. 2021, and Akresh et al. 2023). Our results help explain disparate findings in the literature: we show that catch-up may occur during adolescence depending on how SES affects the AGS, which may vary across countries and cohorts.

The rest of the paper is organized as follows. Section 2 describes the data; Section 3 describes the results; Section 4 explores mechanisms; and finally, Section 5 concludes.

2. Data and measurement

We use data from a large number of surveys that broadly belong to three separate data collection initiatives, that is, DHS, YLS, and CLHNS. In this section we provide some details on these data sources, and describe our main variables of interest.

2.1. Data

Demographic and Health Surveys (DHS). The primary purpose of these cross-sectional household surveys is to provide a detailed snapshot of each country surveyed, with a focus on demography, health, and fertility choices and preferences. Data are typically nationally representative and comparable across surveys. The primary respondents are women–in some cases only if ever married–'of fertility age', defined as 15–49. Detailed information is also available for their children under the age of five years, including measurements on weight and height taken by trained enumerators.[4] Several of the more recent surveys also include detailed information on adult men.

We make use of all data available at the time of writing that contain information on child height. For children under five we drop less than 0.2% of observations for which height was <30 cms or >1.4 m, that is, very likely measured with error. Table A.1 in the Online Appendix includes a complete list of all the surveys we use together with selected summary statistics on height. We restrict attention to children with non-missing anthropometric measures and maternal education. Overall, our data include height measurements for about 1.6 million children born in 1981–2018 from 245 surveys and 73 countries.

Young Lives Study (YLS). YLS is an international longitudinal study of childhood poverty conducted in four countries: Ethiopia, India (only in the state of Andhra Pradesh, part of which in 2014 was separated into a new state, Telangana), Peru and Vietnam. While the sample was not designed to be nationally representative (or, in the case of India, state representative), a comparison of key child outcomes or socio-economic variables to those collected in nationally representative surveys show similar patterns and variations (Barnett et al., 2013).

The study follows two cohorts of children in each country since 2002, totaling roughly 12,000 children, over 15 years. Children in the younger cohort were first sampled in 2002 at ages 6–18 months and subsequently surveyed and measured in 2006, 2009, 2013 and 2016, at about 5, 8, 12 and 15 years of age, respectively. The older cohort was around 8 years of age in 2002, and then about 12, 15, 19 and 22 years old at the following survey rounds of in-person data collection. Attrition in this panel is low, around 10% over 15 years, with some variation across cohorts (younger cohort: 8%; older cohort: 16.5%) and countries (Ethiopia: 14%; India: 7%; Peru: 14%; Vietnam: 9%). The final analysis sample contains 7195 children for the Younger Cohort, and 2991 children

[4] In a small number of cases there is some variation in the target population. For instance, the 2004 Bangladesh DHS interviewed ever-married women 13–49, while in India only children below 4 were included in 1992–93 and only the last two births below three years of age were included in 1998–99. We ignore these differences.

for the Older cohort. Panel A in Online Appendix Table A.2 shows summary statistics for these data. We discuss the extent to which attrition in YLS and CLHNS might affect our findings in the robustness checks section.

Cebu Longitudinal Health and Nutrition Survey (CLHNS). The CLHNS is a panel data set of mothers and children from the Philippines' Metropolitan Cebu area originally designed to study how different infant feeding patterns in early life directly affect various health and socioeconomic outcomes in the lives of the mother, child, and household (Adair et al., 2010). The CLHNS surveyed–using a clustered design–a cohort of women sampled from both urban and rural communities (or *barangays*) who gave birth between May 1983 and April 1984. The baseline survey collected information about the mother's behaviors during pregnancy, demographics, socioeconomic status, as well as information on other household members. The initial sample included 3080 non-twin live births. These children were measured at birth, then regularly at the end of every subsequent two-months period following their birth up until roughly 2 years of age. The children's health was assessed again in 1991, 1994, 1998, 2002 and 2005, when they were roughly 8, 11, 15, 18 and 21 years of age respectively.[5] The rate of attrition was higher than in the YLS, at 38% from birth until 2005. Again we limit our sample to children with non-missing maternal education and height measurements in all waves, leaving a sample of 1686 children. We report selected summary statistics in Panel B of Online Appendix Table A.2.

2.2. Height, SES and other variables of interest

Height. We focus on child height, instead of other commonly used measures of health used in the literature such as self-reported status, or presence of health conditions. Aside from genetic factors, height is primarily determined by the availability and diversity of nutrients, and the prevalence of disease (Martorell and Habicht 1986, Tanner 1989, Steckel 1995). Indeed, economic historians have often used adult height as an indicator of economic or human development (Fogel 1994, Steckel 1995, 2009).

As a health indicator, height has multiple advantages. First, it is relatively easy to measure objectively, and does not suffer from reporting biases. Second, height is a widely available health indicator for both children and adults in LMICs, and it is easily comparable across all age groups. Third, height is a good measure of overall health, and it correlates with other objective measures of health, such as disease incidence and mortality (Fogel 1994, Steckel 1995, 2009, Perkins et al. 2016). Fourth, height is an important predictor of economic outcomes. On average, taller individuals have more human capital and earn higher wages, an association that is likely mediated by several determinants, including physical strength (Haddad and Bouis 1991, Strauss and Thomas 1998), social factors (Persico et al., 2004), occupational choices (Vogl, 2014) and cognitive ability (Case and Paxson, 2008). In addition, transmission of low height from parents (especially mothers) to their children has been identified as one of the drivers of substantial persistence in SES inequalities in human capital across generations in both high- and low-income settings (Ramakrishnan et al. 1999, Osmani and Sen 2003, Kozuki et al. 2015, Behrman et al. 2017).

Since height measured in centimeters is our primary outcome of interest, the sex and age-specific SES gradients we estimate should be interpreted as average differences (in cms) between children from high- vs low-SES families. In the literature, there are two alternative measures of height performance: height-for-age 'z-scores' (HAZ) and height-for-age deviations (HAD).

HAZ standardizes individual height relative to growth charts from a reference population of healthy children: it is computed as height minus the median height in the reference population of the same age and sex, divided by the corresponding standard deviation. Such charts were first developed in the United States by the National Center for Health Statistics (NCHS) and the Center for Disease Control and prevention, and were adopted by the World Health Organization (WHO) and as such have been widely used internationally (CDC-WHO77 charts hereafter, see Waterlow et al. 1977, World Health Organization 1978). The WHO subsequently created new charts for children below the age of five using data from several countries worldwide (WHO2006 hereafter, see WHO Multicentre Growth Reference Study Group and de Onis 2006), and then adapted the CDC-WHO77 standards for children 5–19 to ensure a smooth transition around age 5 with the WHO2006 charts, as described in de Onis et al. (2007). New charts have also been introduced for the United States by the CDC for ages up to 20 years (CDC2000, see Kuczmarski et al. 2000).

We prefer employing raw height in our estimates given that our focus is on how the gap between high- and low-SES children in height evolves with age, rather than on how the performance of high- vs. low-SES children changes with age *relative to a reference population*. In addition, HAZ is by construction normalized relative to the standard deviation of height in the reference population, and this standard deviation increases with age. This implies that for a constant difference in raw height between high- and low-SES children, the gap in HAZ will *decline* with age due to the increase in the denominator (Leroy et al., 2015). By contrast, the use of height in cms as dependent variable allows us to interpret a reduction in the gradient at later ages as a reduction in the height difference between high and low SES children, rather than a reduction possibly driven by a change in the standardization, as would be the case with HAZ.

Nevertheless, we check the robustness of our results by using z-scores for children. In DHS, we use the CDC-WHO77 charts or, whenever available, the more recent WHO2006 reference charts.[6] For the younger cohort of YLS and CLHNS, we also rely on the WHO2006 reference standards for under-5 children, while for children aged 5–19 years we use CDC-WHO77 standards adapted to ensure a smooth transition around age 5, as described in de Onis et al. (2007). For the older cohort, we used the CDC2000 standards as these provide a reference for children up to 20 years, but the results are similar if we use the same standards as for the younger cohort. We use references for 20-year-olds for individuals older than this age.

[5] Two more surveys were conducted in 2007 and 2009, but children's heights were not measured, and so data from these rounds are not used in this paper.

[6] Table A.1 in the Online Appendix shows that a large fraction of children in the countries we study are shorter than children in the reference populations, leading to high prevalence of stunting, see also Ssentongo et al. (2021).

An alternative measure of height performance is height-for-age deviations (HAD), calculated as the difference between the height of a child and median height for children of the same age and sex in a reference population. That is, HAD is the numerator of HAZ, and is thus not affected by the increase in the standard deviation of height in the reference population as children grow old (Leroy et al., 2015). Note that all our estimates are age- and sex-specific, and thus would remain numerically identical if we replaced height with HAD, given that in each regression using the latter would be equivalent to subtracting a constant from height, see Online Appendix A.1 for a formal argument.

Our choice of height in cms as dependent variable also implies that our assessment of 'catch-up' describes whether the gap in raw height between high- and low-SES children shrinks beyond a certain age. This stands in contrast to an alternative definition of catch-up which compares the performance of stunted to those of well-fed populations.[7]

Maternal Schooling. Maternal education, as reported by the mother herself in all surveys, is our main proxy for SES. Measuring SES inequalities in health outcomes is challenging because of the conceptual difficulties of capturing the complexity of SES, a theoretical construct of socioeconomic hierarchies within societies (Conway et al., 2019). Individual measures of income, education, and occupational social class are commonly used SES indicators. In our context, we argue that maternal education is a meaningful proxy for SES. In LMICs, a large share of employment is concentrated in the agricultural and informal sectors, where occupations vary little and may not reflect a family's status in their community. Similarly, consumption and income measures are not always available and can be difficult to measure (Deaton and Grosh, 2000).

While maternal education is a coarse measure, it is a simple and fairly comparable measure across years and countries, and it is assessed in all our data sources which, in contrast, do not include consistent measures of income or consumption. Maternal education is significantly correlated with other measures of resources or SES in surveys where different indicators are available. For instance, in the YLS data, the correlation of maternal education with total real *per capita* consumption expenditure is 0.2 ($p < 0.001$). This correlation is even stronger (0.47, $p < 0.001$) with a wealth index constructed as a composite indicator of asset ownership, access to services, and housing quality. In the DHS surveys that include a wealth index–constructed with principal components methods from information on asset ownership–the correlation between the index and maternal schooling ranges between 0.22 and 0.30.

Maternal education is a well-known correlate of child health (Caldwell 1986, Heath and Jayachandran 2017) and although we reiterate that we see our results as primarily descriptive, some studies in LMICs do find support for the notion that this association can be causal (e.g. Grépin and Bharadwaj 2015 or Andriano and Monden 2019). In addition to being a proxy for household resources, maternal schooling is also typically correlated to the *returns* to those resources: *ceteris paribus*, better educated mothers may have an advantage when making choices for their children in terms of nutrition and health care (e.g. Andriano and Monden 2019). A large literature also associates maternal education with women's increased ability to control household resources in a way that can be beneficial to children (see Thomas 1990 for an early contribution). Further, maternal schooling will typically be correlated not only to child height (the focus of this paper) but also to the height of the mother herself, driven by both genetic factors and investments made by her own parents. Given these considerations, we see maternal education as a proxy for the broad set of the resources–social, informational, economic, and genetic–available to the child.

We measure maternal education by constructing an indicator of whether the mother has completed at least secondary school. DHS measures both completed schooling and the number of years of schooling for each household member, so we define SES as a binary variable = 1 if the mother completed at least secondary schooling, and zero otherwise. In contrast, YLS only records the last grade completed, and CLHNS records the number of years completed in the most recent schooling level (i.e. three years of primary, four years of secondary, etc.). We use these variables to construct a SES indicator comparable to DHS, based on the number of years of schooling that each country requires for graduation from high school. In YLS, the binary variable for secondary education is thus set = 1 when the mother has completed a minimum of 10 years of schooling in Ethiopia, 12 in India, 11 in Peru, and 9 in Vietnam. In CLHNS, the dummy is = 1 if the mother has completed at least four years of secondary school at the time of the first survey wave. About 19, 18 and 23 percent of women have completed at least secondary education in the DHS, YLS and CLHNS respectively. In robustness checks, we show that results remain qualitatively similar if we use alternative measures, such as the number of years of education completed by the mother, a dummy indicator of whether the mother has completed primary education, or paternal schooling.

Alternative measures of SES. As noted above, there are no consistent measures of income or consumption in our surveys, except in YLS, where household consumption expenditures are collected between Rounds 2 and 5 for the Younger Cohort only. An alternative measure of material well-being is a wealth index, which is often constructed by aggregating data on asset ownership and availability of services such as electricity, improved toilets, and so on. A higher score in the wealth index should reflect greater household wealth (Filmer and Pritchett, 2001). The DHS and YLS do include a wealth index, while we construct a similar indicator for the CLHNS dataset. In the DHS, an asset index is calculated in each survey as the first principal component from a list of asset ownership indicators.[8] The list of assets is not identical across all surveys, so the resulting measures are not directly comparable between countries and, in the case of DHS, even within country over time. In YLS, the wealth index is constructed by aggregating data on

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7 Hirvonen (2014) refer to this kind of catch-up as *within* population convergence, as opposed to *between* population convergence. The latter would be measured by an increase in HAZ, due to height velocity that is above that expected (based on growth patterns in a reference population) given child age and sex, and occurring after a period of growth retardation, see also Anand et al. (2018) for further discussion. An alternative approach interprets catch-up as the ability to reach a predetermined height regardless of past growth, see for instance Hoddinott and Kinsey (2001) and Alderman et al. (2006).

8 For details on the construction of these 'standard of living' indexes in each survey see https://dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm.

household access to services (e.g. electricity, water, sanitation, and so on), ownership of durable assets, and measures of housing quality. These three dimensions are aggregated through a simple average. Country-specific assets were included to reflect local contexts and better discriminate across levels of wealth in different countries (Briones, 2017). Similarly, in CLHNS, the wealth index is constructed by using data on household access to services, durable assets, and housing quality. We use principal component analysis to derive the wealth index in the style of Filmer and Pritchett (2001). Given these differences in the way the wealth index is computed across data sets, we use an indicator of whether the household is in the top quintile of the wealth index distribution within each country and survey. For the DHS, the indicator is based on the contemporaneous wealth index. For the longitudinal data, we rely on the wealth index at birth (CLHNS) or at age 1 (YLS), as in CHLNS assets were only measured at birth.

Other data We use self-reported information on age at menarche (the first occurrence of menstruation) from the longitudinal surveys and from four countries covered by DHS: Gabon (2000), Ghana (1998), India (2015–16), and Turkey (2013). Online Appendix A.2 has more details on why data limitations in the DHS only allow us to focus on these countries, and on how we construct the samples for the analysis of age at menarche. Lastly, we use information in the YLS on behaviors during adolescence. Specifically we look at whether adolescents marry or have children, whether they sleep enough, work a lot, have a diverse diet, or undertake risky behaviors (drinking and smoking). Online Appendix A.3 has more details on how we construct these variables.

3. Empirical approach and results

We start by documenting the key empirical pattern motivating our analysis: the steep rise of SES gradients during childhood and their subsequent decline around puberty in low- and middle-income countries. We first show the results using cross-sectional data from DHS, before moving to longitudinal data from YLS and CLHNS.

3.1. Empirical strategy

For children of sex s and a months of age, we estimate the following equation:

$$height_{isacy} = \alpha_{as} + \beta_{as} \times MomEd_{isacy} + \gamma_{1sac} + \gamma_{2say} + e_{isacy}, \quad (1)$$

where $height_{isacy}$ is the height in centimeters of a child measured in year y in country c, and $MomEd_{isacy}$ is an indicator equal to one if the mother of that child completed at least secondary education. We include dummy variables for each country (γ_{1sac}), and (when we use DHS data) for each survey year (γ_{2say}).[9] Given that our results are primarily descriptive and not causal, we do not include additional controls. The standard errors are clustered at the level of the survey-specific primary stage unit.

The coefficient of interest is β_{as}, which captures the SES gradient at a given age a, estimated as the difference in height between children whose mothers have at least secondary education and those whose mothers do not. Of course, while these associations are interesting, they should not be interpreted as causal, given that maternal schooling is typically correlated with numerous predictors of child height.

3.2. Cross-sectional results for children under 5 from the DHS

Before turning to the regression results, we show how the non-parametric relationship between years of schooling and height changes with age measured in years. Fig. 1 presents age-specific associations between the average height of boys and girls and maternal schooling. The categorical variable for maternal schooling distinguishes between no education, incomplete primary, complete primary, incomplete secondary, complete secondary, and higher. The figure shows two salient patterns. First, for both genders there is a clear positive association between average height and maternal schooling. Second, the line is almost flat at age 1, but it rotates counterclockwise (that is, it becomes steeper) as children grow older, indicating that the association becomes stronger with age, similar to the patterns documented by Case et al. (2002).

We confirm these patterns by estimating the model in Eq. (1) for age measured in months. Fig. 2 plots the point estimates of the gradient together with 95% confidence intervals. The results are very similar between genders, with the gradient increasing almost monotonically with age. At birth the slope is small (less than 1 cm) and either not or barely statistically significant. But one-year-old children of mothers with secondary education are already more than 1 cm taller than those of mothers with less schooling (95% C.I. [1.18, 1.72] for boys and [0.91, 1.42] for girls). The gap increases to more than 2 cms at age 2 (95% C.I. [1.71, 2.29] for boys and [2.03, 2.66] for girls), and to almost 3 cms at age 3 (95% C.I. [2.49, 3.16] for boys and [2.36, 3.03] for girls). The gradient flattens out thereafter, especially for girls, though the slopes are estimated less precisely.[10]

The pattern of gradients increasing with age in the DHS is also observed *within* countries. In Fig. 3, we show box plots of age and gender-specific coefficients estimated separately for each country. Instead of confidence intervals as in Fig. 2, the graphs describe the distribution of the 73 country-level coefficients estimated for each age and gender. The diamonds show the median coefficients while

[9] In the longitudinal data all children were measured during a short period of time in each survey wave, and so age and year of measurement are approximately collinear.

[10] The results also remain very similar if we use the sampling weights included in the surveys. This is true regardless of whether we use the weights as is in the data (variable v005), or if we use de-normalized weights to take into account the relative size of different countries (see ICF International 2012). We show the corresponding results in Online Appendix Figures A.2 and A.2.

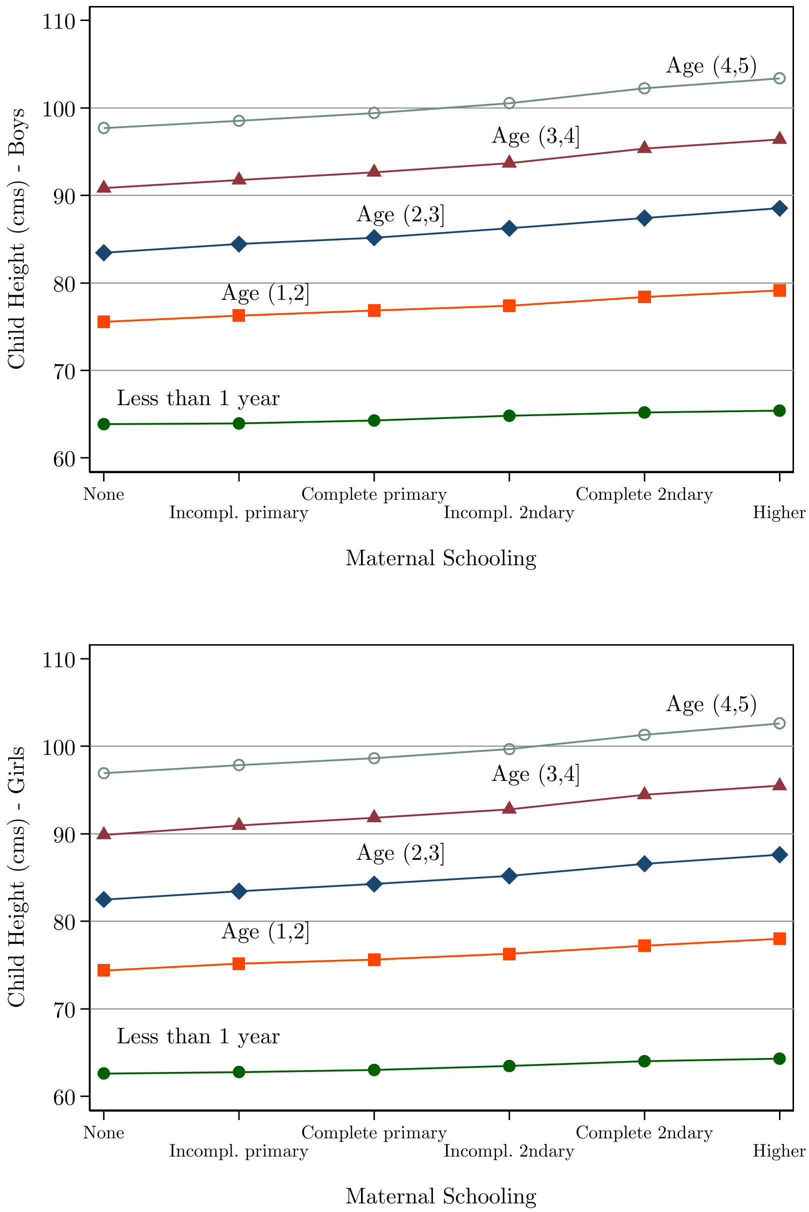

Fig. 1. DHS: SES Gradient by Child Age .
Source: Authors' calculations from DHS data. For each age interval, each line shows the relationship between average height and maternal schooling. Sample size $n = 1,570,217$.

the darker central sections of the vertical lines plot the inter-quartile ranges. The broader thinner lines show the whole variation excluding outliers, which are shown separately. The pattern of these box plots is similar to that of the estimated OLS slopes, and it also shows that the variation in coefficients increases with age. The median gradients start close to zero but then steadily increase until they reach about 4 cms by age 5.

3.3. Results for adolescents in the DHS

We now investigate if the gradients continue to increase after age 5. Ideally, we would have height measured for all children and adults in the surveys. However, the DHS only measure heights for children under 5, and for women (in most surveys) and men (in some surveys) between 15 and 49 years old. In principle, this allows the analysis of the age profile of the gradient at age 15 or higher. In practice, this is only possible for very young individuals, because parental education is only recorded if the individual still resides with the parents. In addition, several DHS surveys do not include identifiers to link individual to parental information

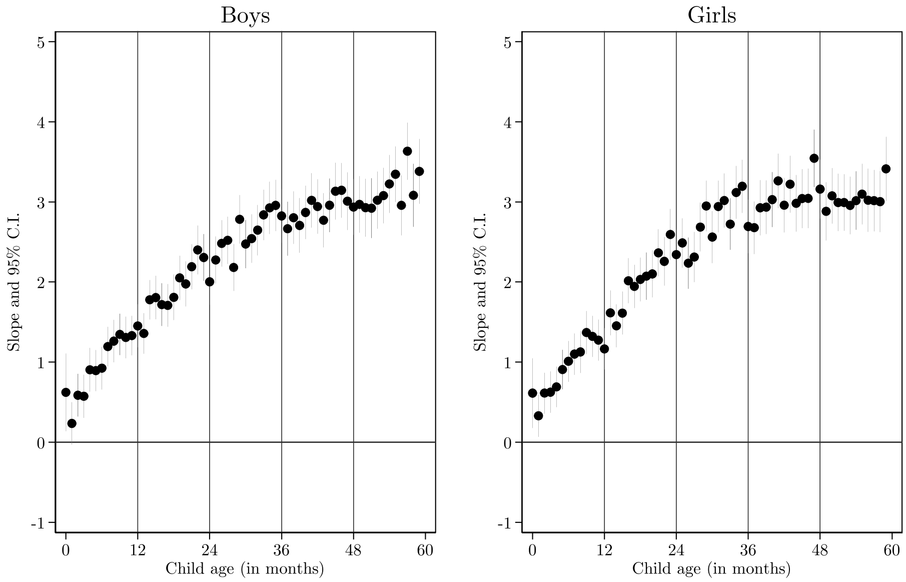

Fig. 2. DHS: Child height vs. Maternal education .
Source: Authors' calculations from DHS data. For each age (in months) the figure shows the point estimate and a 95% confidence interval of the slope of a regression, estimated with OLS, of child height (in cms) on a dummy variable equal to one if the mother has completed at least secondary education, and with country and survey year fixed effects. All estimates do not use sampling weights, and the confidence intervals are calculated allowing for correlation of residuals within each survey primary stage unit. Total sample size is $n = 1,570,217$.

Table 1
Height vs. maternal schooling, DHS, Girls and Boys 0–4 and 15–17.
Source: Authors' calculations from DHS data.

	Age (years)							
	0	1	2	3	4	15	16	17
	Girls							
Mother at least secondary	1.22	2.11	2.96	3.29	3.25	2.48	2.3	2.16
(s.e.)	(0.162)	(0.139)	(0.223)	(0.242)	(0.313)	(0.106)	(0.106)	(0.11)
R^2	0.015	0.048	0.069	0.082	0.087	0.157	0.177	0.192
Obs.	169,171	164,390	156,460	145,430	134,869	54,531	51,199	43,246
Mean dependent variable	63.1	75.5	84	91.6	98.5	152.7	153.6	154
% maternal education missing	0.04	0.05	0.05	0.02	0.02	0.26	0.30	0.37
	Boys							
Mother at least secondary	1.11	2.05	2.8	3.22	3.33	0.68	2.11	2.58
(s.e.)	(0.191)	(0.136)	(0.188)	(0.267)	(0.286)	(1.333)	(0.589)	(0.335)
R^2	0.015	0.049	0.070	0.083	0.089	0.111	0.077	0.105
Obs.	175,045	171,416	161,934	150,703	140,799	9,940	9,780	8,124
Mean dependent variable	64.4	76.7	85	92.4	99.3	159.9	162.4	164.5
% maternal education missing	0.04	0.04	0.04	0.02	0.02	0.25	0.29	0.36

Notes: For each age (in years) the table reports estimates and standard errors of the slope of a regression, estimated with OLS, of height (in cms) on a dummy variable equal to one if the mother has completed at least secondary education. Regressions for children under five include all children of a given age (in years) born of women of fertility age in the sample. Regressions for 15 to 17-year old boys and girls only include individuals who are still co-residing with their mother, and for whom maternal schooling can be identified through unique individual identifiers in the data, see text for additional details. All regressions include country FE and do not use sampling weights. Standard errors are calculated allowing for correlation of residuals within each survey primary stage unit.

(except for children under five), and those that do almost exclusively do it for boys and girls younger than 18. This generates an obvious selection problem. Selection, however, is not too severe among the youngest individuals, the large majority of which are still co-resident.[11]

With these caveats in mind, in Table 1 we show the coefficients for maternal education for adolescents 15, 16 and 17 years old, separately by gender. For reference, we also report estimates for children under five, estimated using the same sample used

[11] In DHS surveys where young women and men can be linked to their mother (which is only possible in case of co-residency), maternal education is missing for 26%–36% of observations. Among older individuals, maternal education is available for less than 10% of observations.

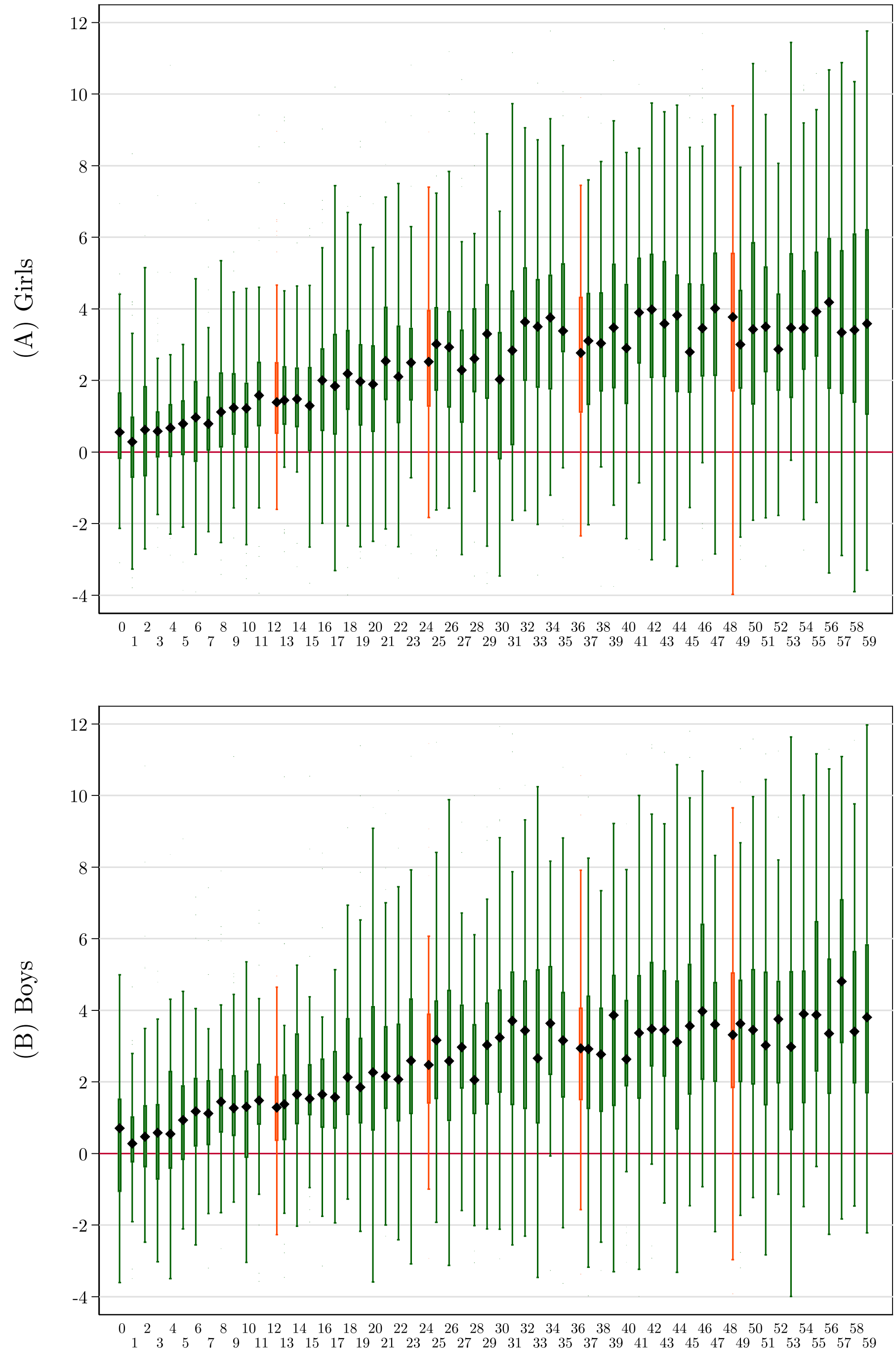

Fig. 3. DHS: Child height vs. Maternal education .
Source: Authors' calculations from DHS data. For each age (in months) the figure shows a box plot of the estimated country-specific OLS slopes of regressions, estimated with OLS, of child height (in cm) on a dummy variable equal to one if the mother has completed at least secondary education. All estimates do not use sampling weights. If more than one DHS was completed for a given country all observations were pooled together.

in Fig. 2, but measuring age in years rather than months. When we look at teenagers, all but one of the estimated gradients are large and very precisely estimated, with magnitudes above 2–2.5 cm among both boys and girls (and standard errors around 0.1 for girls and 0.3 for boys). The only exception is the coefficient for 15-year old boys, where the slope is 0.7 and not significant at standard levels. This result is apparently driven by the very low prevalence of high-SES mothers in this sub-sample (only 37 of

9,940), which generates very noisy estimates. With this exception, the age profile is fairly flat among both boys and girls. Most interestingly, the estimated slopes are *smaller* than the corresponding coefficients for children age 4, suggesting a decline in the gradient in adolescence.[12]

3.4. Evidence from panel data

Given the potential selection bias in the DHS adolescent sample, we now use longitudinal data to investigate whether the decline in the gradients during adolescence persists when we follow the same children over time. While the longitudinal data allow us to track individual growth over time, they force us to focus on a limited number of LMICs for which such data are available, and on a limited number of birth cohorts.[13]

Tables 2 and 3 report estimates of the gradient by age using data from YLS (Ethiopia, India, Peru and Vietnam) and CLHNS (the Philippines), for girls and boys, respectively. Panels A.1 and A.2 show estimates for YLS, respectively at around ages 1, 5, 8, 12 and 15 years for the younger cohort, and 8, 12, 15, 19 and 22 years for the older cohort. The regression includes country dummies (as in model (1)) but not year dummies, given that all measurements were taken in a short period of time. To account for the fact that children were interviewed at slightly different ages in each wave, we also include dummies for age in months. For illustrative purposes we also show the estimated slopes and the corresponding 95% confidence intervals using bar graphs in Fig. 4.

Consistent with the results using DHS data, the patterns in the YLS show that the gradient has an inverted U-shape with age. In the younger cohort the gradient increases from 1.6 cm (about 2% of the average height) to 3.6 cm (about 3.4% of average height) between age one and five for children. The gradient then continues to increase until 12 years of age reaching around 5 cm for both boys and girls, something that we could not document in the DHS due to the lack of height measurements in this age range. We also observe a sudden and substantial drop from 4.7 cm at 12 years to 2.3 cm at 15 years for girls, while the coefficient remains relatively stable for younger cohort boys.

A similar pattern is also apparent in the older cohort, where the slope of the gradient increases monotonically between 8 and 12 years for both genders, but then declines from 3.4 to 2 cm for girls between 12 and 15 years and keeps decreasing reaching 1.4 cm at age 22.[14] By contrast, the gradient continues to grow among boys until age 15 and declines thereafter, with the coefficient moving from 5.1 cm to 3.1 cm between 15 and 19 years, and then declining further to 2.7 cm at age 22.[15] For both cohorts, all slopes are estimated precisely, with standard errors in the 0.2–0.6 range, and all are statistically significant at the 1 percent level. Estimates are similar but less precise if we estimate the regressions separately by country.

The same pattern of inverted-U shapes is also evident in the CLHNS data from the Philippines, as shown in Panel B of Tables 2 and 3. In this sample, there is a monotonic increase in the SES-gradient up to age 11 for both boys and girls, followed by a decline for girls from 3.8 cm at 11 years to 2.1 cm at 15 years and from 3.9 cm at 15 years of age to 2.7 cm at 18 years for boys. By age 21, when the large majority of individuals have reached their adult height, the gradient is about 100 percent larger for boys as compared to girls but still significant for both.[16]

For both genders, the gradient at age 21, while still large, is substantially smaller than at the onset of adolescence, when it reaches its peak. Given that girls, on average, reach sexual maturity earlier than boys–in LMICs, pubertal development occurs on average at age 13.5–15.5 among girls and about 2 years later among boys (Thomas et al., 2001)–these results suggest that the timing of the inversion of the age profile of the gradient takes place around puberty. The results also suggest that the rise and fall of the gradient varies across time and space, which would be consistent with the observed variation in the onset of puberty, a point to which we return later in the paper.

Fig. 5 summarizes our main findings across the various data sets. The figure plots all the estimated gradients by age, together with fitted values from regressions of the point estimates on a quadratic in age, or using a more flexible Fractional polynomial. The age profile follows an inverted U-shape peaking earlier among girls than boys. By adulthood there are still positive differences in height by SES for both males and females, but the difference is larger among males.

3.5. Robustness checks

In this sub-section we discuss a number of robustness checks, including alternative measures of SES or height performance, the possible role of maternal height in explaining the gradients, and the extent and nature of attrition in the longitudinal data.

[12] These comparisons are further complicated by the fact that not all DHS have data on adult heights, so comparisons between age groups may, in fact, be driven by differences in the countries or cohorts represented in each survey. However, the age profiles for children under 5 remain very similar if we only include observations from DHS where height was recorded for children as well as adults of both genders (results not shown). Perhaps more importantly, comparisons in the gradients between children 0–5 and adolescents are complicated by the cross sectional nature of these estimates. This implies that composition effects could in principle explain the differences in the findings.

[13] We did not use other existing longitudinal data sets either because of small sample size or because the data are not made publicly available.

[14] Note that one should not expect the gradients in Panels A and B to be identical conditional on age, given that the same age is reached in different years for the two cohorts. For instance, children in the young cohort were about 8 in 2009, while those in the older cohort were this age at the time of their first measurement, in 2002.

[15] Given that maternal education is time invariant, the slope in these regressions should not change once the child has achieved adult height, as long as height is measured consistently and the sample itself does not change due to attrition. However, in LMICs adult height is often achieved after age 20.

[16] This larger gradient for boys is consistent with evidence suggesting that mortality among males is higher than for females during crises or conditions of extreme hardship, underlying a potential higher sensitivity of males–especially infant boys–to environmental inputs, see e.g. Drevenstedt et al. (2008) and Zarulli et al. (2018).

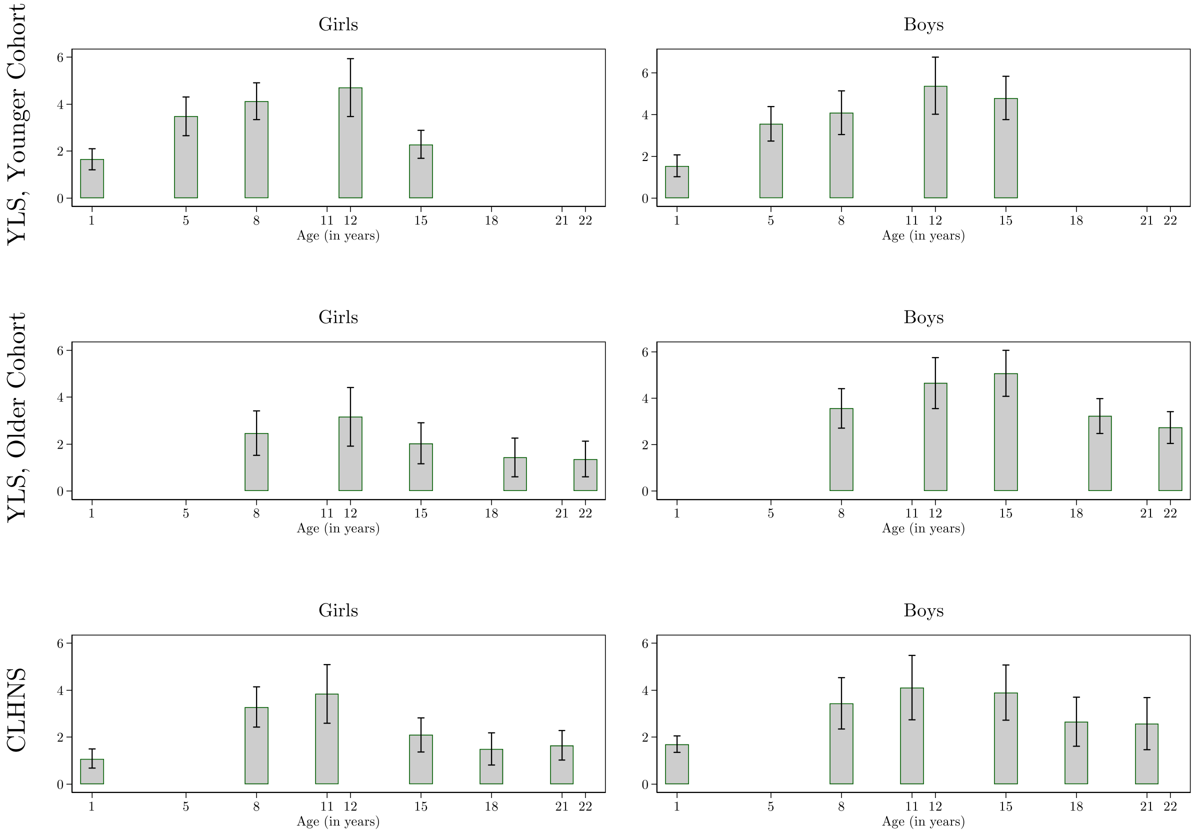

Fig. 4. YLS and CLHNS, age profile of SES gradient.
Notes: The figure displays visually estimates from Tables 2 and 3. Each bar shows the point estimate and the 95% confidence interval of an age and sex-specific OLS regression of height (in cms) on a dummy variable equal to one if the mother has completed at least secondary education. All estimates do not use sampling weights and include dummies for country and age in months. Standard errors are clustered at the level of primary stage unit of residence in the first wave ('sentinel site' in YLS and *barangay*–district or village–in CLHNS).
Source: Authors' calculations from Young Lives and Cebu Longitudinal Health and Nutrition Survey.

3.5.1. Alternative measures of SES

So far, our analyses used a dummy for whether the mother completed secondary schooling as a proxy for SES, but the results are very similar if we use maternal years of education (see Online Appendix Figure A.3 for the DHS data for children under 5, and Figure A.10 for the longitudinal data) or if we use a dummy for having completed at least primary schooling (Online Appendix Figure A.4 and A.11). The results also remain similar if we use paternal education (Online Appendix Figures A.5 and A.12, although this variable is more frequently missing.

We also estimate model (1) using an indicator of material well-being as the measure of SES. Given that we do not have consistent measures of income or consumption for all surveys, we use a binary variable equal to one if the child lives in a household with an asset index in the top quintile of its survey-specific distribution. Figures A.6 and A.13 show that once again the results are qualitatively similar, with gradients that increase with age until puberty and then start declining (with sharper declines for girls by the time they turn 15), while remaining positive for young adults.[17]

3.5.2. Alternative measures of height performance

The increase in the gradient with age is not a mechanical product of the increased scale of the dependent variable (height) when age increases.[18] In fact, the patterns remain similar if we use the logarithm of height as the dependent variable, in which case the slope can be interpreted as the predicted proportional change in height associated with having a mother with at least secondary

[17] Wealth is measured in early childhood in the longitudinal studies, while it is contemporaneous in DHS (see Section 2). However, in YLS, where wealth information was collected in all rounds, results are qualitatively similar if we use a dummy for being in the top wealth quintile in each country- and round-specific wealth distribution.

[18] In a simple univariate OLS regression, if the scale of the dependent variable increases the slope will increase even if the correlation between the dependent variable and the regressor stays the same, as long as the standard deviation of the regressor does not change.

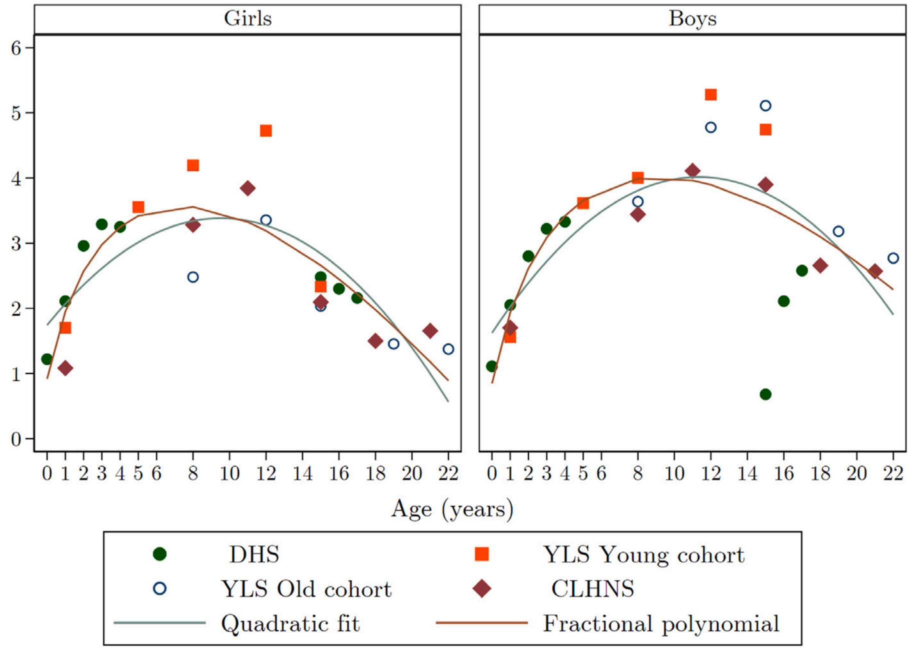

Fig. 5. All estimates.
Notes: The figure displays visually estimates the point estimates from Tables 1–3. Also shown are fitted values from regressions of the point estimates on a quadratic in age ("Quadratic fit") or using a more flexible Fractional polynomial.
Source: Authors' calculations from DHS, Young Lives and Cebu Longitudinal Health and Nutrition Survey.

schooling. In DHS data the gradient flattens out after age 3 (see Figure A.7 in the Online Appendix), but the inverted U-shape is still clearly visible when we use longitudinal data (Figure A.14).

The patterns remain similar, with some differences that we describe below, when we use HAZ instead of raw height as the dependent variable. In Online Appendix Figure A.8 we show that the patterns for children under five remain similar to those for log-height, with the gradient steeply increasing and then becoming stable, even somewhat declining, after age 2–3. These results are consistent with the well-known and typical age profile in LMICs of child height-for-age z-scores, which decline with age until about two years of age, and somewhat stabilize after that, see Shrimpton et al. (2001): sub-optimal growth conditions generate a growth gap relative to the reference population that accumulates over time, especially during the first two years of life. A similar age profile has also been shown for the association between HAZ and GDP at birth, see Aiyar and Cummins (2021). When we look at longitudinal data (Online Appendix Figure A.15), we see that the use of z-scores lead to less pronounced inverted U-shaped patterns, especially for the younger cohort in YLS, and for boys in CLHNS.[19]

3.5.3. Controlling for maternal height

Although our results should be interpreted as primarily descriptive rather than causal, it is interesting to see whether the age profile of the SES gradients remain similar if we control for maternal height. Better educated mothers, in addition to having taller children, are also likely to be themselves taller. This means that the gradient may be partly explained by intergenerational transmission of health, also due to genetic factors. Although the point estimates decline in magnitude somewhat, the estimated patterns remain very similar when we control for maternal height in DHS data (Online Appendix Figure A.9) or in the longitudinal data (Online Appendix Tables A.3 and A.4). This is despite the fact that, as expected, maternal height is a very strong predictor of child height.

3.5.4. Attrition

A potential concern with the panel results is attrition. Our results are derived from a balanced panel of individuals that have observations in all waves (around 90% of the original data in YLS, and 62% in CLHNS). This sample may not be representative of the original sample. Furthermore, attrition may bias our estimates if its extent and timing are correlated with SES.

[19] In this latter case the gradient actually declines fairly steadily as children grow into adults. As noted earlier, the results using z-scores depend on the reference population used. This normalization can cause z-scores to behave differently from gaps, particularly due to the increases in the standard deviation of the height distribution as individuals age. Understanding why the use of z-scores leads to different results in some settings is beyond the scope of this paper but has been noted before (Wang et al. 2006, Wang and Chen 2012, Tarozzi 2008).

Table 2
Girl height vs. maternal schooling, YLS and CLHNS.
Source: Authors' calculations from Young Lives and Cebu Longitudinal Health and Nutrition Survey.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A.1	Young Lives: Younger Cohort						
	Age 1y	Age 5y	Age 8y	Age 12y	Age 15y		
Mother at least secondary	1.701***	3.554***	4.195***	4.727***	2.333***		
	[0.2266]	[0.4137]	[0.4429]	[0.6214]	[0.3135]		
Observations	3,433	3,433	3,433	3,433	3,433		
R-squared	0.4483	0.2260	0.1399	0.1289	0.0941		
Mean height	70.84	103.8	120	143	153.6		
Panel A.2			Young Lives: Older Cohort				
			Age 8y	Age 12y	Age 15y	Age 19y	Age 22y
Mother at least secondary			2.480***	3.356***	2.035***	1.454***	1.374***
			[0.4869]	[0.6130]	[0.4016]	[0.4123]	[0.3769]
Observations			1,494	1,494	1,494	1,494	1,494
R-squared			0.0758	0.0687	0.0872	0.1276	0.1971
Mean height			117.9	142.1	151.7	154.6	155.3
Panel B	CLHNS						
	Age 1y		Age 8y	Age 11y	Age 15y	Age 18y	Age 21y
Mother at least secondary	1.083***		3.282***	3.844***	2.095***	1.500***	1.655***
	(0.208)		(0.437)	(0.637)	(0.369)	(0.346)	(0.321)
Observations	677		677	677	677	677	677
R-squared	0.033		0.058	0.119	0.057	0.037	0.030
Mean height	69.99		117.6	135.2	149.1	151	151.3

Notes: This table presents OLS regression estimates of girl height (in cms) on a dummy variable equal to one if the mother has completed at least secondary education. All estimates do not use sampling weights and include dummies for country and age in months. Standard errors are clustered at the level of primary stage unit of residence in the first wave ('sentinel site' in YLS and *barangay*–district or village–in CLHNS). In YLS, secondary education is set = 1 when the mother has completed a number of years of schooling corresponding to the country-specific typical requirement, that is, 10 in Ethiopia, 12 in India, 11 in Peru and 9 in Vietnam. In CLHNS it is = 1 if the mother has completed at least 4 years of secondary school at the time of the first survey wave. Results in Panel A are estimated pooling all observations for girls from Ethiopia, India, Peru and Vietnam, for the Younger Cohort (born 2001/02, Panel A.1) and the Older Cohort (born 1994/95, Panel A.2).

To investigate these issues, we start by noting that, in both datasets, maternal education is not predictive of attrition (Online Appendix Table A.5). While this alleviates concerns, it may still be that the patterns we observe and in particular the decline in the gradient in adolescence might be driven by differential attrition by SES during adolescence. For example if tall (short) children from high (low) SES families leave the sample in adolescence, then the height gap between high and low SES could shrink. To test this we investigate if height predicts attrition at each wave, and whether it does so differently by SES (see Online Appendix Table A.6). In the YLS, height predicts attrition between age 1 and 5 for low SES children but not for high SES children in the younger cohort. Since tall low SES children are less likely to drop out, the gap between high and low SES children is underestimated. We also observe that taller children from high SES families are more likely to drop out between ages 8 and 12, and thus gradients are underestimated at this age. Most importantly, however, we do not observe statistically significant differences in attrition by SES from age 12 onward. Thus, the decline in the gaps in adolescence cannot be explained by differential attrition. In CHLNS data we also observe differential attrition in early childhood, but not during adolescence. These results suggest that attrition may bias the gradients during childhood but not in adolescence. As a final check, we re-estimate the SES gradient by age using all observations in all waves. The results remain remarkably similar (Online Appendix Tables A.7 and A.8). Thus, while attrition affects the exact magnitude of the gradient at some ages, it does not appear to drive the overall evolution of the height gradient in the panel data. Most importantly, we do not find evidence to suggest that the decline of the gradient in adolescence is due to attrition.

4. Why does the gradient decline in adolescence?

Our primary hypotheses to explain why the gradient falls in adolescence relates to the physiology of human growth: if high-SES children have an earlier adolescent growth spurt and stop growing earlier, then low-SES children may catch-up to some extent. In this section we show that our data are strongly consistent with this hypothesis. Below we also describe alternative explanations based on the idea that behavior of taller adolescents may be different from that of their shorter peers, in ways that differ by SES. However, we do not find support for this hypothesis and so we relegate the corresponding results to the Online Appendix.

4.1. Pubertal maturation, SES and the age profile of the gradient

Our hypothesis is that the increasing and then decreasing association between height and maternal education may be explained by the physiology of human growth, and SES-based variation in the timing and duration of such growth. Among girls, it is well

Table 3
Boy height vs. maternal schooling, YLS and CLHNS.
Source: Authors' calculations from Young Lives and Cebu Longitudinal Health and Nutrition Survey.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A.1	Young Lives: Younger Cohort						
	Age 1y	Age 5y	Age 8y	Age 12y	Age 15y		
Mother at least secondary	1.558***	3.614***	4.002***	5.281***	4.744***		
	[0.2664]	[0.4195]	[0.5316]	[0.6808]	[0.5107]		
Observations	3,762	3,762	3,762	3,762	3,762		
R-squared	0.4247	0.2235	0.1427	0.1582	0.1522		
Mean height	72.27	104.6	120.3	140.9	159		
Panel A.2			Young Lives: Older Cohort				
			Age 8y	Age 12y	Age 15y	Age 19y	Age 22y
Mother at least secondary			3.638***	4.778***	5.111***	3.182***	2.771***
			[0.4526]	[0.5961]	[0.5342]	[0.3900]	[0.3530]
Observations			1,497	1,497	1,497	1,497	1,497
R-squared			0.0950	0.1132	0.0992	0.1137	0.1323
Mean height			118.5	140	156.4	166.5	167.6
Panel B	CLHNS						
	Age 1y		Age 8y	Age 11y	Age 15y	Age 18y	Age 21y
Mother at least secondary	1.703***		3.443***	4.110***	3.899***	2.658***	2.579***
	(0.179)		(0.559)	(0.698)	(0.603)	(0.536)	(0.565)
Observations	748		748	748	748	748	748
R-squared	0.069		0.073	0.175	0.125	0.067	0.062
Mean height	71.46		117.6	132.1	158.1	162.3	162.8

Notes: This table presents OLS regression estimates of boy height (in cms) on a dummy variable equal to one if the mother has completed at least secondary education. All estimates do not use sampling weights and include dummies for country and age in months. Standard errors are clustered at the level of primary stage unit of residence in the first wave ('sentinel site' in YLS and *barangay*–district or village–in CLHNS). In YLS, secondary education is set = 1 when the mother has completed a number of years of schooling corresponding to the country-specific typical requirement, that is, 10 in Ethiopia, 12 in India, 11 in Peru and 9 in Vietnam. In CLHNS it is = 1 if the mother has completed at least 4 years of secondary school at the time of the first survey wave. Results in Panel A are estimated pooling all observations for boys from Ethiopia, India, Peru and Vietnam, for the Younger Cohort (born 2001/02, Panel A.1) and the Older Cohort (born 1994/95, Panel A.2).

known that the adolescent growth spurt precedes menarche–the onset of menstruation–by about one year, and that growth stops within the following year or two (Gluckman et al., 2016). If the growth spurt varies with SES, with high-SES experiencing it earlier in LMICs, then this would explain our findings.[20]

This hypothesis is plausible. It has been observed that as economic conditions improve and nutritional intakes and dietary diversity increase, the onset of menarche occurs earlier (de Muinck Keizer-Shrama and Mul 2001, Lam et al. 2021). Consistent with this, Thomas et al. (2001), summarizing results from 67 countries, find a strong negative association between average age at menarche and different measures of development, including female life expectancy and literacy rates. Simondon et al. (1998) use longitudinal data from 1650 children in Senegal and show that girls who were stunted before schooling age had menarche later than non-stunted girls but their height grew faster–leading to some catch-up-in late adolescence. Delayed menarche among lower-SES groups was also observed in past UK cohorts (Krzyżanowska et al., 2016), but not in contemporaneous ones (Kelly et al., 2017).[21]

Given these insights, if within LMICs there is a negative association between age at pubertal maturation and measures of material well-being, high-SES children will grow–on average–faster than their low-SES cohort peers both before and during the adolescent growth spurt, which they will reach, on average, sooner. At this point the gap between high- and low-SES children may reach a maximum. However, once low-SES children reach their adolescent growth spurt, a degree of catch-up may take place, especially if physical growth continues well after adolescence or if pubertal maturation occurs very late. Indeed it has also been shown that poor or poorly fed populations grow more slowly and reach their final height at later ages (Steckel, 1986). This is also consistent with our longitudinal data, where we observe that both girls and boys continue to grow past age 18, see Tables 2 and 3. This catch-up mechanism may thus lead to a reduction in the height-SES gradient after puberty.

[20] Compared with girls, there is less evidence available for boys on the relationship between pubertal maturation and SES in LMICs. This is partly due to the greater challenges in measuring pubertal timing for boys in the absence of a clearly defined marker of pubertal maturation such as menarche. This evidence gap is equally marked for high-income settings. The only paper we are aware of that examines the relationship between SES and pubertal maturation among boys is Sun et al. (2017), which documents an inverse relationship in an Australian cohort. This is consistent with a wide body of evidence showing that in high-income settings *lower* SES predicts earlier maturation, the opposite of what we find in LMICs.

[21] From a biological perspective, the relationship between SES and pubertal onset and tempo may be mediated by recently-uncovered mutations in brain receptors that are activated by caloric deprivations in childhood (Lam et al., 2021). In turn, these mutations are associated with delayed pubertal onset and reduced linear growth rate throughout childhood and adolescence, which are then partially offset by a longer period of limb growth due to a later pubertal onset, allowing for an extended period of growth.

Table 4
Association between early menarche and maternal schooling.
Source: Authors' calculations from DHS, YLS (both cohorts), and CLHNS data.

	(1)	(2)	(3)	(4)	(5)
Panel A: DHS	India	Turkey	Gabon	Ghana	
Mother at least secondary	0.030***	0.017	0.192	0.146	
	(0.007)	(0.052)	(0.128)	(0.095)	
Observations	63,989	862	541	409	
R-squared	0.000	0.000	0.007	0.014	
Mean of dependent variable	0.200	0.306	0.197	0.064	
Age range	15-17	15-17	15-19	15-19	
Panel B: YLS and CLHNS	Ethiopia	India	Peru	Vietnam	Philippines
Mother at least secondary	0.024	0.191*	0.106**	0.204***	0.182***
	(0.029)	(0.106)	(0.046)	(0.044)	(0.034)
Observations	1,163	1,301	1,135	1,328	787
R-squared	0.02	0.057	0.091	0.126	0.154
Mean of dependent variable	0.03	0.32	0.55	0.34	0.41

Notes: The dependent variable is a dummy = 1 if the individual had menarche before 13 years of age. See Online Appendix A.2 for additional details on data construction for DHS. All estimates do not use sampling weights and include dummies for age in months. In the DHS estimates, we control for country binary variables, while in the YLS data, for whether the child is from the Younger Cohort. Standard errors are clustered at the level of primary stage unit (PSU) of residence (in DHS), or the PSU in the first wave ('sentinel site' in YLS and *barangay*–district or village–in CLHNS). In YLS, secondary education is set = 1 when the mother has completed a number of years of schooling corresponding to the country-specific typical requirement, that is, 10 in Ethiopia, 12 in India, 11 in Peru and 9 in Vietnam. In CLHNS it is = 1 if the mother has completed at least 4 years of secondary school at the time of the first survey wave.

To investigate the association between SES and age at pubertal maturation, we start by examining data on age at menarche in DHS data using the four countries where the data allow it, namely, Gabon, Ghana, India, and Turkey.[22] For each of these countries, we estimate models such as Eq. (1) but with a binary dependent variable equal to one if the girl had menarche before age 13. Although the four countries differ considerably in their level of development, there is a *positive* association between early menarche and maternal education in all of them, although the coefficient is only statistically significant in India, and its magnitude is small for Turkey (Table 4, Panel A). In India, high maternal education increases the predicted probability of early menarche by 3 percentage points (95% CI [0.016, 0.044]), relative to the mean (20%). In Gabon and Ghana, both very poor countries where fewer girls have already reached menarche before 13, the association is even stronger, although very imprecisely estimated and thus not significant at standard levels: in Gabon high maternal education predicts a 100% increase in the probability (from 20 to 39%, 95% CI of the change [−0.061, 0.445]), while in Ghana it predicts a 228% increase (from 6.4 to 21%, 95% CI of the change [−0.04, 0.333]). In wealthier Turkey, where average female education is also higher, the association is still positive but much weaker and not significant at standard levels.

The negative association between SES and age at menarche is confirmed when we use the longitudinal data from both cohorts from YLS and from CHLNS, as reported in Table 4, Panel B. With the exception of Ethiopia, where the association is weak and not significant at standard levels, early menarche is substantively more likely among daughters of high-SES mothers, with point estimates ranging from 0.11 in Peru to 0.2 in Vietnam. These simple associations are of course not necessarily causal, but they are consistent with the hypothesis that high-SES girls grow faster and stop growing sooner. Ethiopia may be an exception due to the very low prevalence of early menarche among girls in the sample, at less than 4%.[23]

Altogether this evidence suggest that indeed the onset of adolescence occurs earlier among high-SES children in the contexts we are analyzing. This evidence is, however, incomplete because we cannot link the onset of adolescence directly to the SES gradients in heights at various ages. To do this we now estimate a model of growth separately for boys and girls by SES.

4.1.1. A model of the age profile of growth velocity and SES

In this sub-section we describe and estimate a simple model where both the timing and speed of height growth depend on SES. We model the growth rate of heights assuming that it follows the well-known patterns described in the literature (e.g. see Tanner et al. 1966, Fig. 8, or Gluckman et al. 2016, Fig. 5.8). We estimate a model where the parameters are the growth rates in different developmental periods and the age at which each period starts. In this model there are four key periods: early childhood (before

[22] Age at menarche is available for several other DHS countries, but they cannot be linked to maternal schooling due to the data structure, see Online Appendix A.2 for details.

[23] The associations between SES and early menarche we observe in both DHS and panel data may be driven at least in part by a higher prevalence of overweight among high-SES girls, as excess adiposity in childhood is an important factor associated with earlier pubertal onset (Marcovecchio and Chiarelli, 2013). Overweight girls in the pre-pubertal phase tend to grow faster than leaner peers, but this advantage in growth tends to decline during puberty, when overweight girls display a reduced growth spurt. This, again, could lead to a degree of catch-up in height among poorer girls, who are less likely to be overweight. We check whether taking into account overweight and obesity changes the point estimates for maternal education in both the DHS and YLS panel data for girls, but we do not find evidence that this is the case. We also note that overweight and obesity are generally limited in these samples.

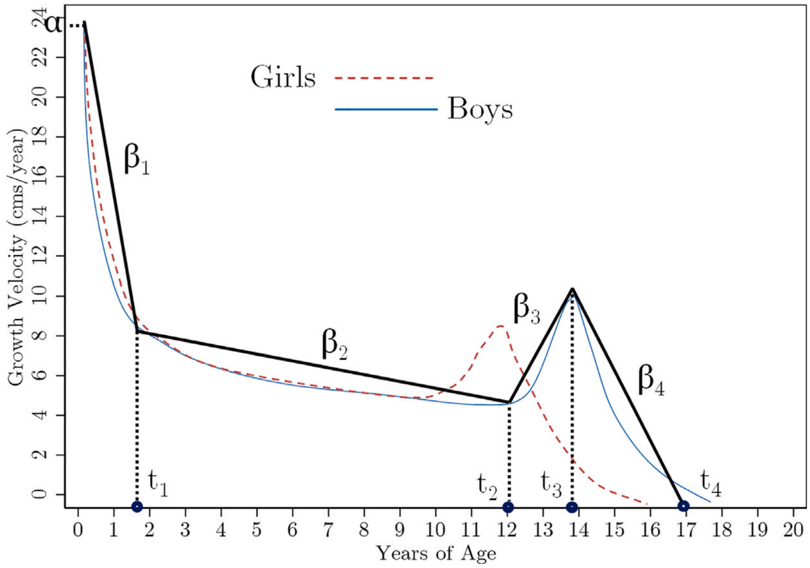

Fig. 6. Growth velocity.
Source: Authors' elaboration from Tanner et al. (1966, Fig. 8). The labels indicate the parameters estimated for boys using the procedure described in Section 4.1.1: α is growth velocity at birth; t_1, t_2, t_3, and t_4 show the age of the most salient changes in growth velocity, while β_1, β_2, β_3, and β_4 are the slopes of the piecewise linear curve in each interval.

age 2–3), childhood (roughly ages 3–10), the adolescent growth spurt (sometime after age 10), and adulthood (once growth is completed). The exact duration of each period varies across time and place, and may depend on SES.

In Fig. 6 we illustrate the typical velocity curves for boys and girls, as illustrated for instance in Tanner et al. (1966, Fig. 8). We superimpose on the figure an illustration of the model we estimate, with labels corresponding to the parameters that we describe in detail below. Growth is typically highest at birth, and falls rapidly during early childhood. During childhood, velocity declines slowly until the adolescent growth spurt (AGS). At this point growth velocity increases, reaches a peak and then declines at a steady rate until adult height is achieved. The shape of the velocity curves is thus well approximated by a piece-wise continuous linear function, with three slope changes: a first change at the end of the fastest growth period in early childhood, a second at the beginning of the AGS, and a third at its peak.

Formally, let t_1, t_2, and t_3 denote the timing of the kinks in the piece-wise linear velocity curve, and let t_4 be the time when adult height is achieved. Let also h_t denote height of an individual at age t (measured in months). For an individual who has not yet achieved adult height (that, is for $t < t_4$), growth between $t-1$ and t can be written as

$$\begin{aligned} h_t - h_{t-1} &= \alpha + \beta_1 \left(\min\{t, t_1\} - 1\right) + 1\left(t > t_1\right) \beta_2 \left(\min\{t, t_2\} - t_1\right) \\ &\quad + 1\left(t > t_2\right) \beta_3 \left(\min\{t, t_3\} - t_2\right) + 1\left(t > t_3\right) \beta_4 \left(\min\{t, t_4\} - t_3\right), \end{aligned} \quad (2)$$

where the coefficients β_1, β_2, β_3, and β_4 are thus the slopes of the four linear intervals. Because adult height is achieved at $t = t_4$, growth must be equal to zero at this time, so that the following constraint must hold:

$$\alpha + \beta_1 \left(t_1 - 1\right) + \beta_2 \left(t_2 - t_1\right) + \beta_3 \left(t_3 - t_2\right) + \beta_4 \left(t_4 - t_3\right) = 0. \quad (3)$$

This model cannot be estimated directly in our data, given that for the same child we never observe height measured in two consecutive months. However, in Online Appendix A.4 we show that Eq. (2) can be used in an iterative fashion to write down height at age t as:

$$h_t = h_0 + \alpha 1(t \le t_4)t + \beta_1 v_1 + \beta_2 v_2 + \beta_3 v_3 + \beta_4 v_4 + \delta 1(t > t_4), \quad (4)$$

where the v functions are somewhat complex but deterministic and known functions of age and/or of the location of the kinks such that

$$\begin{aligned} v_1 &= 1(t \le t_4)\frac{\min(t,t_1)(\min(t,t_1)-1)}{2} + 1(t_1 < t \le t_4)(t-t_1)(t_1-1) \\ v_2 &= 1(t_1 < t \le t_4)\frac{(\min(t,t_2)-t_1)(\min(t,t_2)-t_1+1)}{2} + 1(t_2 < t \le t_4)(t-t_2)(t_2-t_1) \\ v_3 &= 1(t_2 < t \le t_4)\frac{(\min(t,t_3)-t_2)(\min(t,t_3)-t_2+1)}{2} + 1(t_3 < t \le t_4)(t-t_3)(t_3-t_2) \\ v_4 &= 1(t_3 < t \le t_4)\frac{(t-t_3)(t-t_3+1)}{2}, \end{aligned}$$

Table 5
YLS: A model of growth velocity and maternal schooling.
Source: Authors' calculations from pooled YLS data.

	(1) Boys		(2) Girls	
	Low schooling	Sec. schooling	Low schooling	Sec. schooling
Intercept (Height at 6 months, h_6)	61.0718	61.6517	55.6757	59.4736
	(0.15201)	(0.26354)	(0.69938)	(0.47361)
Total growth up to adult height (δ)	105.8816	106.3238	99.2212	96.4303
	(0.18033)	(0.32247)	(0.70180)	(0.49974)
Initial growth velocity (α)	0.9869	1.0933	1.7036	1.2080
	(0.01432)	(0.02532)	(0.10908)	(0.05174)
Slope of velocity curve:				
$-t \leq t_1$: Early childhood (β_1)	−0.0106	−0.0127	−0.0757	−0.0189
	(0.00040)	(0.00071)	(0.00856)	(0.00202)
$-t_1 < t \leq t_2$: Before AGS (β_2)	−0.0011	−0.0009	−0.0038	−0.0030
	(0.00007)	(0.00013)	(0.00009)	(0.00031)
$-t_2 < t \leq t_3$: AGS (β_3)	0.0070	0.0182	0.0168	0.0135
	(0.00027)	(0.00120)	(0.00060)	(0.00083)
$-t_3 < t \leq t_4$: End of growth (β_4)	−0.0109	−0.0143	−0.0071	−0.0067
	(0.00009)	(0.00022)	(0.00005)	(0.00004)
Kinks (months)				
$-t_1$: End of early childhood	47	47	14	32
$-t_2$: Start of AGS	143	148	108	93
$-t_3$: AGS Peak	170	161	122	106
$-t_4$: Adult height	223	207	206	198
Root MSE	6.8750	6.1726	6.6904	5.5289
Observations	23,776	5,037	22,112	4,928
No. children	5,010	1,057	4,673	1,033

Notes: The table shows the estimates of the model described in Section 4.1.1, and illustrated graphically in Fig. 7. AGS indicates the adolescent growth spurt.

and where in addition to constraint (3) the following should also hold

$$\delta = t_4\alpha + \left[\frac{t_1\left(t_1-1\right)}{2} + \left(t_4-t_1\right)\left(t_1-1\right)\right]\beta_1 + \left[\frac{\left(t_2-t_1\right)\left(t_2-t_1+1\right)}{2} + \left(t_4-t_2\right)\left(t_2-t_1\right)\right]\beta_2 + \left[\frac{\left(t_3-t_2\right)\left(t_3-t_2+1\right)}{2} + \left(t_4-t_3\right)\left(t_3-t_2\right)\right]\beta_3 + \frac{\left(t_4-t_3\right)\left(t_4-t_3+1\right)}{2}\beta_4. \quad (5)$$

This second constraint imposes that height be constant once adult height is achieved, that is, at time $t = t_4$. Both these constraints are linear in parameters, and given that in our data we observe both height and age for each child, the coefficients in (4) can be estimated in a straightforward way using constrained OLS, *once the location of the kinks is known.* Given that such location is actually unobserved, we use an approach analogous to that developed in Hansen (2017) for the estimation of regression kink models with an unknown threshold. First we set the positions of the kinks t_1, t_2, t_3, and t_4. Then we estimate (4) using constrained OLS, and we calculate and store the corresponding sum of squared residuals (SSR). Finally, we choose the estimates that minimize the SSR over the whole grid. Because the kinks are naturally ordered, we always impose $t_1 < t_2 < t_3 < t_4$, but in our optimization algorithm we also impose a minimum of twelve months between t_2 and t_3, that is, between the beginning and the peak of the AGS. This is because, due to the timing of the height measurement, the number of children measured around this period is sometimes small, and this leads to estimates of the duration of the AGS that are unreasonably short when compared to what is suggested by the literature on human growth.[24]

4.1.2. Model estimation results

In order to increase precision, we pool together data from each of the four YLS countries and cohorts. YLS data include measurements of the same individuals at different ages. The frequency of measurements is too sparse to allow estimating individual growth velocity at frequent intervals, but there is sufficient variation in the exact age at measurement around the mean age that we can use the model described above to estimate the age profile of growth velocity around ages 1, 5, 8, 12, 15, 19 and 22. We do not include data from CLHNS because the timing of the measurements only partly overlaps with YLS, and it is undesirable to have different sets of countries driving results over different age ranges.

[24] The small number of observations at these two kinks means that the SSR obtained with or without imposing such minimum duration are very close, and so the choice between constrained and unconstrained estimates lead to very similar values of the objective function (the SSR) but to quite different estimates.

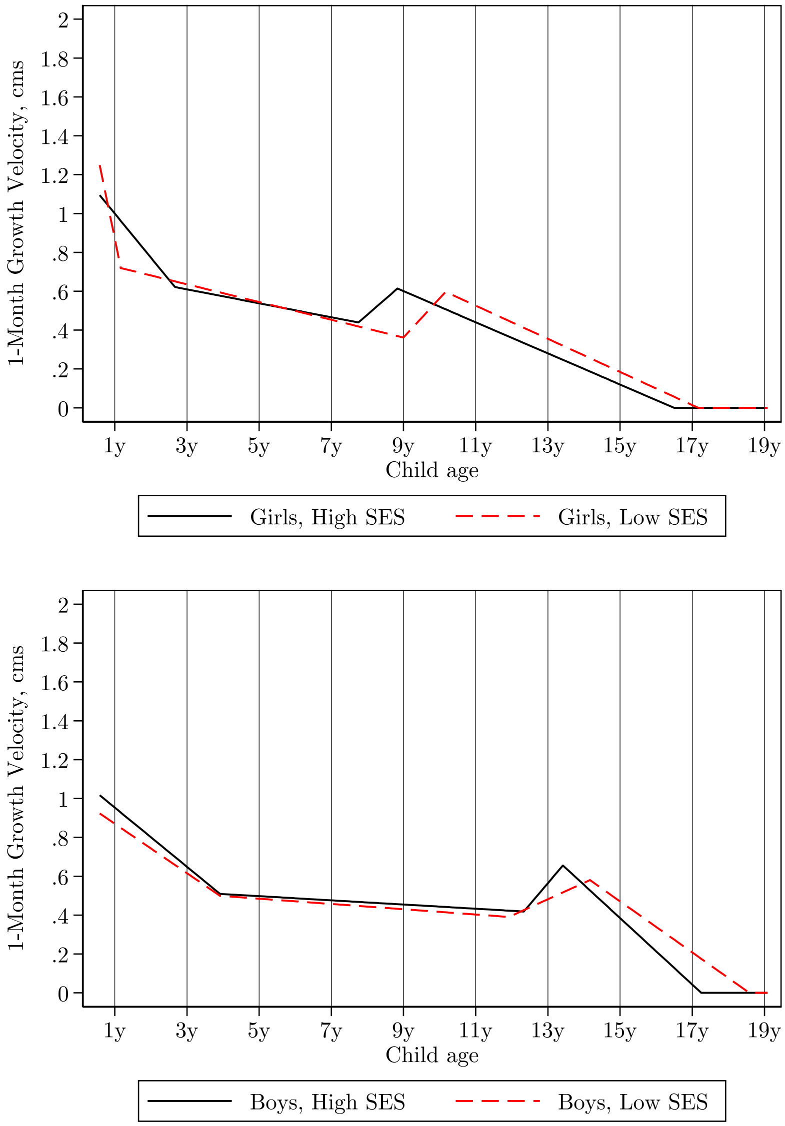

Fig. 7. YLS: Growth velocity and SES.
Source: Authors' calculations from YLS data. The lines show height growth velocity predicted by the piece-wise continuous regression model described in Section 4.1.1, estimated separately for boys and girls, and by SES. High-SES is binary and equal to one when the mother has completed at least secondary schooling.

We show graphically the results of the estimation in Fig. 7, while the details of the estimations are in Table 5.[25] As expected, the AGS takes place significantly sooner among girls relative to boys, and girls achieve their final height earlier than boys. And, perhaps unsurprisingly given our earlier results, there are visible differences in growth velocity by maternal education. In particular, three patterns are apparent. First, growth velocity is faster among high-SES children until a few months after the AGS peak: among boys the gap is small but persistent until the start of the AGS (t_2), while among girls it is large especially between 1 and 3 years of age and after t_2. Second, the AGS starts about one year sooner among high-SES girls. Both boys and girls in high SES groups have an earlier AGS peak. Third, growth continues for a longer period among low-SES children, especially among boys.

The model-implied SES gradient, shown in Fig. 8, rises until adolescence and then falls, monotonically for boys and less so for girls. The average height gap between high and low-SES increases gradually with age, opens up further when high-SES have their AGS, but then low-SES catch-up both because their AGS peak occurs when growth is already slowing down for high-SES children

[25] In Online Appendix Figure A.16 we also report the country-specific patterns. The country-specific point estimates and standard errors of the slopes are available upon request from the authors.

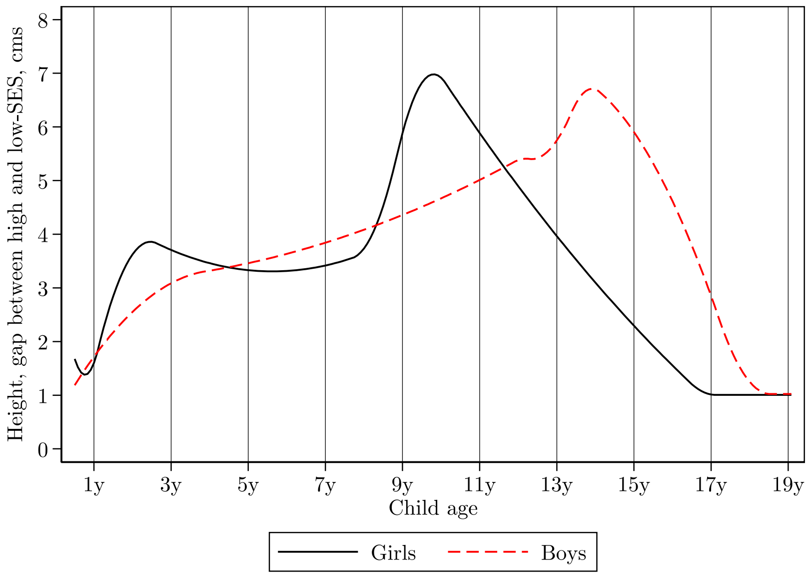

Fig. 8. YLS: Height high vs. low-SES gap .
Source: Authors' calculations from YLS data. The lines show differences in height growth velocity between high-SES and low-SES children, as predicted by the piece-wise continuous regression model described in Section 4.1.1, estimated separately for boys and girls. High-SES is binary and equal to one when the mother has completed at least secondary schooling.

and because they achieve their adult height at an older age. This indicates a degree of catch-up, although this is only partial. Indeed the parameter estimates in Table 5 shows that average adult height ($h_6 + \delta$) is 167 cms among low-SES boys and 168 cms among high-SES boys, while among girls the two estimates are 154.9 cm and 155.9 cm, respectively.[26] Also noteworthy is that high-SES boys finish growing 16 months earlier than low-SES boys, with a smaller gap of 8 months between high- and low-SES girls.

4.2. Alternative explanations for the decline in the height-gradient in adolescence

A complementary hypothesis is that the onset of adolescence, a period of transition into adulthood, may lead to behavioral changes that affect later growth, and may do so differentially by SES in a way that could explain the fall of the gradient we observe around this time. That is, higher-SES children–which are more likely to reach pubertal development before lower-SES peers–may also start earlier to engage in behaviors that may harm their growth. In turn, this could reduce their relative height advantage. For instance, in LMICs, girls who have an earlier menarche are more likely to drop out of school, marry and have children earlier than peers with a later menarche (Field and Ambrus 2008, Khanna 2020). By the same token, children with an earlier pubertal growth spurt may be more likely to engage in physically demanding labor as compared to peers that have a delayed pubertal growth spurt. Both early childbearing and increased work may impose a 'height cost' by increasing a child's nutritional expenditures and slowing down growth (Johnson and Moore, 2016). Decreased nutritional investments for children that appear taller than their peers could be another potential behavioral explanation (Wang et al., 2020). Early puberty may also disrupt sleep patterns and lead to fewer sleeping hours. As growth hormones are produced during sleep, this can hamper growth. Finally, earlier pubertal timing has been shown to predict higher sensation seeking and engagement in risky behaviors (Steinberg et al., 2008), which in turn may decelerate adolescents' subsequent growth. However, our data do not support such alternative hypothesis. In Online Appendix A.5 we show that, while we confirm that there are behaviors in adolescence that are negatively associated with growth during this period (in particular early marriage), we find no evidence that these behavioral differences can account for the decline in the SES gradients in adolescence. In fact, if anything, we find the opposite.[27]

5. Discussions and conclusions

Using a large number of LMICs countries and cohorts we have shown that the association between height (a measure of long-term health) and maternal education (a proxy for SES) follows an age profile with an inverted U-shape. This pattern is similar when we

[26] These figures suggest a height gap between high vs. low-SES adults that is smaller than the ones of 1.4–2.7 cms documented in Tables 2 and 3. This is likely due to the approximation induced by the piece-wise continuous shape of the growth velocity curve that we impose for the estimation.

[27] However, these results have a silver lining in that they suggest that catch-up could be larger among low-SES children if marriage and childbearing during adolescence could be avoided.

use other proxies for SES, such as current wealth. We show that such a profile is likely mediated by the physiology of human growth, as SES predicts the timing and duration of puberty. In our data, children from high-SES families have their adolescent growth spurt earlier, on average, than children from low-SES families. This, together with the fact that low-SES children achieve their adult height at older ages, allows them to partly compensate the height disadvantage they have accumulated during childhood.

Our results suggest that the timing of puberty and its relation to SES is a key factor in allowing for catch-up in height. The age of the onset of puberty has declined substantially in rich countries and it varies widely around the world today. The reasons for this decline are not fully understood, as are the health consequences of these changes. Similarly the age of the onset of puberty is related to socio-economic status, but this association varies across time and place. In LMICs, girls from high-SES families have menarche earlier whereas the opposite is true in rich countries today. Given that the onset of puberty and its association with SES varies across locations and over time, our results suggest that the evolution of the height gradient during adolescence will vary across contexts as well—most notably our results suggests that in rich countries where menarche occurs later for high-SES children, the gradient will continue to grow throughout adolescence. The reasons for these differences are poorly understood. Our research points to the importance of understanding these phenomena further as they hold the key to understanding whether catch-up is possible, and how we might achieve it if we wish to intervene during adolescence. Data on pubertal development for boys is especially scarce, and more research on how the AGS is interlinked with SES is needed, including in high-income settings.

A related and important point is that catch-up in height does not necessarily imply catch-up in other dimensions of human capital. In fact, while height can be important in and of itself (for instance due to returns to physical strength), child stunting is also a marker for nutrition and health conditions since conception (Case and Paxson, 2008; McGovern et al., 2017; Leroy and Frongillo, 2019). A large literature documents that early-life insults can have long-lasting consequences for health and economic conditions (Almond et al., 2018), and so the reduction in the height gradient in adolescence does not necessarily mean that gradients in other dimensions will be similarly reduced. Our work is silent about this, but this is an important qualification that must be kept in mind even from a policy perspective: partial catch-up in height does not necessarily mean that we should worry less about large gradients that may have existed during childhood. However to the extent that final (adult) height has direct consequences on adult and intergenerational outcomes (for example through better maternal and child health during pregnancy and child-birth), then catch-up in adolescence will ameliorate some economic and health disparities.

Finally, our results also suggest that height, often used as an indicator of long-term health or quality of health environments during childhood (e.g. by economic historians), is not an equally good indicator of these outcomes at different ages. Indeed, height appears as a particularly poor indicator of SES around birth. The decline in the gradient at older ages could also help explain the weak association documented by Deaton (2007) in DHS data between adult height of women and GDP at birth. Deaton (2007) and Bozzoli et al. (2009) argue that a key contributing factor is mortality selection. That is, in poor countries where infant mortality is high, increases in GDP at birth predict not only improvements in SES, but also a decrease in mortality. However, the latter decrease likely leads to the survival of individuals of poor health and likely smaller height, who would have died under less favorable conditions. Such decline in 'harvesting' will then weaken the cross-sectional association between GDP at birth and the average height of the surviving adults.[28] In this paper, we provided another explanation for why gradients among adults in developing countries are smaller than among children: there is some amount of catch-up during adolescence. While the catch-up is not complete, it is possible that a better understanding of the factors that increase catch-up can both help explaining the 'Deaton puzzle' and provide avenues for interventions that would lower SES gradients in height. Future research in this area should further investigate these.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2023.102797.

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[28] Although this is beyond the scope of this paper, we find that, in DHS data, child height is very weakly associated with GDP at birth at age 0, but the correlation increases substantively with age. These results are available upon request.

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