Endogenous inclusion in the Demographic and Health Survey anthropometric sample: Implications for studying height within households

Dean Spears a,⁄, Diane Coffey a, Jere R. Behrman b

a University of Texas at Austin and the Research Institute for Compassionate Economics (r.i.c.e), United States of America
b University of Pennsylvania, United States of America

ARTICLE INFO

Keywords:
Demographic and Health Surveys
Birth order
Fertility
Height
India
Selection into identification

ABSTRACT

Development economists study both anthropometry and intra-household allocation. In these literatures, the Demographic and Household Surveys (DHS) are essential. The DHS censors its anthropometric sample by age: only children under five are measured. We document several econometric consequences, especially for estimating birth-order effects. Child birth order and mothers’ fertility are highly correlated in the age-censored anthropometric subsample. Moreover, family structures and age patterns that permit within-family comparisons of siblings’ anthropometry are unrepresentative. So strategies that could separate birth order and fertility in other data cannot here. We show that stratification by mother’s fertility is important. We illustrate this by comparing India and sub-Saharan Africa (SSA). Children in India born to higher-fertility mothers are shorter, on average, than children of lower-fertility mothers. Yet, later-born children in India are taller, adjusted for age, than earlier-born children of the same sibsize. In SSA, neither of these associations is large.

1. Introduction

For developing economies, anthropometric measures, particularly height, are important markers of human capital (Behrman and Deolalikar, 1988; Victora et al., 2008; Deaton, 2013; Hoddinott et al., 2013; Black et al., 2017). For example, stunting – short height compared to average, than children of lower-fertility mothers. Yet, later-born children in India are taller, adjusted for age, than earlier-born children of the same sibsize. In SSA, neither of these associations is large.

The DHS censors its height (and other anthropometric measures) sample by age. Although the DHS asks about early-life mortality, for example, for all children yet born to a mother, it measures the height only of children who were born in the five years before the day of the interview. One immediate consequence is that only younger children of mothers are in the height subsample. Another consequence is that the subset of families with multiple children whose heights can be compared differs from the full population. For example, they have different age distributions and shorter birth spacing, an important (but methodologically challenging) predictor of child outcomes (Potter, 1988). A third consequence is that the correlation between children’s birth orders and their mothers’ fertility is stronger in the height subsample than in the full population. This matters, in part, because the magnitudes and even the signs of correlations between fertility and

1. The reversed alphabetical order of authors reflects equal leading contributions of Coffey and Spears. We are grateful for comments from Farzana Afridi, Harold Alderman, Jadu Ban, Sandra Black, Shoumitro Chatterjee, Joe Cummins, Jean Drèze, Karen Grépin, Michel Guillot, Raymond Guiteras, Derek Headey, Devesh Kapar, Reetika Khera, Brendan Kline, Ilyana Kuziemko, Nicholas Lawson, Erin Lentz, Will Masters, Grant Miller, Joe Potter, Kjell Salvanes, John Straus, Duncan Thomas, Steve Trejo, and Sangita Vyas; for excellent research assistance by Aashish Gupta and Melissa LoPalo; for discussion of presentations at Penn, Princeton, UQAM, and UT-Austin; for correspondence with Seema Jayachandran and Rohini Pande about prior drafts of this paper; for the guidance of Andrew Foster, Tom Vogl, and two referees; and especially for conversations with Anne Case, Angus Deaton, and Michael Geruso. This research is supported by grants K01HD098313 and P2CHD042849 awarded to the Population Research Center at The University of Texas at Austin by the NICHD and by the Bill and Melinda Gates Foundation (OPP1125318); the content is solely the responsibility of the authors and does not represent the official views of the National Institutes of Health or the Gates Foundation. Annotated Stata do files and log files are available at the JDE website. Further detailed results are available in our companion IZA Discussion Paper Spears et al. (2019).

E-mail address: dpspears@utexas.edu (D. Spears).

https://doi.org/10.1016/j.jdeveco.2021.102783
Received 17 May 2021; Received in revised form 30 October 2021; Accepted 6 November 2021
Available online 27 November 2021
0304-3878/© 2021 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
socioeconomic status range widely across developing-country populations (Vogl, 2015).

Thus, the fact that the DHS censors the height sample by age matters for researchers using within-family empirical strategies, and especially for those studying birth order. In particular, (Blake, 1989)'s recommendation that studies of birth order should be stratified by number of siblings is critical when using the DHS' age-censored anthropometric subsample. Despite the importance of both birth order and nutritional outcomes, to our knowledge these implications for using the DHS have not previously been comprehensively documented.

In Section 2, we discuss the DHS data that we use. We show that the age-censoring of the anthropometric subsample introduces econometrically-relevant properties that differ from the full population. Throughout, we compare India and sub-Saharan Africa (SSA) because these two populations are at different points in the demographic transition: in India, high fertility is uncommon and negatively-selective for health and wealth, but in SSA, high fertility is common and less negatively-selective (indeed, it is positively-selective by some measures). In Section 3, we document this important background for any effort to estimate an effect of birth order in this context. Because a mother having higher fertility, rather than lower fertility, implies more socioeconomic disadvantage within India than within SSA, family size must be accounted for.

Section 4 presents the methodological challenge that is our focus: we show that, even in regressions where there should be no “effect” of birth order, the endogenous censoring of the DHS height subsample exacerbates the omitted variable bias threat from fertility. Age censoring also undermines some common empirical strategies that could resolve this issue with full birth histories but cannot in the height subsample. Our results point towards stratification by mothers’ fertility as an important procedure.

We use stratification in non-parametric summaries in Section 5. We show that Indian children born to higher-fertility mothers are notably shorter, on average, than Indian children of lower-fertility mothers. And yet, later-born children in India of a given sibsize are taller, adjusted for age, than earlier-born children of the same sibsize. This pattern is in striking contrast with evidence of later-born disadvantage in other studies of birth order, especially in developed countries (e.g. Black et al., 2005). In SSA, neither of these associations is very large. Finally, in Section 6 we present a practical application: a reinterpretation of a study published in the American Economic Review of height and birth order in the DHS.

2. Data

We compare India and SSA, two populous regions at different points in the fertility transition. For India, we use the 2005–6 Indian DHS, which is called the National Family Health Survey-3 by the Government of India. For SSA, we use 27 comparably-timed DHS survey rounds from 25 countries. To study birth order, we exclude multiple births such as twins.

We use three samples from the Indian and SSA DHS birth histories:

- **Full birth history**: \( n = 987,447 \). These are all children ever born alive (prior to the survey) to the mothers surveyed by the DHS. 83% of these do not have measured height.
- **Main height sample**: \( n = 166,153 \). These are children under 60 months old who are alive at the time of the survey and who have their heights measured.
- **Mother-fixed-effects subsample**: \( n = 80,785 \). These are children under 60 months old who are alive at the time of the survey, who have their heights measured, and who have at least one sibling who also meets these criteria.

Table 1 describes the make-up of the main height sample by birth order and sibsize. Panels (a) and (b) show that the age-censoring makes sibsize and birth order highly correlated in the main height sample. The correlation between birth order and sibsize is 0.98 in the age-censored main height sample, compared with 0.63 in the full birth history of children ever born in the same DHS rounds. In the main height sample, 72% of measured children are the last born to their mother and 97% are the last or next-to-last born at the time of the survey, compared with 28% and 50% in the full birth history.

Another implication of Table 1 is that, within any sibsize, the heights of last-born and next-to-last-born children can be compared. But comparing first-borns with third-borns in sibships of 3, for example, is constrained by the age censoring. Panel (c) focuses on children’s eligibility for the mother-fixed-effects subsample. Consider using these data to answer the seemingly simple question of whether third-born children tend to be shorter than their first-born siblings. In the framework of Panel (c), a first-born child is 2 or more from last-born, if in a sibsize of 3 or more. Table 1 shows that such a child is an unusual observation in these age-censored data. In India, only about 3% of the measured first-borns are in sibsizes of 3 or more; less than 6% of measured children in a sibsize of 3 are first-born. Less than 5% of third-borns in the height data have a measured first-born sibling (even though, by definition, 100% of them had one born alive).

The few large families in which early-borns are young enough to be measured are negatively selected for their families’ short birth spacing. For example, controlling for child age and sex, third-borns in India in sibships of 3 with a measured first-born sibling are shorter than third-borns without a measured first-born sibling by a gap almost as large as that between urban and rural Indian children. Short birth spacing has important consequences, itself, and is correlated with other disadvantages.

Additionally, these measured pairs are at the two extreme ends of the five years of measured age. The average first-born and third-born in the height subsample are both 28 months old (the mortality-weighted middle of the 0–59 range) but are 51 and 8 months old, respectively, among the selected subset that can be compared with one another within households. Age predicts height-for-age. These facts illustrate that the age-censored height sample is not constructed to permit such within-sibship comparisons.

3. Background

Birth order is necessarily correlated with other variables that are correlated with child outcomes, including child age, mothers’ fertility, mothers’ age at birth, and birth spacing. These identification challenges have been well-studied. As Blake (1989) writes to introduce an “outline of confounding factors in the analysis of birth order”: “…” most findings appear to involve highly selective reporting of what are, in reality, sibsize, period, parental background, child-spacing, and other selection effects for which controls have not been instituted” (p. 300). Among these, sibsize has received special attention in the economics literature because higher-fertility mothers are different, on average, than lower-fertility mothers (Black et al., 2005). In an early study of birth-order effects in the economics literature, Behrman and Taubman (1986) note this problem, citing Ernst and Angst (1983) and observing that “many studies … fail to control for family size and family background. Later birth orders, for example, are only observed for larger families that have different child quantity/child quality trade-offs. If so, then 1

---

1 Regressing height-for-age (HAZ, introduced below) on an indicator for having a measured first-born sibling and 119 age-in-months-by sex indicators among Indian third-borns in sibships of 3 yields a coefficient of −0.28 (r > .5). Regressing HAZ on an indicator for urban residence and the same age-by-sex controls among the same sample yields a coefficient of 0.30 (r > .5). These differences are about twice as large as the overall India-SSA difference.
birth-order effects from interfamilial data may be reflecting only differential child quality/quantity shadow prices across families and not within-family birth-order effects" (p. S131).

Average fertility is lower in India (Das Gupta and Mari Bhat, 1997; Drèze and Murti, 2001) than in SSA (Caldwell and Caldwell, 1987; Kohler and Behrman, 2014). For the 2005–2010 interval—which is the period that includes the Indian DHS that we use here—the UN World Population Prospects estimates that SSA’s total fertility rate was 5.4 live births per woman, compared with 2.8 in India. The relationship between fertility and socioeconomic status is understood to be positive to negative. India and SSA are at different points in this transition.

Fig. 1 documents that an omitted-variable-bias threat from sibsize is present among the children whose heights we study here. Fig. 1 shows that higher fertility predicts greater disadvantage by more in India than in SSA, in the sense of difference-in-differences. Panel (a) is particularly noteworthy, because it plots the average height-for-age $z$-score of all of a mother’s measured children. Height is steeply decreasing in sibsize in India. In SSA, mothers who have more children are taller and have more body mass, on average; in India they are shorter and have less body mass. So an omitted-variable threat from endogenous fertility is an observed property of these populations.

4. Example: “Effects” of birth order where there are none

Suppose for example that larger families were poorer and had children in worse health, but within each family all children were exactly equally healthy. A regression including children from multiple families of health on only birth order would find a negative association between being later-born and health (i.e., the regression would suggest an advantage for earlier-birth-order children). But this finding would be a spurious artifact of the bias created by the key omitted variable of sibsize.

Holding sibsize constant may be both especially important and especially challenging when a sample is age-censored to young children, as is the DHS anthropometric subsample. Techniques in the literature that are thought to account for a group-level omitted variable can fail when selection into the group (in this case, into a group of siblings young enough to have measured height) is endogenous (compare Ardington et al., 2009).

Table 2 uses the India and SSA DHS samples described in Section 2 to run regressions where birth-order indicators are the independent variables. The dependent variables are mother’s height (in Panels A and B) and mother’s literacy (in Panels C and D), both measured by the DHS at the fixed time of the survey. For these unusual regressions, we know a priori that there is zero causal effect of birth order on these
Fig. 1. Background: Higher-fertility mothers are more disadvantaged in India, relative to lower-fertility mothers in India, than higher fertility mothers are in SSA, relative to lower-fertility mothers in SSA.

Note: Observe that in every panel, the India line slopes more negatively than does the SSA line. In all panels, the sample is the same in Fig. 2, described in Section 2 as our “main height sample.”

dependent variables, because the “outcomes” must be the same for all siblings. As standalone research, these regressions make no sense. But they illustrate the challenges of using the height subsample. If a regression with such a specification does not yield a zero coefficient, we should investigate whether there exists a threat to identification.

In Table 2, columns 1 and 3 (and the corresponding columns in Panels B and D) use the full birth history. Columns 2, 4, and 5 use only the height subsample; column 5 further restricts the sample to sibling pairs in sibsizes of two with both siblings measured, to implement stratification by sibsize. Only stratification by sibsize yields a
zero coefficient on birth order — although including sibsize covariates comes close in the full birth history.

In the first two columns of each panel, sibsize is not controlled at all. Compare these results with the fertility gradients in Fig. 1. Increasing birth order has negative coefficients for mother’s height in India but positive coefficients in SSA, matching the slopes in panel (b) of Fig. 1. Moving from the first to the second column of each sample preserves the lack of sibsize covariates while restricting the sample from the full birth history to the main height sample. In each case, the coefficients increase in absolute magnitude, moving away from zero as the sample moves from the full birth history to the height subsample. This is because the correlation between birth order and sibsize is larger in the height subsample than in the full birth history. This makes accounting for endogenous sibsize even more important.

In the next two columns of each panel, indicators for sibsize are included as regression covariates. Columns 3 and 8 use the full birth history; columns 4 and 9 use the height subsample. If the full birth history is used, the estimate comes close to the correct zero coefficient. But in the height subsample, the coefficients are positive and large, and smaller in India than in SSA (more negative in India in a difference-in-differences sense). This is because of selection into the height subsample by birth order and sibsize is larger in the height subsample than in the full birth history. This makes accounting for endogenous sibsize even more important.

5. Stratification results

How can researchers investigate the relationship between birth order and height, given these challenges? The simplest place to start is to plot stratified, non-parametric summary statistics. Fig. 2 does so. Here, and in the rest of this paper, children’s height is operationalized as a height-for-age z-score (HAZ) within sex and age-in-months, based on international WHO norms (World Health Organization et al., 2006). For clarity, only the last or next-to-last births to a mother are included in Fig. 2; 97% of the main height sample is either last-born or next-to-last born. Section 2 documented that the remaining 3% is unrepresentative.

Panel (a) plots local polynomial regressions of HAZ on age. No further controls, residualization, or restrictions are used beyond stratifying the sample by birth order and sibsize. There is a well-studied relationship between HAZ and age in children under two in developing countries (Victora et al., 2010; Aiyar and Cummins, 2021): mean HAZ falls over the first two years of life and flattens (as a function of age) at age two. This pattern is visible in Panel (a). Panel (a) also shows that not all ages can be observed for all combinations of birth order and sibsize: in sibsizes of 2, for example, no first-borns were measured when they were 6 months old.

In SSA, neither birth order nor sibsize is predictive of HAZ: within a sibsize, at the same age, HAZ lines for different birth orders overlap. India is different. Across sibsizes, there is a downward trend: children from larger sibsizes are shorter, on average. Within a sibsize, at the same age (and where the same age is measured for both birth orders), later-born children are taller, on average. More specifically, in sibsizes of 2 there is no evidence that first-borns are taller than second-borns. Fig. 2 shows that in sibsizes of 3 and 4, later-borns are taller at the same age.

The rest of this paper considers how to compress the information in Panel (a) of Fig. 2 into informative means, regression coefficients, and other statistics. One clear message from Fig. 2 is that any appropriate empirical strategy must account for the declining pattern of HAZ in sibsize that is apparent for India but not for SSA.

Table 2: Example regressions, which should have zero coefficients, of fixed properties of mothers on birth order.

| inclusion in sample: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| height subsample?    | no (full) | yes | no (full) | yes | yes | no (full) | yes | no (full) | yes | yes |
| birth order          | ≤3 | ≤3 | ≤3 | ≤3 | ≤2 | ≤3 | ≤3 | ≤3 | ≤3 | ≤2 |
| sibsize              | any | any | any | any | 2 only | any | any | any | any | 2 only |
| measured children per mother | any | any | any | 2 only | any | any | any | any | 2 only |

Panel A: India, dependent variable is mother’s height (cm)

| birth order 2 | -0.0485*** | -0.0737 | -0.0009 | 0.0714 | 0.0000 |
|----------------|-------------|---------|---------|--------|-------|

Panel B: SSA, dependent variable is mother’s height (cm)

| birth order 3 | -0.342*** | -0.519*** | 0.0001 | 0.135 | 0.0000 |
|----------------|------------|----------|--------|-------|--------|

Panel C: India, dependent variable is mother’s literacy

| birth order 2 | -0.0437*** | -0.0748*** | -0.0003* | 0.0140* | 0.0000 |
|----------------|------------|-----------|----------|---------|-------|

Panel D: SSA, dependent variable is mother’s literacy

| birth order 3 | -0.157*** | -0.250*** | 0.0001 | 0.0284** | 0.0000 |
|----------------|-----------|----------|--------|----------|-------|

Note: For clarity of interpretation, the data are restricted to children of birth orders 1, 2, or 3 only. Otherwise, columns 1, 3, 6, and 8 use the full birth history. Columns 2, 4, 5, 7, 9, and 10 use the main height sample, with columns 5 and 10 further restricted to pairs of measured siblings in sibsizes of 2. Standard errors are clustered by survey primary sampling unit (PSU). "corr.: birth ord. & sibsize" is the correlation between birth order and sibsize in that panel and column's subsample. Two-sided p-values: * p < 0.1; ** p < 0.05; *** p < 0.001.
Another important lesson of Panel (a) in Fig. 2 is that, conditional on sibsize, age is predictive of birth order. Because HAZ, too, is predicted by age, age is a potential confounding factor. Age is endogenously selected in any within-household comparison, as detailed in Section 2. So any credible empirical strategy must robustly account for child age.

In the birth-order literature, there is a standard non-parametric tool described in detail by Blake (1989) and used more recently by Black et al. (2005): a plot of mean outcomes by birth order and sibsize. This is the next step towards reducing the information in Panel (a) into regression coefficients. Panels (b) and (c) present such a plot. The horizontal axis is sibsize. Unlike investigations of birth order in the literature that study outcomes at a fixed age, here we must first account for age. The vertical axis is the average residual of children’s height-for-age z-scores after regression on a set of 120 age-by-sex indicators and no other covariates, computed in the entire main height sample, without restrictions or stratification.

6. Application: Comparing birth order gradients

What would we learn if we attempted to summarize Fig. 2 with regressions? Jayachandran and Pande (2017) – hereafter JP – have
investigated birth-order gradients in height in India and SSA. Their main result reports that HAZ is more negatively associated with birth order in India than in SSA. JP interpret this correlation as evidence that parents in India discriminate against later-born children within households.

We apply the methodological observations of this paper to ask whether the correlations between birth order and sibsize in India and SSA can be understood as causal effects. More specifically, we ask what JP would have found if they had stratified by sibsize.

Our purpose here is to illustrate the importance of endogenous fertility in the age-censored DHS child height subsample — not to assess each econometric choice of JP. JP recognize the potential that sibsize could be an important confounder. They discuss the threat and implement several robustness checks. Here we show how these strategies are limited by the structure of the available data.

6.1. Regression empirical strategy

JP estimate the following regression specification, their Eq. (1):

\[ H_{AZ_{inc}} = \alpha_{India} + \alpha_{India} \times second - born_{inc} + \alpha_{India} \times third - or - later - born_{inc} + \beta_{1} \times second - born_{inc} + \beta_{3} \times third - or - later - born_{inc} + \gamma X + \epsilon_{inc}. \]

where \( i \) indexes children, \( m \) indexes mothers, \( e \) indexes the country, and \( India_{i} \) is an indicator that is 1 for Indian observations and 0 for SSA. The coefficients of interest are \( \alpha_{2} \) and \( \alpha_{3} \), which are the difference-in-differences estimators for the birth-order gradients. \( \beta_{2} \) and \( \beta_{3} \) are average HAZ differences between first-borns (the omitted group) and second- and third-borns respectively, in SSA. Sibsize is not accounted for in regression Eq. (1), nor in JP’s corresponding Figure 2. In this way, Eq. (1) is like the uncontrolled specifications in columns 2 and 7 of Table 2.

JP are aware that sibsize could be an omitted variable in their analysis. They write: “Higher birth order children are more likely to come from larger families, and family size could be correlated with child height; family size could affect child height via its effect on the available resources per child, plus larger families tend to be poorer” (p. 2609; they do not, however, raise the possibility that this correlation may be different between India and SSA, where larger families are advantaged by some relevant measures). They argue against including a regression control for sibsize, as observed at the time of the survey, because women’s childbearing careers will often be incomplete: “the nature of DHS sampling implies that a large fraction of households in our sample have not completed childbearing… our regressions cannot control for total family size in general, raising an omitted variable bias concern”. This is a different concern about including sibsize as a covariate than we raise in Section 4: our concern there was that inclusion in the height sample is negatively selective for birth orders that are early, relative to their sibsize. Here, JP note another constraint for any effort to study birth order and height in the DHS: By the construction of a subsample that only includes young children, completed sibsize for many children is unobserved (and, in fact, undetermined) at the time of the survey. JP’s proposed solution, which we adopt below, is to make a further restriction of the sample to mothers who they interpret to be likely to have completed fertility.

In many other birth-order studies, age is held constant in the dependent variable, so the time period of interest differs across siblings: for example, Black et al. (2005) study educational attainment by age 25, Coffey and Spears (2021) study mortality in the first month of life, and Buckles and Kolka (2014) study inputs at specific gestational and early-life ages. When studying height with the DHS, however, age cannot be held constant. The DHS measures height at one point in time per family, so children are measured at different ages. Because later-born children are younger, and therefore more likely to be on the declining HAZ path shown in Fig. 2, they appear taller if age is not controlled. Our \( X_{inc} \) therefore includes 119 age-in-months-by-sex indicators, which is the resolution of the WHO reference tables.

Eq. (1) considers differences in height by birth order relative to first-born children, the omitted category. And yet, Section 2 suggests that first-borns can only be compared plausibly, in these data, to second-borns. Section 2 shows that almost 40% of the children in the main height sample are third-born or later. In SSA, where the average women had almost twice as many children as in India during this time, 50% of the sample is of sibsize 4 or more and 45% are fourth-born or later. Because JP topcode birth order at “3 or greater”, such larger sibsizes and later-born children contribute little to JP’s identifying variation.

6.2. Regression results

Throughout, we have used the same set of Indian and SSA survey rounds as JP. Table 3 investigates the consequences of stratifying by sibsize for these regression results. Panel A uses the full main height sample. We build upon JP’s isolation of a subsample of families that they identify as likely to have completed childbirth. Panel B uses the “completed fertility” subsample as identified and named by JP. For these families, JP interpret sibsize at the time of the survey to be an adequate measure of final sibsize.

Column 1 of Panel A is our replication of JP’s main result, presented in their column 2 of their Table 2. Our estimates in Column 1 are quantitatively similar to what JP find: First-born children in India with height measured in the DHS are taller, on average, than first-born children of the same age in SSA; HAZ differences by birth order in SSA are small; and the average later-born child with height measured in the DHS in India is shorter than the average first-born with height measured. In Section 4 and elsewhere, we have discussed the inadequacy of merely adding covariate controls for sibsize \( \times \) India. But such regression controls do offer a simple response to any concern that fertility is an omitted variable. So, for completeness, we add these covariates in column 2. Consistent with the non-parametric results of Fig. 2, the apparent negative interaction from column 1 is eliminated or reversed in column 2.

The next step is to stratify by sibsize. To permit a clear comparison with our stratified results, column 3 restricts the sample to the minority subsample with two measured height observations per family. In the four combinations of columns 1 and 3 of Panels A and B, the interactions of interest between birth order and an India indicator are quantitatively stable. The non-interacted coefficient on India becomes much smaller because this coefficient reflects first-borns, many of whom are now excluded. Restricting the sample to sibling...
by sibsize eliminates or reverses the negative interaction between India of 2. Columns 5 and 7 further include mother fixed effects. Stratifying born and a second-born both have measured height are from a sibsize in sibsizes of 2; columns 6 and 7 restrict the sample to children in with siblings.

Consistent with the non-parametric evidence of Fig. 2, the interaction for third-borns is robustly positive.7

6.3. Why are these results different?

Because of the correlation between child height and sibsize, the negative correlation between birth order and child height in India cannot be interpreted as a negative effect of birth order. Some results even suggest a positive effect. Our conclusion, however, is that the structure of the available DHS data prevents researchers from being able to interpret these results with confidence as an effect of birth order on child height.

Beyond its econometric importance for internal validity, the age-censoring of the DHS height subsample also influences the external validity of these results. JP propose that their results are due to a within-family process of discrimination. They write in their abstract: “We posit that India’s steep birth order gradient is due to favoritism towards eldest sons, which affects parents’ fertility decisions and resource allocation across children”. But, as Table 1 shows, the DHS is not structured to study within-family processes. For 71% of the families in the main height sample (corresponding to over half of the child-level

4 Even though each stratified household is a balanced panel of two children, adding mother fixed effects yields results that are quantitatively distinct from merely stratifying by sibsize. This is consistent with the possibility that we raise in the next subsection that mother fixed effects reweights the sample (across child ages and birth spacings).

In short, sibsize makes an important difference. Table 3 essentially replicates JP’s finding in column 1 without accounting for endogenous fertility. But there is no evidence in the DHS that India shows a special later-born disadvantage once sibsize is held constant — whether by direct regression control (column 2), by stratification (columns 4 through 7), or by mother fixed effects (columns 5, 7, and 8). This is true whether all available observations are used (Panel A) or whether

The sample is restricted to the completed-fertility subsample (Panel B). Consistent with the non-parametric evidence of Fig. 2, the interaction for third-borns is robustly positive.7

Note: In all columns the dependent variable is the child’s height-for-age z-score. Column 1 of Panel A uses the main height sample; other columns are restricted to subsets of this sample, as noted in the table. All columns include fixed effects for 119 age-in-months by sex categories. Standard errors are clustered by survey primary sampling unit (PSU).

Two-sided $p$-values: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

4 Even though each stratified household is a balanced panel of two children, adding mother fixed effects yields results that are quantitatively distinct from merely stratifying by sibsize. This is consistent with the possibility that we raise in the next subsection that mother fixed effects reweights the sample (across child ages and birth spacings).

Even though each stratified household is a balanced panel of two children, adding mother fixed effects yields results that are quantitatively distinct from merely stratifying by sibsize. This is consistent with the possibility that we raise in the next subsection that mother fixed effects reweights the sample (across child ages and birth spacings).

In short, sibsize makes an important difference. Table 3 essentially replicates JP’s finding in column 1 without accounting for endogenous fertility. But there is no evidence in the DHS that India shows a special later-born disadvantage once sibsize is held constant — whether by direct regression control (column 2), by stratification (columns 4 through 7), or by mother fixed effects (columns 5, 7, and 8). This is true whether all available observations are used (Panel A) or whether

The sample is restricted to the completed-fertility subsample (Panel B). Consistent with the non-parametric evidence of Fig. 2, the interaction for third-borns is robustly positive.7

6.3. Why are these results different?

Because of the correlation between child height and sibsize, the negative correlation between birth order and child height in India cannot be interpreted as a negative effect of birth order. Some results even suggest a positive effect. Our conclusion, however, is that the structure of the available DHS data prevents researchers from being able to interpret these results with confidence as an effect of birth order on child height.

Beyond its econometric importance for internal validity, the age-censoring of the DHS height subsample also influences the external validity of these results. JP propose that their results are due to a within-family process of discrimination. They write in their abstract: “We posit that India’s steep birth order gradient is due to favoritism towards eldest sons, which affects parents’ fertility decisions and resource allocation across children”. But, as Table 1 shows, the DHS is not structured to study within-family processes. For 71% of the families in the main height sample (corresponding to over half of the child-level

7 JP present further results including triple-interacting birth order, India, and child sex (compare Barellos et al., 2014); stratifying the sample within India by religion or by state; and interacting covariates with the sex of older siblings. In investigations requested by referees, we find that each of these is fragile to accounting for sibsize. These results are presented as Table C, Table D, and Figure E with the Stata replication files on the journal website. JP also discuss sex-biased fertility stopping (compare Clark, 2000).
observations), only one child’s height is observed. Only 2% of families have measured height from three or more children.

One question is why JP’s analysis – despite its extended set of robustness checks – suggests a negative relationship between height and birth order, particularly in a robustness check with mother fixed effects. It is understandable that an econometrician might consider mother fixed effects as a solution for confounding heterogeneity at the sibship level. The fact that sibsize can be an omitted variable in a study of birth order is simple and straightforward. The failure of mother fixed effects, in an age-censored subsample, for two estimates of the effect of birth order in two populations, on an outcome measured at different ages for different siblings, is not. We propose that the age-censoring of DHS data causes an instance of what Miller et al. (2019) have recently defined and described as a “selection into identification” problem. Selection into identification occurs in cases of parameter heterogeneity, when a fixed-effects subsample is misleadingly different from the population of interest.

In this case, using mother fixed effects selects for very short birth spacing (Behrman, 1988). Short birth spacing predicts low birthweight among babies; low birthweight predicts disadvantage. To clarify, short birth spacing is not an omitted variable here to be controlled, but rather is an interactor with birth order that marks heterogeneity in the parameter of interest. Because birth spacing is a difference between two siblings and is a correlate of age, it violates the strict exogeneity requirement of fixed effects (Wooldridge, 2010). A separate example of the consequences of mother fixed effects concerns SSA. JP’s summary statistics and main Eq. (1) find that second-borns in SSA are slightly taller than first-borns in SSA. But JP’s fixed-effects column claims that second-borns in SSA are much shorter than first-borns in SSA (by even more than the overall India-SSA height gap). Fixed effects claim an even larger disadvantage for SSA second-borns. These fixed-effects results are incompatible with JP’s main results.

Of course, mother fixed effects can be a useful tool in data without the constraints of the DHS anthropometric subsample. Coffey and Spears (2021) find a relative later-born advantage in India when studying consequences for early-life mortality in the full birth histories of the same set of DHS surveys that we and JP use. They find similar results whether they stratify by sibsize, use mother fixed effects, or include regression controls for sibsize directly. DHS mortality data are not censored by child age. Nor are age controls involved, because infant and neonatal mortality rates are age-specific. Finally, DHS birth histories include children of mothers whose fertility is long-completed. Coffey and Spears present evidence that such a later-born neonatal survival advantage in India reflects improvements in maternal nutrition over the course of childbirth careers, in a population where young women are especially likely to be underweight. These facts are consistent with the interpretations we have presented here — and with our argument that stratification by sibsize can be an important tool in some contexts.

CRediT authorship contribution statement

Dean Spears: Participated in all aspects of this research. Diane Coffey: Participated in all aspects of this research. Jere R. Behrman: Conceptualization, Writing – review & editing.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2021.102783.

References

Aiyar, Anaka, Cummins, Joseph R., 2021. An age profile perspective on two puzzles in global child health: The Indian enigma & economic growth. J. Dev. Econ. 148, 70–89.

Ardington, Cally, Case, Anne, Hinegood, Victoria, 2009. Labor supply responses to large social transfers: Longitudinal evidence from South Africa. Am. Econ. J. Appl. Econ. 1 (1), 22–48.

Barcello, Silvia Helena, Carvalho, Leandro S., Lleras-Muney, Adriana, 2014. Child gender and parental investments in India: Are boys and girls treated differently? Am. Econ. J. Appl. Econ. 6 (1), 157–189.

Behrman, Jere R., 1988. Nutrition, health, birth order and seasonality: Intrahousehold allocation among children in rural India. J. Dev. Econ. 28 (1), 43–62.

Behrman, Jere R., Deolalikar, Anil B., 1988. Health and nutrition. In: Handbook of Development Economics, Vol. 1. Elsevier, pp. 631–711.

Behrman, Jere R., Taubman, Paul, 1986. Birth order, schooling, and earnings. J. Labor Econ. 4 (3, Part 2), S121–S145.

Black, Sandra E., Devereux, Paul J., Salvanes, Kjersti G., 2005. The more the merrier? The effect of family size and birth order on children’s education. Q. J. Econ. 120 (2), 669–700.

Black, Maureen M., Walker, Susan P., Fernald, Lina C.H., Andersen, Christopher T., Di Girolamo, Ann M., Lu, Chunling, McCoy, Dana C., Fink, Günther, Shawar, Yusra R., Shiffman, Jeremy, Deverecelli, Amanda E., Wodon, Quentin V., Vargas-Barón, Emily, Grantham-McGregory, Sally, 2017. Early childhood development coming of age: science through the life course. Lancet 389 (10064), 77–90.

Blake, Judith, 1989. Family Size and Achievement. Univ of California Press.

Buckles, Kasey, Kolka, Shauwa, 2014. Prenatal investments, breastfeeding, and birth order. Soc. Sci. Med. 118, 66–70.

Caldwell, John C., Caldwell, Pat, 1987. The cultural context of high fertility in sub-Saharan Africa. Popul. Dev. Rev. 409–437.

Clark, Shelley, 2000. Son preference and sex composition of children: Evidence from India. Demography 37 (1), 95–108.

Coffey, Diane, Spears, Dean, 2021. Neonatal death in India: Birth order in a context of maternal undernutrition. Econ. J. 131 (638), 2478–2507.

Das Gupta, Monica, Mari Bhat, P.N., 1997. Fertility decline and increased manifestation of sex bias in India. Popul. Stud. 51 (3), 307–315.

Deaton, Angus, 2013. The Great Escape: Health, Wealth, and the Origins of Inequality. Princeton University Press.

Dreze, Jean, Murthi, Mamta, 2001. Fertility, education, and development: Evidence from India. Popul. Dev. Rev. 27 (1), 33–63.

Ernst, Cecile, Augs, Jules, 1983. Birth Order: Its Influence on Personality. Springer, Berlin.

Hoddinott, John, Behrman, Jere R., Maluccio, John A., 2005. The more the merrier? J. Econ. 4 (3, Part 2), S121–S145.

Hoddinott, John, Behrman, Jere R., Maluccio, John A., Melgar, Paul, Quisumbing, Agnes R., Ramirez-Zea, Manuel, Stein, Aryeh D., Yount, Kathryn M., Martorell, Reynaldo, 2013. Adult consequences of growth failure in early childhood. Am. J. Clin. Nutr. 98 (5), 1170–1178.

Jayachandran, Seema, Pande, Rohini, 2017. Why are Indian children so short? The role of birth order and son preference. Amer. Econ. Rev. 107 (9).

Kohler, Hans-Peter, Behrman, Jere R., 2014. Population and Demography: Assessment Paper. Copenhagen Consensus Project, Copenhagen, Denmark.

Miller, Douglas L., Shenhar, Na`ama, Grone, Michel Z., 2019. Selection into identification in fixed-effects models, with application to head start, Working paper. National Bureau of Economic Research.

Potter, Joseph E., 1988. Birth spacing and child survival: A cautionary note regarding the evidence from the WFS. Popul. Stud. 42 (3), 443–450.

Schult, T. Paul, 1981. Economics of Population. Addison-Wesley.

Spears, Dean, Coffey, Diane, Behrman, Jere, 2019. Birth Order, Fertility, and Child Height in India and Africa. Discussion Paper 12289, IZA.
Strauss, John, Thomas, Duncan, 1995. Human resources: Empirical modeling of household and family decisions. In: Handbook of Development Economics, Vol. 3. Elsevier, pp. 1883–2023.

Victora, Cesar G., Adair, Linda, Fall, Caroline, Hallal, Pedro C., Martorell, Reynaldo, Richter, Linda, Sachdev, Harshpal Singh, 2008. Maternal and child undernutrition: consequences for adult health and human capital. Lancet 371 (9609), 340–357.

Victora, Cesar Gomes, de Onis, Mercedes, Hallal, Pedro Curi, Blössner, Monika, Shrimpton, Roger, 2010. Worldwide timing of growth faltering: revisiting implications for interventions. Pediatrics peds-2009.

Vogl, Tom S., 2015. Differential fertility, human capital, and development. Rev. Econom. Stud. 83 (1), 365–401.

 Wooldridge, Jeffrey M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.

World Health Organization, et al., 2006. WHO Child Growth Standards: Length/Height-For-Age, Weight-For-Age, Weight-For-Length, Weight-For-Height and Body Mass Index-For-Age: Methods and Development. World Health Organization, Geneva.