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Local Social Inequality, Economic Inequality, and Disparities in Child Height in India

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Abstract

This study investigates disparities in child height—an important marker of population-level health—among population groups in rural India. India is an informative context in which to study processes of health disparities because of wide heterogeneity in the degree of local segregation or integration among caste groups. Building on a literature that identifies discrimination by quantifying whether differences in socioeconomic status (SES) can account for differences in health, we decompose height differences between rural children from higher castes and rural children from three disadvantaged groups. We find that socioeconomic differences can explain the height gap for children from Scheduled Tribes (STs), who tend to live in geographically isolated places. However, SES does not fully explain height gaps for children from the Scheduled Castes (SC) and Other Backward Classes (OBCs). Among SC and OBC children, local processes of discrimination also matter: the fraction of households in a child's locality that outrank her household in the caste hierarchy predicts her height. SC and OBC children who are surrounded by other lower-caste households are no shorter than higher-caste children of the same SES. Our results contrast with studies from other populations where segregation or apartheid are negatively associated with health.

Keywords

Social inequality; Height; Children; India; Caste

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Introduction

Inequality in child health among population groups can be caused by inequality in socioeconomic status (SES), can cause socioeconomic inequality, or can be independent of SES. Examples of each of these patterns have been found in both developed and developing countries (Elo 2009). In developing countries, because malnutrition and disease among children are common and often severe, unequal child health outcomes among population groups may contribute even more to perpetuating inequality than they do in developed countries (Palloni 2006).

To better understand relationships between inequality and health, a large literature in demography has focused on quantifying the extent to which differences in SES between population groups can explain differences in health outcomes (Williams and Collins 1995). In this literature, evidence of disparate outcomes at the same level of SES is a common indicator of discrimination (Cramer 1995; Elo and Preston 1996; Rogers 1992; Williams 1999). For example, Burgard (2002) found that the distribution of socioeconomic resources across households and geographic areas can explain differences in rates of stunting between children of different racial groups in Brazil; however, in South Africa, differences in stunting between white and nonwhite children are not fully explained by these factors.

Literature on discrimination has increasingly progressed beyond documenting the existence of disparities among people with the same SES, toward identifying processes and asking how discrimination has its effects. In the health literature, Sastry and Hussey (2003) studied differences in birth weight between non-Hispanic whites and Mexican-origin Hispanics; they found not only that inputs such as SES and neighborhood factors differ between these groups but also that the effects of these inputs also differ between groups. More generally, the relationships between socioeconomic variables and child outcomes within a society may change over time; they may depend on neighborhood-level factors as well as household-level factors, or they may interact with social group (Hummer 1993; Reichman et al. 2009; Sastry 1996, 2004). Demographers have particularly focused on the effect of segregation: they have often asked whether racial or other types of segregation contribute to health disparities (LaVeist et al. 2011; Leung and Takeuchi 2011; Massey 1990; Williams and Collins 2001).

In this article, we advance both literatures, making two contributions to understanding disparities in child height in rural India. First, we show that some disparities can be only partially explained by SES, with an important remaining role for discrimination. Second, we study the process of discrimination's effect by documenting the role of the local social context. Rural India's combination of mixed and segregated localities offers an informative contrast with research from other societies, such as the United States and South Africa, where scholars have posited a relationship between segregation and health. We find that in rural India, lower caste children have worse height outcomes than higher caste children of similar SES only if they are surrounded by higher caste households in the same locality. This result has implications for theories of discrimination. In this context, discrimination is, in part, channeled through one's rank within the local area.[1] Our results contrast with studies of other populations, where segregation or apartheid harm health, in part by denying access to public services or other resources. In rural India, being surrounded by other households from lower castes appears to advantage lower caste children.

Beyond the ways in which this case contributes to a broader understanding of processes of discrimination in health, both caste and child height are important demographic topics in their own right. Caste is strongly associated with poverty, education, land ownership, consumption, use of health services, and even subjective well-being (Borooah 2005; Desai and Dubey 2011; Deshpande 2000; Roy et al. 2004; Spears 2016). Child height is an important marker of population health and a predictor of adult human capital and mortality (Deaton 2007). Within populations, children whose early-life health allows them to grow taller go on to reach higher levels of cognitive achievement, on average (Case and Paxson 2010). The association between childhood height and cognitive achievement is considerably steeper in India than in the United States (Spears 2012).

Because height is such an important marker of health and well-being, and because the Demographic and Health Survey (DHS) that we study shows that the average child under 5 in rural India is about 2 standard deviations shorter than the World Health Organization (WHO) reference population for healthy growth, better understanding disparities of height among Indian children is important for human development. To our knowledge, our study is the first to investigate explanations for height disparities and processes of discrimination among different population groups in India.[2]

We present results in two parts. First, we conduct a reweighting decomposition of average child height, constructing counterfactual average child height among three disadvantaged population groups: Scheduled Tribes (STs), Scheduled Castes (SCs), and Other Backward Classes (OBCs).[3,4] We ask what the mean height for age of children in each group would be if they had the same distribution of socioeconomic characteristics as higher caste Indian children. In contrast with our results for lower caste SC and OBC children, SES variables can explain height disparities for ST children, a geographically isolated and socioeconomically disadvantaged population group that is not comparably ranked by the caste system.

Although the average gap in height between higher caste and lower caste (SC and OBC) children in rural India cannot fully be explained by household-level SES variables, these variables can fully explain the caste height gap in those localities where SC and OBC children do not live with higher caste neighbors. This suggests a process of local discrimination that is the focus of the second set of results. We use regression analysis to document that SC and OBC children are shorter in contexts where a larger fraction of

[1]In this study, as in the relational approach described by Cummins et al. (2007), place has a different relationship with health for higher caste children than it does for lower caste children.

[2]The literature on health disparities by caste and tribe has largely focused on disparities in the use of health services (Acharya 2012; Baru et al. 2010; Borooah 2012). A larger literature explores gender disparities in health outcomes (Arnold et al. 1998; Barcellos et al. 2014; Das Gupta 1987;Murthi et al. 1995; Pande 2003). Some examples of research on health disparities by religion include Bhalotra et al. (2010), Brainerd and Menon (2015), Desai and Temsah (2014), Geruso and Spears (2018), and Guillot and Allendorf (2010).

[3]The government of India categorizes caste and tribal groups in this way for the purpose of affirmative action programs. We discuss these programs in the Background section.

[4]We classify households as they report themselves to the DHS surveyor. These categories are reported for both Hindus and non-Hindus. Table A1 in the online appendix tabulates SC, ST, OBC, and general caste status separately for Hindus, Muslims, and other religions.

the households in their primary sampling unit is from a higher caste. Together, SES and local caste rank can account for the entire height gap between lower caste and higher caste children.

This article proceeds as follows. The Background section explains why rural India is an informative context in which to study health inequalities. The Conceptual Framework section links caste, tribal status, and local processes of discrimination to child height in rural India. Next, we present our data and empirical strategies. Our results use reweighting decomposition and regression to understand the role of local caste rank. The Discussion section suggests possible mechanisms for our results, and the Conclusion considers implications for policies to reduce inequality.

Background: Caste, Tribe, and Inequality in India

Caste and tribal status are important dimensions of social stratification in India.[5] The contemporary manifestation of caste comprises 6,000 endogamous social groups called *jatis*.[6] These groups were traditionally occupation-specific and hereditary.[7] Caste is also relevant to a person's social networks and voting choices (Deshpande 2017). People from India's tribal communities, referred to as *adivasis* (indigenous people), are considered to have a social identity outside the caste system. Tribal communities speak many different languages and have many different cultural practices, including tribe-specific religions. According to the 2011 census, adivasis make up approximately 9 % of India's population. Ninety percent of adivasis live in rural areas, often in isolated villages that are not well served by public resources. People from adivasi backgrounds are among the most economically and educationally deprived in India (Maharatna 2000; Mitra 2008).

Recent research has investigated whether disparities in wages, employment, and consumption between lower castes and adivasis and higher castes have been narrowing in recent decades (Desai and Kulkarni 2008; Hnatkovska et al. 2012). The extent to which these gaps have narrowed since independence is subject of debate, with clear evidence suggesting that many people from disadvantaged social groups continue to face discrimination (Deshpande 2017; Deshpande and Ramachandran 2016; Thorat and Newman 2012).

India's affirmative action program has been designed to address disparities and discrimination along these axes of disadvantage.[8] The government "reserves" seats in schools, government jobs, and public office for people from STs, who belong to the adivasi groups described above, and from SCs, whose members were once (and in some circumstances, still are) treated as "untouchable." Reservations or quotas for these two

[5]The caste system is traditionally associated with India, but aspects of caste also operate in other South Asian countries, including Nepal, Pakistan, and Bangladesh (International Dalit Solidarity Network 2009; Jodhka and Shah 2010).
[6]Although the caste system has its origins in Hinduism, many non-Hindus—including Muslims and Christians whose ancestors converted to these religions—also have a jati identity.
[7]Many occupations in the modern economy do not have a caste counterpart; that is, these are not hereditary caste-specific occupations. Thus, in an obvious sense, the caste-occupation overlap has weakened. However, the overlap between caste and occupational status continues in that higher-ranked castes are disproportionately represented in more prestigious and better-paying occupations.
[8]One important affirmative action program that is not related to caste or tribe is the reservation of some seats in public office for women.

groups are constitutionally mandated, and the names of jatis and tribes are listed in a government schedule. A third group, OBCs, is also eligible for some affirmative action programs. OBCs are castes and communities that have been identified by the government as disadvantaged, even though they were not considered untouchable, and so are not stigmatized in the same way as people from SCs. When we refer to “lower castes,” we are referring to SCs and OBCs collectively. People who do not fit into any one of the three broad and internally diverse categories are not eligible for affirmative action programs. Hereafter, we use the terms “general caste” and “higher caste” interchangeably when referring to people who, by virtue of their caste identity, are ineligible for affirmative action programs. This is the term that the National Family Health Survey, our data source, uses in its survey documentation.

Conceptual Framework: Child Height and the Social Context

Processes of discrimination affect people in the ST, OBC, and SC categories differently. STs are the poorest of these four groups and, as we will show, tend to live in localities with other STs. In government circles and in the popular imagination, the regions where STs live are considered remote and difficult to serve. Although the government has many on-paper laws and policies to promote development in predominately ST regions, infrastructure and public services in these regions are sorely lacking in practice (Jones 1978; Mosse 2005). Literature on health and human development outcomes among STs has focused on how STs suffer from exclusion from government services as well as from displacement from productive land (Nathan and Xaxa 2012).

People from lower castes, on the other hand, face discrimination of a different nature. They are not stereotyped as remote: many SCs and OBCs live in heterogenous localities, alongside people from higher castes. Many lower caste households have historically been expected to work for higher caste households. Sociologists of India have described the ways in which these cross-caste economic and social relationships have changed over time but nevertheless remain an important part of village life (Jeffrey 2001; Kumar 2016; Srinivas 1955). Therefore, although lower caste people certainly face institutional discrimination, they are also exposed to day-to-day discrimination in their interactions with people from higher castes.

This is particularly true of people from SCs, who were once considered untouchable. Untouchability status is often justified with reference to hereditary occupation: people from castes that performed menial and ritually impure jobs, such as slaughtering animals for meat and leather, and manual scavenging (which involves physically carrying human excreta for disposal), are considered to be unclean. The fact that people from SCs do or have done “dirty” work has been used to justify excluding them from water sources, temples, social events, and at one time, even schools (see Valmiki 2003). Such labeling was also used to justify a number of discriminatory practices of daily interaction. For example, in some villages, people from untouchable castes were not allowed to sit in front of people from higher castes or were not allowed to wear shoes in village lanes. In most places, untouchables and non-untouchables were prohibited from eating together (Ambedkar 2014; Srinivas 1976). The specific ways in which untouchability is enforced vary from place to place; what these practices have in common is that they are intended to exploit, exclude, and humiliate. Despite evidence that the most severe practices of untouchability are less common in rural India than they were a few decades ago (Shah et al. 2006), this discrimination nevertheless persists. Thorat and Joshi (2015) analyzed the nationally representative 2012 India HDS and found that roughly one-third of households admit that at least one member practices untouchability.

How do these processes of discrimination shape child height? We hypothesize that the neglect and social exclusion of STs will be reflected in their SES and that this will explain the height disadvantage of ST children relative to general caste children. After all, considerable evidence suggests that variables capturing economic status and education predict child height, likely in part because they are correlated with the quality and quantity of food and other health inputs that young children need to grow (Case et al. 2002; Desai and Alva 1998). For lower castes, we hypothesize that exposure to higher caste people in their locality will also matter. Higher caste neighbors might enforce the social rank of lower caste households, especially SCs, in ways that could create stress and limit access to common resources, such as clean water, which would matter for child health but would not show up in household economic status. We would not expect neighbors of similar caste rank, however, to have the same detrimental effects on stress or access to common resources. Although our data will not permit us to definitively pin down the mechanisms linking local exposure to higher caste neighbors and child height, we discuss possible mechanisms and areas for future research in the Discussion section. Maternal stress (shown to matter for child health in other contexts; Lauderdale 2006; Torche 2011) and differential disease exposure (shown to be particularly relevant for height in the South Asian context; Hathi et al. 2017) may be promising areas for future research.

Data and Empirical Strategy

Data—Our sample includes children in rural households measured by the 2005 National Family Health Survey-3 (NFHS-3), India's DHS. The NFHS-3 is a nationally representative, two-stage random sample survey. Throughout the analyses, we use sampling weights provided by the NFHS.

Health Outcome—The NFHS-3 measures the height of children under 5 years old. Throughout the analyses, we scale child height according to the 2006 WHO international reference population (Onis 2006).[9] This transforms measured child height into height-for-age z scores, or differences between Indian children and children of the same age and sex in a healthy reference population. Extensive field verification has documented that the WHO norms are appropriate for Indian children. For example, children raised in affluent south Delhi grow, on average, to the international norms (Bhandari et al. 2002).

Population Group Data—We follow the division of Indian children into the four population groups as described above and recorded in the NFHS-3: SC, ST, OBC, and general castes. Data on population group are missing for 3.5 % of the rural children whose

[9]As the WHO recommends, we exclude children more than 6 standard deviations from the mean of the reference population.

heights were measured by the DHS.[10] Summary statistics in Table 1 are presented for each of the four population groups. In the weighted sample of children we study, 21.7 % are SC, 11.9 % are ST, 42.7 % of children are OBC, and the remaining 23.7 % are from a general caste background.

SES Variables Used in the Demographic Decomposition—We ask what the average height of ST, SC, and OBC children would be if the distribution of two core socioeconomic characteristics among each of these three groups of children matched the distribution of these characteristics among general caste children. The two characteristics we use in the reweighting decomposition are the type of floor of the child's household (four categories)[11] and the education level of the child's mother (six categories). Table A2 in the online appendix presents the results of OLS regressions showing that floor type is associated with height among children in rural India. Summary statistics for each floor type and mother's education level are given in Table 1.

As we discuss below, the number of socioeconomic variables used in a reweighting decomposition is necessarily small because reweighting is done nonparametrically, using the 24 intersecting bins of these two variables.

SES Variables Used in Regression Results—We conduct a further analysis of the process of discrimination using a regression analysis that permits us to control for a wider range of SES variables in addition to floor type and mother's education (used in the demographic decomposition). In the regression analysis, we additionally control for indicators for every combination of (1) mother's education; (2) household electricity; (3) ownership of phone, radio, TV, refrigerator, bicycle, motorcycle, car, land; (4) floor type; and (5) whether the household uses a toilet or latrine. These variables are summarized in Table 1. These summary statistics show that SC, OBC, and ST children grow up in poorer households, on average, than general caste children.

Measuring the Local Social Context—We construct a local social context variable that depends on both a child's caste group and the caste composition of child's locality. The NFHS data permit measurement of local context variables at the primary sampling unit (PSU) level.[12]

The sampling frame for rural PSUs in the NFHS-3 was villages in the 2001 census.[13] In large villages (greater than 500 households), PSUs were selected from clusters of 100–200 households within the village.[14]

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[10] Table A1 in the online appendix shows the fraction of children with measured heights for whom social group data are missing.Muslims are more likely than Hindus to have missing caste data: 17 % of ruralMuslim children do not have a caste designation in the NFHS-3.

[11] Table A2 in the online appendix presents the results of OLS regressions showing that floor type is associated with height among children in rural India.

[12] Hathi et al. (2017) also examined the effect of PSU-level variables on child health. They used the fraction of households that do not use a toilet or latrine in a PSU as a measure of disease externalities.

[13] According to the Office of the Registrar General and the Census Commissioner of India, for the purposes of the 2001 census, a village was defined as "the smallest area of habitation, viz., the village generally follows the limits of a revenue village that is recognized by the normal district administration" (Government of India 2001). This geographic unit is different from a gram panchayat, which is a village or cluster of villages represented by an elected local leader.

PSUs are a useful measure of place for studying local caste interactions because they capture the caste status of those households that live in closest proximity to the observed child. Yet, considering how important the measurement of place can be to our understanding of the extent, causes, and consequences of segregation (Lee et al. 2008; Reardon et al. 2008), future research using higher geographic levels of aggregation, such as the village or the block, may produce additional informative results.

The NFHS-3 randomly selected approximately 20 households in each PSU to interview.[15] We use the caste composition of the sampled households to construct a measure of her household's local caste rank. This variable is defined only for SC, OBC, and general caste children; ST children are omitted from this analysis because their households are not comparably ranked by the caste system. We operationalize local caste rank by constructing a *fraction higher ranking* variable, which is defined as follows:

- For all general caste children, this variable is 0.
- For OBC children, this variable is the fraction of non-ST households in their PSU that are general caste.
- For SC children, this variable is the fraction of non-ST households in their PSU that are general caste or OBC.

This variable reflects an interaction between household and village properties: two children living in the same village will have different values if they belong to different caste groups. Similarly, two SC children in different villages may have different values ranging from close to 0 (if their village is almost all SC) to close to 1 (if their village is almost all OBC or general caste). We do not summarize the *fraction higher ranking* variable in Table 1 but instead show the cumulative density of this variable for OBCs and SCs in Fig. 2 later in the article.

Variables Used in Placebo Test and Robustness Checks—In order to verify that our main result—that SES and local caste rank explain height gaps between general and lower-caste children—is not driven by other variables that influence height, we present a placebo test and several robustness checks. For the placebo test, instead of using the *fraction higher ranking* variable described above, we use the fraction of households in child's PSU that have a higher NFHS asset index (wealth index) score than that child's household.[16]

For the robustness checks, we add variables about local infrastructure and the caste composition of the child's village. Local infrastructure variables are the fraction of households in the child's PSU that have electricity and the fraction of last births to a given mother in a child's PSU that received prenatal care. Caste composition variables are

[14]To further elaborate on the NFHS-3 study design, the survey manual explains that PSUs and households are selected as follows: "A uniform sample design was adopted in all states. In each state, the rural sample was selected in two stages, with the selection of Primary Sampling Units (PSUs), which are villages, with probability proportional to population size (PPS) at the first stage, followed by the random selection of households within each PSU in the second stage" (IIPS and Macro International 2007:12–23).

[15]Because not all households in a PSU are surveyed, any constructed PSU mean (such as these fractions) is an unbiased estimate with sampling error of the true PSU mean. This sampling error will tend to attenuate estimated effects of PSU means, with the consequence being that the importance of local caste composition for child health outcomes could be even greater than we document.

[16]For more on the construction of the NFHS wealth index, see IIPS and Macro International (2007).

the fraction of households in the child's PSU belonging to SCs, the fraction belonging to OBCs, and the fraction belonging to general castes. We also add controls for demographic variables: number of household members, birth order of the child, sex of the child, and whether the child lives with her paternal grandparents in a joint family.[17] Means of these variables by caste group can be found in Table 1.

Empirical Strategy—We first ask what would the average height of rural ST, SC, and OBC children be if the distribution of socioeconomic characteristics among these groups of children matched the distribution of socioeconomic characteristics among rural general caste children? We find that SES variables largely explain the height gap for STs, but not for SCs and OBCs. For these groups, the remaining height gap is explained by local processes related to social inequality.

We use two complementary empirical strategies to arrive at these results. First, we use a reweighting decomposition to quantify the fraction of height disparities that can be explained by SES. Second, we use regression to show that the remaining gap can be explained by the fraction of a child's locality that outranks her family in the caste hierarchy.

Reweighting Decomposition Method—We apply a reweighting decomposition similar to that proposed by DiNardo et al. (1996) and implemented by Geruso (2012) and Coffey (2015) in prior research on health disparities. The reweighting function, Ψ, that we use to produce the means and confidence intervals presented in the section Reweighting Decomposition Results is defined as

$$\Psi(\mathbf{x}) = \frac{f(\mathbf{x} \mid g = 1)}{f(\mathbf{x} \mid g = 0)}, \tag{1}$$

where x is a single set of indicators for the intersections of the four categories of floor type in the child's household and the six categories for the educational attainment of her mother.

In this case, reweighting is done over 24 floor type/education category bins. The function $f(\mathbf{x}|g)$ is the empirical probability mass function for bin x among the general caste population ($g = 1$) or a disadvantaged population ($g = 0$). In other words, $f(\mathbf{x}|g)$ is the fraction of the population group g sample in SES bin x, computed using survey sampling weights. The reweighting function $\Psi(\mathbf{x})$ is multiplied by the sampling weight of each observation in the disadvantaged population so that sample means can be computed for a counterfactual disadvantaged population that matches the distribution of SES of the general caste population. Thus, the counterfactual reweighted mean height is computed as

$$\bar{h}^{RW} = \frac{\sum_i \Psi(x_i) w_i h_i}{\sum_i \Psi(x_i) w_i} \tag{2}$$

[17]See Allendorf (2013) for an investigation of the association between living in a nuclear or joint family on Indian women's health.

where h_i is the height of child i; x_i is the SES bin of child i; and w_i is the survey sampling weight of child i.

Unlike a regression approach that matches only the mean, this reweighting strategy has the advantage of matching the full distribution of these SES variables among general caste children. Further, it flexibly allows any nonparametric interaction between the education and floor type variables, and does not require any ad hoc combination of variables into a single SES index.[18] Instead, for example, the few lower-caste children who have highly educated mothers and good housing (as measured by floor material) would receive a large weight in the reweighted calculation of mean SC height because these are the children with a large Ψ, meaning that their SES matches a larger fraction of general caste children than lower caste children. Therefore, if these children are much taller than the average SC child, the reweighed average SC height will increase. The extent to which it increases is the measure of the amount of height difference that is due to SES.

However, the nonparametric nature of the approach inherently limits the number of SES variables that can be used. If the sample is partitioned into many bins, computing reweighted mean heights for disadvantaged groups would not be possible without dropping some general caste children from the sample because the denominator in Eq. (1) would be 0 if there are general caste children who have no counterparts among the sample for the relevant disadvantaged group. When we reweight over only floor type and mother's education, no general caste children need to be dropped in order to compute reweighted mean height. This dimensionality limit is one motivation for our further regression strategy.

Modified Reweighting Decomposition Using Local Caste Rank—The reweighting method reports what the mean heights of rural ST, SC, and OBC children would be if these children were exposed to the same distribution of SES variables as rural general caste children. The remaining gap can be interpreted as the average consequence for height of discrimination. However, perhaps not all disadvantaged children are exposed to the *average* level of discrimination. If effects of discrimination on height in part reflect the role of *local* processes, we might expect post-SES differences to differ across localities.

We use the previously described *fraction higher ranking* variable to measure a child's exposure to people of a higher caste rank in her locality. However, we cannot use the *fraction higher ranking* variable in the reweighting decomposition because *all* general caste children have a fraction higher ranking of 0, whereas only a very few SC and OBC children live in sufficiently segregated localities to have such a very low fraction higher ranking.

Therefore, to investigate the role of local discriminatory processes, we compute many replications of the entire reweighting decomposition, each time progressively restricting the SC and OBC samples to those with smaller and smaller values of the fraction higher ranking. That is, we restrict the SC and OBC samples to children with a fraction higher ranking of less than 0.9, and compute reweighted heights. Then, we restrict the SC and OBC samples to children with a fraction higher ranking of less than 0.88, and so on

[18]See Filmer and Pritchett (2001) for more on creating an index with asset variables in DHS data.

(proceeding in steps of 0.02), until eventually only those SC and OBC children with the smallest values for the fraction higher ranking—that is, children who live in PSUs in which they are surrounded by almost entirely SC, or SC and OBC neighbors, respectively—are included in the reweighting decomposition. This produces a *sequence* of counterfactual SC and OBC average heights, each reweighted to match the general caste distribution of SES but concentrating on SC and OBC children exposed to different levels of local social rank.

Regression Method Using Local Caste Rank—To verify our results using another method, we run ordinary least squares (OLS) regressions in which we control for bins of intersecting SES indicators. In contrast with the reweighting decomposition, the regression method allows us to control for a larger set of SES indicators as well as to control for other variables that might influence child height.

We run regressions of the following form, where each observation is a child under 5 years old:

$$height_{ip} = \beta_0 + \underbrace{\beta_1 SC_{ip} + \beta_2 OBC_{ip} + \beta_3 ST_{ip}}_{\text{group indicators}} + \alpha_{ip} + \mathbf{X}_{ip}\theta + \epsilon_{ip}, \quad (3)$$

where *height* is a child's height-for-age z score, i indexes children and p indexes survey PSUs. The variables SC, OBC, and ST are each indicator variables for group membership, with general caste children as the omitted category. α_{ip} are dummy variable indicators of SES that vary across specifications to explore the roles of different types of explanatory factors. The coefficient estimates $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ can be interpreted as the remaining unexplained discrimination after controlling for these explanatory factors. $\mathbf{X}_{ip}$ is a vector of village caste composition and demographic controls (described earlier) that will be added as a robustness check. We cluster standard errors by survey PSU.

We estimate several regressions of this form. First, we compute average differences in child height by running a regression with no explanatory factors. Then, to estimate differences in child height at the same level of SES, we control for a set of dummy variables about the household's SES. Unlike the decomposition approach, which matches on the entire distribution of included variables, the regression approach matches only on means, so it allows us to control for larger number of SES variables. We use indicators that control for every combination of (1) mother's education category; (2) floor type; (3) use of a toilet or latrine; (4) household electricity; and (5) ownership of a phone, radio, TV, refrigerator, bicycle, motorcycle, car, and land. Any height gap that remains after we control for these indicators reflects a difference that persists even after very detailed SES information has been accounted for.

The further regression analysis investigates the role of local discriminatory processes for SCs and OBCs, using bins constructed from the *fraction higher ranking* variable. From this point forward, ST children are omitted from the regression because their height gap has already been fully statistically explained by the SES variables. We continue our regression analysis by replacing the SES indicators with a new set of indicators that combine SES and local caste rank: each is an indicator for a bin at the intersection of the prior SES bins and the deciles of the *fraction higher ranking* variable. Thus, with these new control variables, we account for the consequences of both SES and local caste rank.

We also perform a placebo test and robustness checks using other variables that may influence child height. For the placebo test, we interact a child's SES bins with deciles of the *local wealth rank* variable described earlier. Controlling for local wealth rank does not account for gaps in child height in the same way that controlling for the fraction higher ranking does. For the robustness checks, we add the neighborhood composition and demographic controls described earlier.

Results

Descriptive Statistics

The Apparent Similarity of the SC and ST Height Deficits—Studies of social disadvantage in India commonly refer simultaneously to SCs and STs as a collective set of the most disadvantaged people in India.[19] Although one conclusion of our study is that the disadvantaged health outcomes of SCs and STs reflect different *processes*, Table 2 documents that their quantitative *levels* of height disadvantage are strikingly similar. This can also be seen in Fig. A1 (online appendix), which plots the empirical cumulative distribution of height-for-age among children in each population group.

Column 1 of Table 2 shows that rural SC and ST children are shorter than rural general caste children by about four-tenths of a height-for-age standard deviation. Columns 2–4 add an "SC or ST" indicator variable, as is commonly found in the literature. So similar are the magnitudes of the ST and SC height gaps that neither a separate SC indicator nor a separate ST indicator appears to add explanatory power to the models in columns 3 and 4; neither the coefficient on SC in column 3 nor the coefficient on ST in column 4 is statistically significant, and R^2 is unchanged. A researcher who does not investigate the processes of discrimination may conclude from statistical tests like those in Table 2 that there is no reason to separate these categories. However, we will see that the unconditional correlations between membership in these categories and child height reflect different processes.

The Distribution of Local Caste Contexts—Figure 1 shows the cumulative distribution of the fraction of households in a child's PSU that are the *same* caste as hers by population groups. It is evident from Fig. 1 that ST households are more likely than members of other population groups to live in separate localities rather than in localities with households belonging to other groups. This is because a child whose value of the plotted variable is 1 lives in a locality where all households are of the same population group as she is. Many ST children are found massed at 1; that is, they live in ST-only localities. Further, the ST distribution stochastically dominates the other distributions. SC children, in contrast, are generally found in localities where the majority of households are not SC.

[19]For example, several states, including Delhi and Bihar, have a department of "SC and ST welfare." Employing a standard practice in the literature, both Burgess et al. (2005) and Azam and Bhatt (2015) (selected as examples of high-quality research) used a single combined categorical variable for "SC or ST." Of course, whether such a combined indicator is inappropriate for studying height would not necessarily imply it is inappropriate for studying other outcomes.

Figure 2 plots the distribution of *fraction higher ranking*, our key explanatory variable, for OBC and SC children. It is clear that wide variation in this variable exists across rural India and that different population groups experience different patterns of local caste composition.

Reweighting Decomposition Results

The Fraction Explained by SES—Figure 3 presents the first of our reweighting decomposition results. It plots the fractions of height gaps between general and ST, SC, and OBC children that can be explained by SES variables.[20] The reweighting function recomputes the height gap for a counterfactual sample of disadvantaged children, reweighted to match the SES distribution of general caste children. Here, the apparently similar SC and ST gaps diverge. The ST–general caste gap can be completely accounted for by SES: the reweighted gap is small, and the confidence interval of the reweighted gap includes 0. This result is likely because ST households are particularly poor and are likely to live in isolated rural villages that are underserved by public resources, such as schools. Indeed, ST children who live in villages that are the most segregated (that is, where the fraction of ST households in the village is larger) are shorter, on average (result not shown). This difference, too, is accounted for by differences in SES.

In contrast, for SC and OBC children, the unexplained gap remains large and statistically significantly different from 0 when the same SES variables are used in the reweighting decomposition. The point estimate of the SC gap unexplained by SES is approximately twice the point estimate of the remaining ST gap unexplained by SES. This suggests that SC children are short not merely because they are poor but perhaps also because of a form of discrimination that is not measured by their SES. The remainder of this article further investigates the remaining SC and OBC height gaps.

The Role of Local Caste Rank—We now turn to an investigation of the role of local caste rank. This will principally be pursued through the parametric regression analysis described in the section Explaining the Process of Discrimination With Regression. However, we first present results from a modified reweighting decomposition that tells a story similar to what we find in the regression analysis. ST children are excluded from these analyses because their height gap has been fully accounted for by SES.

Figure 4 presents the results of a series of reweighting decompositions. The horizontal axis of the figure represents progressive restriction of the samples of SC and OBC children. At the far left of the figure, all SC and OBC children are included in the reweighting decomposition. Therefore, the point estimates match those in Fig. 3. As the lines move along the horizontal axis to the right, the SC and OBC samples are restricted to include only those children exposed to that fraction higher ranking level or lower. At the far right end of the figure, the only SC and OBC children included in the SES reweighting are those with few or no households of higher caste rank in their localities.

[20]If we use father's education instead of mother's education in the reweighting decomposition, the results are qualitatively similar. Figure A2 in the online appendix shows the same comparisons as the ones shown in Fig. 3 using father's education instead of mother's education.

Two aspects of Fig. 4 point to an important role for local discrimination. First, for both SC and OBC children, the curves slope downward, indicating that the post-SES gap between lower caste and higher caste children is increasing in the fraction of the neighborhood that locally outranks a lower caste child. Second, the point estimates at the far right end of the graph are at or close to 0.[21] This suggests that lower caste children who are not outranked are no shorter, on average, than similarly low-SES general caste children living in other localities.

Explaining the Process of Discrimination With Regression

Kernel-Weighted Local Regression—Figure 4 suggests that SC and OBC children do not experience height disadvantages that cannot be explained by their SES in neighborhoods where they are not locally outranked. Figure 5 moves toward testing this hypothesis directly. The vertical axis of Fig. 5 plots the residuals of height-for-age after they are regressed on a detailed set of SES controls, as described in the Data section. The horizontal axis is the explanatory variable *fraction higher ranking*. Because SES has already been residualized out of the vertical axis, any apparent association is an association with local social rank net of SES. This semiparametric technique makes no assumption about the functional form of the relationship between the two variables. For both SC and OBC children, the lines slope down: children whose households are outranked by a larger fraction of households in their locality are shorter, on average, net of SES.[22]

Results of OLS Regression Analysis—Testing the robustness and statistical significance of these conclusions requires parametric regression analysis, introduced in Eq. (3). Estimates are presented in Table 3.[23] The first two columns test the robustness of the conclusions of the decomposition analysis by applying OLS regression with controls. Column 1 presents the apparently similar SC and ST gaps. Column 2 shows that controlling for SES, as described in the Data and Empirical Strategy section, eliminates the ST gap but not the SC or the OBC gap, and leaves the point estimate for the post-SES SC gap twice as large as the point estimate for the post-SES ST gap.

The remaining columns of Table 3 investigate the role of local discriminatory processes. Column 3 verifies that the coefficients in column 2 on SC and OBC are unchanged after we drop ST children from the regression. Column 4 adds controls for *fraction higher ranking* by replacing the SES indicators with a new set of indicators for the intersection of each of the SES bins and decile categories of *fraction higher ranking*. Column 4 shows that adding local caste rank completely accounts for the remaining height gap.

The remaining columns of Table 3 present robustness and placebo tests. Column 5 is a placebo test that repeats the regression from column 4 except that it interacts deciles for a

[21]The SC line ends before the OBC line because very few SC children live in localities with no higherranking households; beyond this point, there are too few SC children to reweight on a set of SES bins.

[22]This figure, drawn only for the disadvantaged SC and OBC groups, includes mainly negative averages of height for age residuals because the residualizing regression includes general caste children, who all have a *fraction higher ranking* of 0.

[23]Motivated by the concern that the caste rank and composition of OBC categorization varies throughout India but that SCs are always of the lowest-ranking castes, Table A3 (online appendix) verifies that our regression results are robust—quantitatively and in their qualitative pattern—to excluding OBC children and focusing only on the SC–general caste height gap.

child's household's *wealth* rank in the neighborhood, rather than deciles of *fraction higher ranking*, with her SES bin. This placebo test verifies that it is local *caste* rank that explains the height gap, rather than *economic* rank or local rank more generally. The coefficients in column 5 are very similar to those in column 3, which verifies that our finding is specific to local caste rank.

As a robustness check, columns 6 and 7 replicate columns 3 and 4 but include two additional sets of regression controls: (1) neighborhood composition controls and (2) demographic controls, as described in the Data section. Each of these—including quantitative counts, such as household size and birth order—is implemented as a semiparametric set of indicators. The purpose of the neighborhood composition controls, which control for the fraction of the neighborhood's households belonging to each population group, is to demonstrate that there is not a spurious correlation between *fraction higher ranking* and neighborhood caste composition.[24] The results shown in columns 3 and 4 are qualitatively confirmed in columns 6 and 7: large SC and OBC gaps persist even after the SES indicators and additional controls (column 6) are added, but this gap is fully accounted for by adding controls for *fraction higher ranking* (column 7).

The results of two additional robustness checks—one related to child sex and one related to the local disease environment—are presented in the online appendix. Because child health in India often differs by sex, Table A4 (online appendix) presents our regression results separately for boys and girls. We find patterns similar to those of the main results presented in Table 3. Table A5 (online appendix) shows the results of Table 3 with an additional control for the fraction of households in a child's primary sampling unit that defecate in the open, rather than use a toilet or latrine. This control is important because prior literature has shown that this measure of the local sanitation and the disease environment is strongly predictive of child height in South Asia (Hathi et al. 2017; Spears 2013). Although the fraction of households that defecate in the open statistically significantly predicts child height in this sample as well (children living in PSUs where all households defecate in the open are one-quarter of a standard deviation shorter, on average, than children living in PSUs where no household defecates in the open), the addition of this control does not change the main results from Table 3. Finally, Table A6 of the online appendix shows the results of Table A5 with additional controls for the number of siblings a child has, her household's religion, and additional asset controls.

The results of different statistical methods tell a consistent story: although SES can account for the ST–general caste height gap, it cannot account for the height deficits that SC and OBC children suffer. SC and OBC children appear to face a process of *local* discrimination based on the caste rank of the households in their locality.

[24]Such a concern regarding omitted variable bias would be misguided because the fraction higher ranking is an *interaction* between neighborhood composition and the population group membership of the child: increasing the fraction of a village that is OBC at the expense of SCs and general castes, for example, would increase the fraction higher ranking for SC children and decrease it for OBC children.

Discussion

In India, hundreds of millions of people have been born into disadvantaged ST, OBC, and SC households. This disadvantage is evidenced not only in their economic and social lives but also in the heights of their children. We find that the SC–general caste and ST–general caste height gaps are quantitatively similar but in fact reflect different processes of SES deficits and local experiences of discrimination. These results suggest that at least for some outcomes, empirical studies should not use “SC or ST” as a single indicator of disadvantage.[25]

The finding that the ST–general caste height gap can be explained by differences in SES coheres with prior literature that finds that household socioeconomic status is strongly correlated with child height (Currie 2009). It also highlights another consequence of the neglect of ST regions discussed in the Conceptual Framework section.

Although encouraging government investment in ST regions and ensuring that such investments reach the poor may not be straightforward (Mosse 2005), this finding suggests that investments that improve the economic and educational status of parents could be effective at reducing the height gap.

The finding that for lower caste children, it is an *advantage* to live in SC-dominated localities presents an informative contrast to research from other countries that finds that segregation is associated with worse health outcomes among disadvantaged groups (Kawachi and Berkman 2003; LaVeist et al. 2011; Leung and Takeuchi 2011; Massey 1990; Williams and Collins 1995, 2001). Although it is beyond the scope of this article to present a comparative analysis of the effects of segregation, the literature on racial segregation in the United States emphasizes how segregation concentrates poverty and creates what Massey (2004:17) called a “uniquely disadvantaged social environment characterized by high rates of joblessness, welfare, dependency, substance abuse, and single parenthood.”[26]

In the Conceptual Framework section, we proposed that in the Indian context, the kind of day-to-day discrimination that arises from interaction between lower and higher castes may be useful in understanding our results. Here, we will discuss what additional data would be useful to further explore this hypothesis. We also discuss the possible mechanisms that we propose can be ruled out.

Ethnographic accounts provide evidence that lower caste people who live near households from higher castes experience high levels of stress and violence (Srinivas 1976; Valmiki 2003). This is in part because where SCs and higher castes live close together, SC households have historically worked for higher caste households as part of an exploitative economic system supported by discriminatory rules limiting their use of common resources, including water (Ambedkar 2014; Shah et al. 2006). Future research might document stress

[25]We do not mean to suggest that there are not important differences *within* SC and ST populations. Indeed, documenting health disparities by subcaste within SCs, or by tribe within STs, would be useful in further elucidating both the extent of and processes behind health inequality in India.

[26]Literature on ethnic and immigrant enclaves, a different form of residential segregation, has found mixed associations between living in segregated neighborhoods and health outcomes (Osypuk et al. 2010; Xie and Gough 2011).

levels among lower-caste people living in different kinds of localities. In order to better understand the effects of local context on child height in particular, this research should focus on measuring stress among pregnant women.

Although one of the robustness checks presented in the Results section found that controlling for village-level mean open defecation in a child's primary sampling unit did not change our main results, future research may identify a mechanism for these results related to differential exposure to enteric infection. The negative effects of a PSU's open defecation may not be equally distributed: survey data on rural sanitation from five states in north India (see Coffey et al. 2014) show that SC respondents are more likely than non-SC respondents to report seeing people defecating near their houses.[27] Table A7 (online appendix) summarizes this result. If open defecation is more likely to occur near SC homes in mixed localities than in homogenous ones, the same level of open defecation may harm SC children by more than it harms other children. However, this evidence can take us only so far: ideally, we would have data on whether SC and OBC children in mixed localities experience more enteric infection than SC and OBC children at the same level of SES in homogeneous localities.

Although it is possible, we find it unlikely that selection of unhealthy lower caste children into mixed localities could explain our results because migration in this context is very low. Although migration for marriage is common for women (Rosenzweig and Stark 1989), and men in many parts of India engage in temporary labor migration (Deshingkar and Farrington 2009), rates of permanent internal migration are considerably lower than in other developing countries (Deshingkar and Anderson 2004). Anderson (2011:242) reviewed the literature on the caste composition of villages in Uttar Pradesh and Bihar, two of India's largest states, and concluded that in most cases, "the origins of the distribution of caste groups at the village level go back hundreds of years."[28]

Another possible—but, we think, unlikely—explanation for our results relates to the measurement of the local caste context. For most of the children we study, the child's PSU and her village are one and the same. As we discuss in the Data and Empirical Strategy section, however, for children in villages of more than 500 households, PSUs are geographically proximate groups of 100–200 households. In principle, it is possible that PSUs that appear in the data as having a high fraction of SC (or OBC) households are in fact lower caste hamlets of large villages in some cases. If so, it might further be the case that PSU caste composition would be correlated with village size, which could be an omitted variable if children in larger villages tend to be taller (or shorter).[29] Unfortunately, the NFHS does not let us test directly for this possibility because it does not report village

[27]Om Prakash Valmiki opens his autobiography, *Joothan: A Dalit's Life*, by describing how, when he was growing up, his neighbors would defecate on the shores of a pond next to his and other SC people's houses (Valmiki 2003:1).

[28]Anderson (2011) found that agricultural yields of lower caste households are higher in villages with only SCs, or with SCs and OBCs, than in villages where general castes live as well. This difference can be explained by the fact that lower caste households in homogenous villages are better able to negotiate irrigation for their crops than those living in villages with general caste households. Although this study suggests that the economic variables measured by the DHS may not be able to paint a full picture of differences in households' economic situations across village types—the DHS does not measure, for example, agricultural yields—research documenting tenuous links between agriculture and child anthropometry (Gillespie et al. 2012) suggests that if we had data on agricultural production, Anderson's (2011) finding about caste-heterogenous villages would be unlikely to explain our results.

[29]Singh et al. (2008) considered the relationship between village size and village-level indicators of development.

size. However, other findings, which we present in the online appendix, suggest that this way of measuring the local context is unlikely to be responsible for our results. First, Fig. A3 (online appendix) uses IHDS data (Desai et al. 2005) to show that SC children in villages with more than 500 households are not taller than SC children in villages with less than 500 households. Table A8 (online appendix) verifies that this result is robust to state fixed effects and other controls. Second, Fig. A4 (online appendix) plots both the cumulative distribution of the fraction of *sampled* households in an NFHS PSU that are SC and then—using census data—the cumulative distribution of the village-level fraction of *all* households in a village that are SC. The two cumulative distribution functions are very similar, suggesting that results based on measuring caste composition at the village level rather than at the PSU level would be similar. Nevertheless, we hope that these findings will generate further study —using different measures and aggregations of local context—to understand exactly how social inequality contributes to child health outcomes in rural India.

Conclusion

Our results are informative for enduring debates in India about how social policy can best respond to discrimination against lower castes and adivasis.[30] Much of the debate about addressing social inequality has been focused on national- or state-level policies of affirmative action, such as admission at government universities or allocation of government jobs. Research has highlighted the success of these policies, including improving the representation of marginalized communities without reducing the efficiency of public services (Deshpande and Weisskopf 2014) and improving class composition of higher education as well as the diversity of social backgrounds (Bertrand et al. 2010). However, these affirmative action policies may be insufficient to respond to local discrimination that appears to have effects early in life. We recommend that future research seek to understand exactly how social inequality gets under the skin in order to inform policies that target local processes and weaken the link between social group and health.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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[30]Local processes of caste discrimination may limit the effectiveness of existing programs intended to promote health and nutrition, such as India's public distribution of food or its rural sanitation programs (Lamba and Spears 2013; Thorat and Lee 2005).

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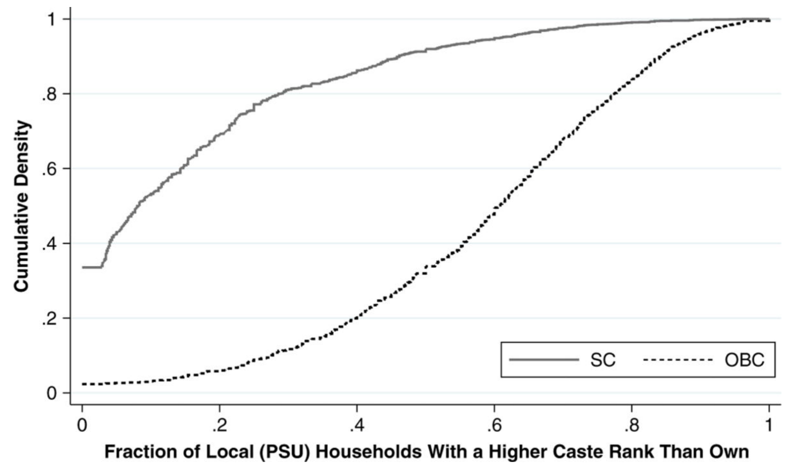

Fig. 1.
Cumulative distribution of the fraction of households in a child's PSU that have a higher caste rank than her own household's. Observations are rural children whose heights were measured by the NFHS-3.

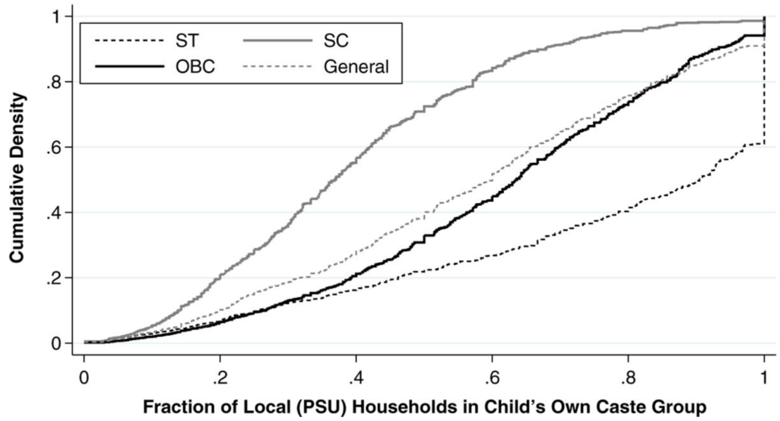

Fig. 2.
Cumulative distribution of the fraction of households in a child's PSU from her own caste group. Observations are rural children whose heights were measured by the NFHS-3.

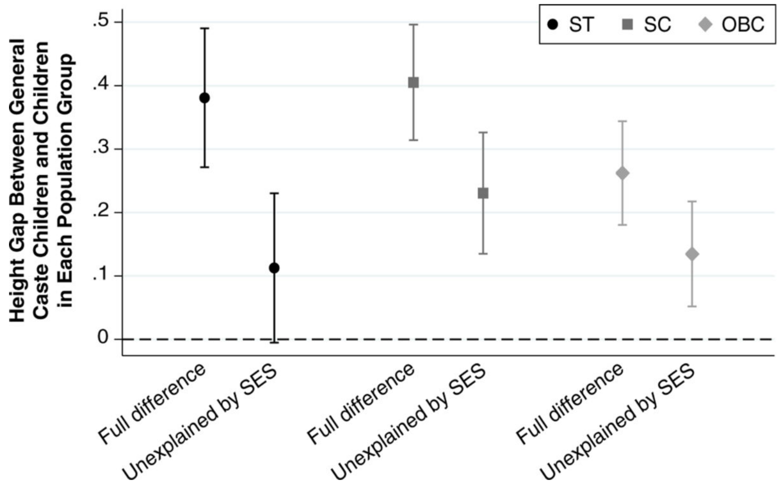

Fig. 3.

Decomposition results: Fraction of the height gap between general caste children and ST, SC, and OBC children unexplained by socioeconomic variables. Estimates represent reweighting decomposition results that describe height gaps between rural general caste children and rural children in other population groups. Confidence intervals represent 95 % confidence, computed using clustered standard error to reflect the survey design of the DHS. The socioeconomic variables used in the decomposition are floor type (four categories) and education level of her mother (six categories), for a combined set of 24 bins. These variables and the reweighting decomposition method are described in the Data and Empirical Strategy section.

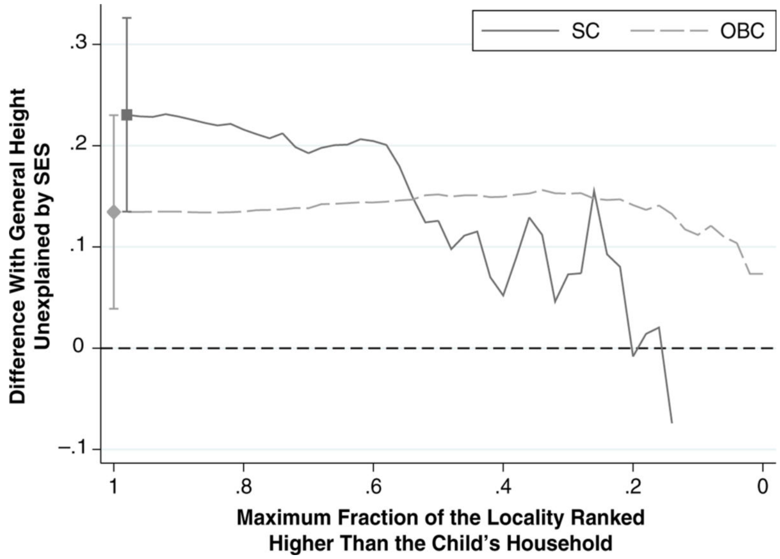

Fig. 4.
Decomposition results. SES explains more of the SC and OBC height gaps for children who are less locally outranked. The figure uses NFHS-3 data on rural India to estimate height gaps between general caste and OBC children, and general caste and SC children, computed using many replications of the reweighting decomposition described in the Data and Empirical Strategy section. The horizontal axis indicates which OBC or SC children are used in the reweighting decomposition. For example, at 0.4, an OBC or SC child is included if she lives in a locality in which 40 % or fewer of households in the PSU outrank her household by caste. The figure proceeds horizontally in intervals of 0.02 and connects points with no smoothing. See the Empirical Strategy section and the Reweighting Decomposition Results section for further details.

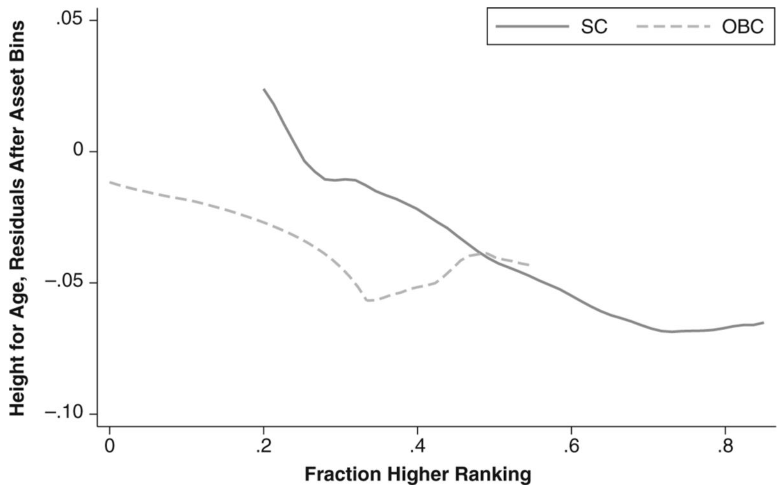

Fig. 5.

Child height, net of SES, and the fraction of households in a child's locality that outranks hers. Local kernel-weighted regression. Epanechnikov kernel, bandwidth = 0.15. The large set of regression SES controls is used. Observations are children included in column 4 of Table 3 for whom the fraction of households that outrank their own is between the 10th and 90th percentiles of this variable for their own caste group.

Table 1

Summary statistics

	ST	SC	OBC	General
Height for Age z Score				
25th percentile	−3.24	−3.22	−3.06	−2.76
50th percentile	−2.20	−2.21	−2.05	−1.77
75th percentile	−1.12	−1.18	−1.00	−0.74
SES Variables Used in Reweighting Decomposition				
Dirt floor	0.80	0.72	0.61	0.55
Rudimentary floor (e.g., brick, stone)	0.05	0.03	0.05	0.05
Finished floor	0.11	0.18	0.25	0.32
Other floor type[a]	0.05	0.07	0.09	0.09
Mother has no education	0.70	0.64	0.58	0.33
Mother did not complete primary education	0.08	0.07	0.07	0.08
Mother completed primary education	0.04	0.07	0.08	0.07
Mother did not complete secondary education	0.15	0.19	0.23	0.36
Mother completed secondary education	0.01	0.01	0.02	0.05
Mother has higher education	0.01	0.01	0.02	0.04
Additional SES Variables Used in Regression				
Electricity	0.41	0.45	0.50	0.58
Owns phone	0.01	0.04	0.07	0.12
Owns radio	0.18	0.22	0.28	0.36
Owns television	0.14	0.25	0.30	0.39
Owns refrigerator	0.02	0.03	0.05	0.13
Owns bicycle	0.44	0.54	0.60	0.57
Owns motorcycle	0.06	0.06	0.13	0.19
Owns car	0.01	0.00	0.01	0.02
Uses toilet or latrine	0.10	0.14	0.16	0.40
Owns land	0.67	0.44	0.66	0.63
Local Infrastructure Controls				
Fraction of households in PSU with electricity	0.44	0.49	0.48	0.51
Fraction of births in PSU with prenatal care	0.71	0.72	0.69	0.76
Local Caste Composition Controls				
Fraction of PSU that is SC	-	0.39	0.18	0.18
Fraction of PSU that is OBC	-	0.35	0.63	0.25
Fraction of PSU that is general caste	-	0.21	0.14	0.53
Demographic Controls				
Number of household members	6.53	6.78	7.53	7.01
Birth order	3.17	3.01	2.90	2.64
Female	0.50	0.49	0.47	0.47
Lives with paternal grandparents	0.19	0.23	0.32	0.32
N	4,730	5,134	8,613	6,354

Notes: Statistics presented are means unless otherwise indicated. Observations are rural children whose heights were measured by the NFHS-3. Because averages are representative of children, they may differ from published India-wide summary statistics. ST = Scheduled Tribes. SC = Scheduled Castes. OBC = Other Backward Classes.

[a]A floor type of “other” is also listed for children whose mothers were not interviewed in their permanent home. Most likely, these women were interviewed in their parents’ home.

Table 2

The apparent similarity of the SC and ST height deficits

	Height-for-Age z Score			
	(1)	**(2)**	**(3)**	**(4)**
SC or ST		−0.397***	−0.381***	−0.405***
		(0.0424)	(0.0559)	(0.0465)
SC	−0.405***		−0.0244	
	(0.0465)		(0.0557)	
ST	−0.381***			0.0244
	(0.0559)			(0.0557)
OBC	−0.262***	−0.262***	−0.262***	−0.262***
	(0.0417)	(0.0417)	(0.0417)	(0.0417)
N	24,840	24,840	24,840	24,840
R^2	.008	.008	.008	.008

Notes: Coefficients are from OLS regressions, weighted using sample weights. Observations are rural children whose heights were measured by the NFHS-3. Standard errors, clustered by PSU, are shown in parentheses. ST = Scheduled Tribes. SC = Scheduled Castes. OBC = Other Backward Classes.

*** $p < .001$ (two-sided tests)

Table 3

Explaining height gaps between general caste children and children from ST, SC, and OBC groups

	Dependent Variable Is Height-for-Age z Score (ref. = general caste children)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ST	−0.381***	−0.0705					
	(0.0559)	(0.0653)					
SC	−0.405***	−0.153**	−0.154**	0.0383	−0.132*	−0.200**	0.0080
	(0.0465)	(0.0545)	(0.0551)	(0.118)	(0.0646)	(0.0622)	(0.159)
OBC	−0.262***	−0.123*	−0.134**	−0.0200	−0.142*	−0.143*	0.0045
	(0.0417)	(0.0485)	(0.0494)	(0.0774)	(0.0598)	(0.0590)	(0.104)
N	24,840	23,111	18,141	18,141	18,141	18,147	18,140
R^2	.008	.201	.222	.364	.344	.229	.369
Own SES Bins		✓	✓			✓	
Own SES × Caste Rank Bins				✓			✓
Own SES × SES Rank Bins					✓		
Demographic and Neighborhood						✓	✓
Composition Controls						✓	✓
STs in the Sample	Yes	Yes	No	No	No	No	No

Notes: Coefficients are from OLS regressions, weighted using NFHS sample weights. Observations are rural children whose heights were measured by the NFHS-3. Standard errors, clustered by PSU, are shown in parentheses. ST = Scheduled Tribes. SC = Scheduled Castes. OBC = Other Backward Classes. The construction of controls for Own SES bins, Own SES × Caste rank bins, and Own SES × SES rank bins are discussed in the Data and Empirical Strategy section. Demographic controls include child birth order, child sex, and whether the child lives in a joint family with his/her grandparents. Neighborhood controls include the fraction of households in a child's PSU with electricity, the fraction of births (last births to the mother) in the child's PSU that got prenatal care, the fraction of SC households, the fraction of OBC households, and the fraction of general caste households in a child's PSU.

* $p < .05$

** $p < .01$

*** $p < .001$ (two-sided tests)