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Gender Gaps in Child Nutritional Status in Punjab, Pakistan

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Child nutritional status has improved over the period 2008 to 2014 in Punjab, Pakistan's largest province with a population of over 100 million, as rates of severe stunting have declined by 8.6 percentage points and average height-for-age (HFA) has increased by 0.19 standard deviations. However, the nutritional status of children in Punjab is still quite poor in comparison to many Sub-Saharan African countries. Recent research from India suggests eldest son preference and son-biased fertility stopping patterns negatively impacts the nutritional status of other children in the household, especially daughters. In order to test for latent gender discrimination in Punjab, Pakistan, a culturally similar neighbour, we apply a finite mixture model to a sample of couples with at least one child of each gender, though we do not find any. We do find, however, that when there is a larger share of children without an elder brother, that is, there is no son or a son is born after several daughters, that the incidence of stunting is higher and average HFA z-score of a couple's children is lower, using an OLS analysis. This suggests that some families might be increasing their fertility beyond the number of children they can support in pursuit of sons. In this way, couples' preferences regarding the gender composition of their children can have subsequent effects on the long-term nutritional status of their children.

JEL Classification: I2, I14, I15
Keywords: Pakistan, Height-for-Age, Gender, Finite Mixture Model

1. INTRODUCTION

South Asia is home to some of the worst rates of child malnutrition in the world, with India, Pakistan, and Bangladesh accounting for more than half of the world's malnourished children (Mehrotra, 2006).[1] Given its levels of income per capita, health and education, South Asia has underperformed in measures of child malnutrition in comparison to Sub-Saharan Africa (Osmani & Sen, 2003). This includes one of the key indicators of long-term health and nutritional status for children, the measure of their height-for-age, in particular when this measure is below international norms.[2] Stunting is

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[1]In Pakistan, 1200 children under the age of 5 years die every day and 35 percent of these deaths occur due to malnutrition (UNICEF, 2012).

[2]According to the World Health Organisation (2013), child growth is a global measure of children's nutritional status, and the three most widely used indicators of poor growth include the states of being "stunted", "wasted", and "underweight". The consequences of stunting are serious and long-term, making these children more vulnerable to repeated bouts of infections and diseases.

a case of chronic malnutrition where a child is too short for their age (Rawe, Jayasinghe, Mason, Davis, Pizzini, Garde, & Crosby, 2012). Researchers give more importance to stunting, or lower than height-for-age, (in comparison to rates of underweight and wasting) since stunting is a cumulative indicator of nutritional status of children starting from the prenatal phase. The consequences of stunting are serious and long-term, making these children more vulnerable to repeated bouts of infections and diseases.

According to the most recent Pakistan Demographic and Health Statistics (PDHS) 2017-18, anthropomorphic measurements taken for around 3500 children under the age of five indicated that 37.6 percent were stunted, 23.1 percent were underweight, and 7.1 percent were wasted (NIPS & ICF, 2019). This marks an improvement over the PDHS 2012-13, where 44.8 percent of children in Pakistan were stunted, 30 percent were underweight, and 10.8 percent were wasted (NIPS & ICF, 2013). The summary statistics also reveal that child nutritional status was better for wealthier families, urban families, children with more educated mothers, and those with longer birth spacing; these patterns were observed in both 2012-13 and 2018-19. Punjab's child nutrition indicators were the best amongst the provinces, with Sindh, Baluchistan, and FATA's levels of child nutrition amongst the lowest nationally, especially in the rural areas where stunting could exceed 50 percent (NIPS & ICF, 2019). Tariq, Sajjad, Zakar, Zakar, and Fischer (2018), using PDHS 2012-13 data, found that high birth order was associated with a child under age two being stunted and underweight. According to the same study, children under age two were also vulnerable to malnutrition if the child's mother was young, married consanguineously, had less education, or was herself underweight. Similar results for the risks of the three measures of malnutrition for an expanded sample of children under age five were found using the PDHS 2012-2013 by Khan, Zaheer, and Safdar (2019). They further found that female children were less likely to be stunted, underweight, or wasted. Asim and Nawaz's (2018) review of the literature on child nutrition in Pakistan suggests that high fertility and its contributing factors (early marriage and lack of birth spacing) as well as feeding practices are major drivers of the country's current levels of malnutrition.

Recently, Jayachandran and Pande (2017) have suggested that India's poor performance, relative to Africa, can at least partly be explained by an eldest son preference and son-biased fertility stopping behaviours. Parents sometimes have more than their ideal number of children in order to have their desired number of sons; this tends to happen when the first-born child (or children) are girls. Further, they find that Indian girls are shorter for their age than children in Sub-Saharan Africa by 0.143 z-score points, where the z-score represents the number of standard deviations from the median of an international reference population developed by the World Health Organisation (WHO). Previous studies had already noted that Indian girls had poorer outcomes as compared to girls in other developing countries (Barcellos, Carvalho, & Lleras-Muney, 2014; Mishra, Roy, & Retherford, 2004).[3] Discrimination against girls has also been detected in Bangladesh, particularly in early studies (Bairagi, 1986; Chen, Haq, & d'Souza, 1981; Dancer, Rammohan, & Smith, 2008; Rousham, 1996).

[3]Barcellos et al. (2014) found, using data spanning 20 years and 58 countries, that while girls in developing countries tend to have higher height- and weight-for-age z-scores than boys on average, the female advantage is significantly smaller in India, which is suggestive of discrimination against girls. Mishra et al. (2004) found that Indian boys were more likely than girls to be stunted in the early-1990s, but less likely to be stunted by the late-1990s.

An interesting comparison with the Indian case is the province of Punjab, Pakistan, which is culturally and linguistically very similar to its neighbouring Indian province of Punjab. In comparison to both India and Bangladesh, incomes are higher in Punjab, which is almost exclusively Muslim, like Bangladesh but unlike India. While there has been much research looking at the child level outcomes in Punjab, we extend this work by asking whether girls are also disadvantaged in Punjab. While Afzal (2013) found a 0.086 height-for-age z-score advantage for girls in Punjab, it is a much smaller advantage in magnitude than that found in Sub-Saharan Africa, where Jayachandran and Pande (2013) measured the female height-for-age advantage to be almost a quarter of a standard deviation in z-score.[4] Some smaller-scale studies have found worse outcomes for girls rather than boys, in the poorest and marginalised populations in Pakistan, like squatter settlements and rural areas (Baig-Ansari, Rahbar, Bhutta, & Baddrudin, 2006; Nuruddin & Hadden, 2015). Gender gaps in Pakistan are not limited to nutrition; Khan (2008) identified them in children's education as well.

In this study, we will apply an alternative test to data from Punjab, in particular the mixture model of Morduch and Stern (1997), to see whether regression averages are hiding a subset of households who discriminate against girls. Morduch and Stern's (1997) analysis is based on the premise that microeconometric studies using child level data (including height-for-age z-scores) may be unable to detect the pro-son bias evident at the macro-level (such as skewed gender ratios) because they pool households exhibiting heterogeneous attitudes toward children based on gender.

For example, if only a fraction of households discriminate against their daughters or households differ in the extent of their pro-son bias, regression-averaged discrimination may fail to come out as statistically significant. Further, OLS estimates may be inconsistent if common factors determine the outcome variable (child health) and group membership (households with strong pro-son bias). Therefore, Morduch and Stern (1997) applied a mixture model approach to a sample of households in Bangladesh that had at least one son and one daughter to divide the sample into two groups based on a latent variable: one with a pro-son bias, and one without.

Standard regression analysis on the full sample (a pooled OLS analysis) in Bangladesh's case yielded no statistically significant difference in height-for-age z-scores based on gender, regressions. However, the analysis on the two groups separately (as differentiated by the finite mixture model approach) indicated that girls had a 7 percent disadvantage in height-for-age in one group, and a 6 percent advantage in the other.

Morduch and Stern (1997) is the only prior work that has applied the finite mixture model to understand household-level gender discrimination, and it used a very small data set consisting of just over 300 observations collected in the late 1980s. Ours is the first study conducted for Pakistan applying the FMM procedure and makes use of a much larger and more recent data set of over 19,000 households. An innovation of our study is that it tests whether son-biased fertility stopping rules is the source of gender gaps and whether there is evidence of residual discrimination once that factor is controlled for in the analysis.

[4]A height advantage for girls of 0.23 standard deviations was observed in Jayachandran and Pande's (2013) sample of 25 Sub-Saharan African countries.

The results of our study will inform policy-makers in the following way. If we find that there is discrimination against the female children of the family, public health officials together with medical staff and lady health workers can be guided to pay special attention to the anthropomorphic growth of the female children under their care, while public health campaigns can target female children. On the other hand, if son-biased fertility stopping behaviours are driving nutritional deficits within families, all children in the household are at risk and public health measures can be directed towards increasing birth spacing and family planning.

The remainder of the paper will proceed as follows:

- Section 2 describes the finite mixture model (FMM) that will be used in the analysis to identify latent gender discrimination.
- Section 3 discusses the data set, which is a pooled cross-section of the MICS Punjab for 2008, 2010, and 2014.
- Section 4 presents the results in three parts: (i) correlates of family-average stunting and height-for-age z-scores, (ii) how child-level HFA is related to child gender and son-biased fertility stopping, and (iii) the results of the finite mixture model.
- Section 5 concludes the study.

2. METHODS

Mixture (or latent class) models are a way of identifying and controlling for unobserved heterogeneity within a population that allow for the unbiased and consistent estimation of sub-population parameters. Finite mixture models (FMM) do this for a limited number of discrete latent classes, modelling statistical distributions as a mixture (or weighted sum) of other distributions. In our case, we will be considering the latent classes as households in Punjab with a pro-son bias and those without, as in Morduch and Stern (1997). More recently, mixture models have been applied to the study of the effectiveness of prenatal care (Conway & Deb, 2005), job loss and health behaviours (Deb, Gallo, Ayyagari, Fletcher, & Sindelar, 2011), and medical care utilisation (Deb & Trivedi, 2002). The FMM estimation procedure is described in Cameron and Trivedi (2005) and summarised below.

Following Cameron and Trivedi (2005), if we assume that the pooled sample is actually a probabilistic mixture of two sub-populations, with probability density functions (pdf) $f_1(t \mid \mu_1(\mathbf{x}))$ and $f_2(t \mid \mu_2(\mathbf{x}))$, then the two-component finite mixture is defined as:

$$\pi f_1(\cdot) + (1 - \pi) f_2(\cdot) \qquad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \qquad (1)$$

where observations are drawn from f_1 and f_2, with probabilities π and $1 - \pi$, respectively. The probability of belonging to the first class, π, might be already known or otherwise may be estimated. The finite mixture model can be extended to include three or more latent classes, such that $\Sigma\pi_j = 1$.

Cameron and Trivedi (2005) define $d_i = (d_{i1},...,d_{im})$ as an indicator variable, where $d_{ij} = 1(d_{ij} = 1)$ indicates that t_i was drawn from the j^{th} latent group or class for $i = 1, \dots, N$. Were the d observed, the log-likelihood of the model would be written:

$$\ln L(\mu, \pi/t, d) = \sum_{i=1}^{N} \sum_{j=1}^{m} d_{ij} \ln f_j\,(t_i; \mu_j) + \sum_{i=1}^{N} \sum_{j=1}^{m} d_{ij} ln\pi_j \quad \ldots \quad (2)$$

Instead, the EM algorithm in which the variables d = (d_1 , . . . , d_n) are treated as missing data will be estimated. Given values of π_j, the posterior probability that observation t_i belongs to the population *j*, *j* = 1,2,...*m*, denoted z_{ij}, is:

$$Z_{ij} \equiv \Pr[y_i \in population\ j] = \frac{\pi_j f_j\,(y_i/X_i, \beta_j)}{\sum_{j=1}^{m} \pi_j f_j\,(y_i/X_i, \beta_j)} \quad \ldots \quad \ldots \quad \ldots \quad (3)$$

According to Cameron and Trivedi (2005), if we average the values of z_{ij} over *i*, we obtain the probability that a randomly chosen observation belongs to subpopulation *j*; hence E[z_{ij}] = π_j.

We start with an estimate, $\widehat{z_{ij}}$, of E[d_{ij}]. Conditional on estimate $\widehat{z_{ij}}$, Cameron and Trivedi (2005) write:

$$EL(\beta_i, \ldots, \beta_m, \pi/t, z^{\wedge}, x_1, \ldots, x_m) = \sum_{i=1}^{N} \sum_{j=1}^{m} \hat{z_{ij}} \ \ln f_i\,(t_i, \mu(x_j, \beta_j)$$
$$+ \sum_{i=1}^{N} \sum_{j=1}^{m} \hat{z_{ij}}\, ln\pi_j \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (4)$$

and this provides us with what is referred to as the E-step of the EM algorithm. The next step of the algorithm, the M-step, maximises EL (above) by solving this pair of first-order conditions:

$$\hat{\pi_j} - N^{-1} \sum_{i=1}^{m} \hat{z_{ij}} = 0, \ \ j = 1, \ldots, m, \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{m} \hat{z_{ij}} \ \frac{\partial ln f_j(t_j/\beta_j)}{\partial \beta_j} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (6)$$

Through this, we are able to calculate new values of $\widehat{z_{ij}}$, which are used to iterate through the aforementioned E- and M-steps until the process converges (Cameron & Trivedi, 2005).

3. DATA

We create a rich dataset by combining three rounds of the district-based Multiple Indicators Cluster Survey Punjab, from 2008, 2011, and 2014 for our analysis. It includes 36 districts and 150 tehsils or towns in urban and rural Punjab. For instance, in 2011, 95,238 households were interviewed, including 66,666 children under the age of five (Bureau of Statistics Punjab, 2011).[5] The variable of interest, the proxy for a child's long-term nutritional status, is measured by standardised z-scores for height-for-age (HFA) for children age 0 to 59 months. The z-scores,[6] recommended by World Health Organisation (WHO) and the National Centre for Health Statistics (NCHS), represent a comparison of

[5]In 2008, 91,075 households were surveyed for the MICS including 70,226 children under the age of five. And in 2014, 38,405 households were interviewed for the MICS including 27,495 children under the age of five (Bureau of Statistics Punjab, 2008; 2016). The sample size of the MICS Punjab is the main reason for focusing on just one province: The nationally representative Pakistan Demographic and Health Survey 2012-13 contained anthropomorphic measurements for fewer than 3,500 children (NIPS & ICF, 2013). The newest PDHS 2017-18 has around the same usable sample size (NIPS & ICF, 2019).

[6]Children's height and weight are standardised according to the following formula: $Z = (x - \mu)/\sigma$, where x is the raw score and μ and σ are the mean and standard deviation, respectively.

the sampled children with an international reference population of the same age and gender (de Onis & Blössner, 2003). Specifically, the z-score measures the number of standard deviations (SD) from an international reference population's median values of height, adjusted for gender and age.

The MICS 2011 data for Punjab indicates that about 15 percent of the children were severely stunted, that is, below –3 SD of the reference group and 20 percent of the children under five years of age were moderately stunted (Table 1). The mean z-score for height-for-age in the sample was –1.46 in 2011, which means that on average, a child in Punjab was 1.46 standard deviations below the median for a reference group child of the same age and gender. Over the time period considered in this study, the share of children severely stunted has fallen from 22.2 percent in 2008 to 13.6 percent of the under-five population in 2014, while the share of moderately stunted children has remained steady at around 20 percent of children. Together, these statistics imply steady improvement in child nutritional status in Punjab over time since the total share of stunted children has fallen. It would also appear to be the case that some children who would previously have been severely stunted (had the distribution remained unchanged) are now only moderately stunted, and some moderately stunted children have moved out of the stunted category altogether.

Table 1

Height-for-Age z-score in the MICS Punjab, 2008-2014

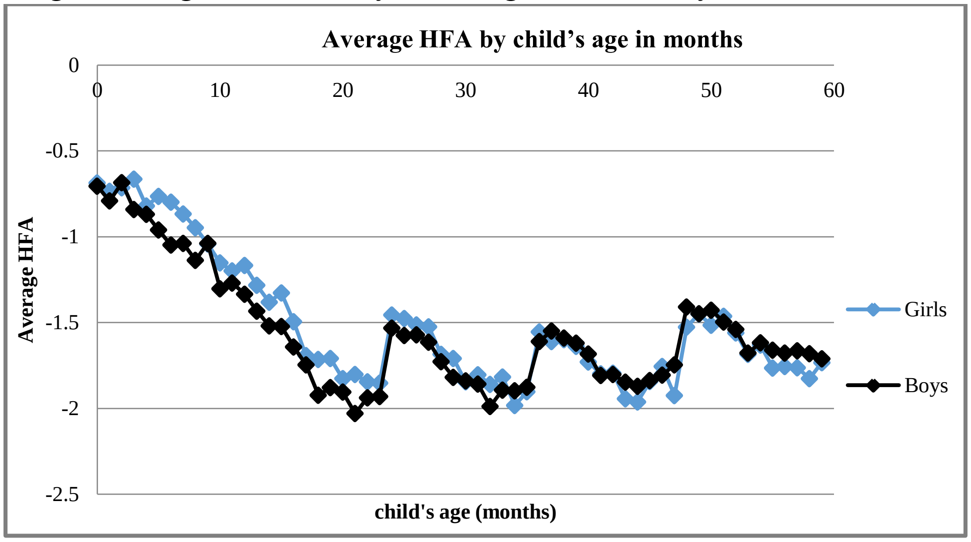
	Number of Observations	Mean HFA z-score	Standard Deviation	Moderate Stunting (z-score= -2 to -2.99)	Severe Stunting (z-score<2.99)
2008	57,349	–1.63	1.81	19.4%	22.2%
2011	62,398	–1.46	1.53	20.1%	14.7%
2014	26,336	–1.44	1.46	20.6%	13.6%

Source: Authors' calculations based on MICS 2008, 2011, and 2014; excluded outliers >5.99 and <–5.99.

If we plot the HFA z-scores for girls and boys at different ages (from birth to age 5 years) using the pooled data of the MICS Punjab 2008, 2011, and 2014, we see that children of both genders start out at birth with z-scores of about –0.7 standard deviations, but then the z-scores dip precipitously until about 20 months of age (Figure 1). The age-profiles HFA of girls and boys track each other closely, though it is mostly higher for girls before the age of 35 months, and marginally higher for boys thereafter.

Using the combined data of the MICS Punjab 2008, 2011, and 2014, we obtain a sample of 86,242 couples with at least one child under the age of five. To obtain this sample, we have dropped outliers that we define as z-scores >5.99 or <–5.99 and children whose parents have been married more than 15 years, since the data only identifies mothers of children age 14 and younger. Of these, 53,945 couples (51,420 couples) have at least one son (daughter) under five years of age and data on the relevant household characteristics (Table 2). The family average HFA is about 1.5 standard deviations below the international reference population's median, and it is slightly higher, by 0.05 standard deviations, for the average daughter than the average son. A bit more than one-third of the average family's children under-five are stunted. Couples have on average 1.5 children of each gender, while about two-thirds of the couple's children are born before the eldest son. Almost half of the mothers have not completed primary education and just over one-third of the sample is living in urban areas.

Fig. 1. Average HFA z-score by Child's Age in Months, Boys vs. Girls 2008-2014



Source: Authors' calculations based on data from MICS 2008, 2011, and 2014. Outliers (z-scores greater than 6 and less than -6 were excluded.

Table 2

Summary Statistics for All Couples with at least One Child < 5 Years Old

Variables	Obs	Mean	Std. Dev.	Min	Max
Average HFA of children born to a mother	86,242	–1.48	1.50	–5.99	5.97
Average HFA of male children born to a mother	53,945	–1.51	1.56	–5.99	5.96
Average HFA of female children born to a mother	51,420	–1.46	1.57	–5.99	5.98
Share of a mother's under-5 children stunted	86,242	.36	.44	0	1
Share of a mother's under-5 sons stunted	53,945	.37	.46	0	1
Share of a mother's under-5 daughters stunted	51,420	.36	.46	0	1
Male share of under-5 children	86,242	0.51	0.34	0	1
Share of children born before eldest son	86,242	0.65	0.32	0.09	1
Number of boys	86,242	1.50	1.16	0	8
Number of girls	86,242	1.50	1.23	0	8
Urban (dummy)	86,242	0.37	0.48	0	1
Landholding (dummy)	86,242	0.32	0.47	0	1
Wealth score	86,242	0.01	0.99	–2.75	2.71
Number of children under 5 years in HH	86,242	1.75	0.99	1	13
Mother educated to primary school (dummy)	86,242	0.18	0.38	0	1
Mother educated to middle school (dummy)	86,242	0.09	0.29	0	1
Mother educated to secondary or higher (dummy)	86,242	0.24	0.43	0	1
HH head educated to secondary or higher (dummy)	86,242	0.30	0.46	0	1
Mother's average age at birth	86,242	27.17	6.77	10	50
Data year=2011 (dummy)	86,242	0.45	0.50	0	1
Data year=2014 (dummy)	86,242	0.19	0.39	0	1
Child age (months)	86,242	29.07	14.31	0	63

Source: Authors' calculations based on MICS Punjab 2008, 2011, and 2014.
The breakdown of observations by year is: 30,547 in 2008; 39,219 in 2011; 16,476 in 2014.

To implement the finite mixture model to identify latent discrimination, we restrict the sample to couples with at least one child of *each* gender under the age of five. This leaves us with a sub-sample of 19,123 couples. Summary statistics for this sub-sample are shown in Table 3. Similar to the full sample, the average daughter's HFA exceeds that of her brother by 0.047 standard deviations. The summary statistics for the sub-sample in Table 3 do not vary much from the full sample described in Table 2.

Details on the other control variables are as follows. The wealth score, provided by the MICS data set, is a composite measure based on a principal component analysis of household assets. The mother's average age at birth is the mean of the mother's age at the birth of each child included in the sample.

Table 3

Summary Statistics for Mixture Model Regression

Variables	Mean	Std. Dev.	Min	Max
Male average less female average of HFA of children 0-5 years of age in HH	–0.047	1.880	–10.560	8.710
Male share of under-5 children	0.490	0.146	0.111	0.889
Share of children born before eldest son	0.572	0.296	0.091	1.000
Urban (dummy)	0.348	0.476	0.000	1.000
Landholding (dummy)	0.317	0.465	0.000	1.000
Wealth score	–0.063	0.981	–2.747	2.695
Number of children under 5 years in HH	2.519	0.909	2.000	13.000
Mother educated to secondary or higher (dummy)	0.220	0.414	0.000	1.000
HH head educated to secondary or higher (dummy)	0.286	0.452	0.000	1.000
Mother's average age at birth	26.703	5.928	10.000	48.500
Data year=2011 (dummy)	0.473	0.499	0.000	1.000
Data year=2014 (dummy)	0.197	0.398	0.000	1.000
Number of Observations = 19,123				

Source: Authors' calculations based on MICS 2008, 2011, 2014 of couples with at least one child of each gender age <5 years.

4. RESULTS

The results are presented in three parts. First, we look at family average stunting and height-for-age z-scores for around 82,000 families included in the pooled MICS data using an OLS analysis. In the second part, we consider the impact on child-level HFA of gender and of not having an elder brother using the pooled MICS data for over 145,000 children under age five, again using OLS. Lastly, we estimate the finite mixture model to search for latent gender discrimination using the data of approximately 19,000 households that had at least one son and one daughter under age-five.

(i) Stunting, Family-Average HFA and Gender Composition of Children

In the first part of the analysis, we examine the role of having a large share of children without an elder brother on the household's share of stunted children and household average HFA in the full sample applying an OLS analysis that includes district fixed-effects. Here, we take as the dependent variable the share of children under-five who are stunted and the family average height-for-age of all children under-five for all couples with at least one child in that age group. This leads to a sample of 86,242 families, using pooled data from MICS Punjab 2008, 2011, and 2014. We also consider the average stunting of male and female children separately. The summary statistics for this sample were described in Table 2. We predict that the share of stunted children will be higher when son-biased fertility preferences are present and the family bears a larger number of children than anticipated in order to have a son, because family resources are stretched further, and each child consequently receives a smaller allocation (Jayachandran & Pande, 2017).

We find that the share of stunted children is higher and the average HFA z-score is lower when the share of children without an elder brother is higher (Table 4, col 1 and 4).[7] These results are suggestive of the hypothesis mentioned earlier, that families might increase their fertility beyond their ability to support their children in pursuit of a son. Interestingly, these son-biased fertility preferences are more likely to hurt sons than daughters, when we look at stunting separately by gender (Table 4, col 2-3). Further, when we run the regressions by wealth quintile, we find that this effect is strongest for the second lowest and the third (middle) wealth quintiles, but insignificant for the poorest and the richest quintiles (Appendix Table 1).

The regressions also lend support to the idea that it is beneficial in general to be in the minority gender-wise. The share of stunted daughters is higher when the male share of under-five children is larger, whereas the reverse is the case for the share of stunted sons (Table 4, col 2-3). Garg and Morduch (1998) had found for Ghana that both boys and girls should benefit nutritionally from a larger number of sisters, because sisters present less competition for household resources; our results for the average stunting of boys coincide with that result, but for girls we get just the opposite. The result for son's under-five being worse off when there is a larger share of boys in the same age group may also reflect the fact that boys have lower HFA scores in general in developing countries (Barcellos et al. 2014). A larger number of total children in the family raises the level of stunting (and lowers the average HFA) of those children under age-five, reflecting quantity/quality tradeoffs.

With 2008 as the base year, the time trend improvements from 2008 to 2011 and 2014 can be seen in the coefficients on the data year dummies (Data year=2011 and Data year=2014). The coefficients on the control variables follow expected patterns: Maternal education and to a lesser extent household head's education confer substantial and statistically significant benefits to child nutrition. Compared to mothers who have not completed primary education (the excluded category), child stunting is lower and average HFA is higher for mothers who have completed each subsequent level of education—primary, middle, and secondary or higher. Landownership and assets overall also

[7]Note that the variable "share of children without an elder brother" takes its highest value (=1) when there is no son or when the first son is the last-born child.

Table 4

Correlates of Share of Children Stunted and Average HFA z-score of a Couple's Children under Age Five, 2008-2014

Variables	(1) Share of under-5 Children Stunted (All)	(2) Share of under-5 Children Stunted (Males)	(3) Share of under-5 Children Stunted (Females)	(4) Avg HFA (all)
Male Share of under-5 Children	0.027***	0.065***	-0.033***	-0.093***
	(0.005)	(0.010)	(0.012)	(0.017)
Share of Children without Elder Brother	0.022***	0.028***	0.002	-0.087***
	(0.007)	(0.009)	(0.011)	(0.023)
Number of Children	0.006***	0.009***	0.008***	-0.010**
	(0.001)	(0.002)	(0.002)	(0.004)
Urban (dummy)	0.024***	0.024***	0.026***	-0.083***
	(0.004)	(0.006)	(0.006)	(0.015)
Landholding (dummy)	-0.037***	-0.037***	-0.036***	0.123***
	(0.003)	(0.005)	(0.005)	(0.012)
Wealth Score	-0.077***	-0.074***	-0.081***	0.288***
	(0.003)	(0.003)	(0.003)	(0.009)
Number of Children under 5 Years in HH	-0.004**	-0.002	-0.005**	0.018***
	(0.002)	(0.002)	(0.002)	(0.006)
Mother Educated to Primary School (dummy)	-0.030***	-0.031***	-0.026***	0.090***
	(0.004)	(0.006)	(0.006)	(0.014)
Mother Educated to Middle School (dummy)	-0.046***	-0.045***	-0.044***	0.145***
	(0.005)	(0.007)	(0.007)	(0.018)
Mother Educated to Secondary or Higher (dummy)	-0.081***	-0.086***	-0.076***	0.304***
	(0.005)	(0.006)	(0.007)	(0.017)
HH Head Educated to Secondary or Higher (dummy)	-0.031***	-0.032***	-0.030***	0.124***
	(0.004)	(0.005)	(0.005)	(0.012)
Mother's Average Age at Birth	-0.001***	-0.001***	-0.001***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
Data year=2011 (dummy)	-0.075***	-0.069***	-0.077***	0.214***
	(0.004)	(0.005)	(0.005)	(0.014)
Data year=2014 (dummy)	-0.089***	-0.087***	-0.088***	0.231***
	(0.005)	(0.006)	(0.006)	(0.016)
Average Child Age (months)	0.010***	0.011***	0.010***	-0.049***
	(0.000)	(0.001)	(0.001)	(0.002)
Squared Avg. Child Age	-0.000***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.264***	0.218***	0.291***	-0.913***
	(0.015)	(0.025)	(0.020)	(0.051)
Number of Observations	86,242	53,945	51,420	86,242
R-Squared	0.086	0.070	0.082	0.108

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.
District fixed-effects included here but not reported.

translate into better nutritional status. All else being equal, children in urban households have higher stunting by about 0.025 points and lower average HFA z-scores, by 0.08 standard deviations. It is unclear what is leading the children of urban areas to experience worse nutritional status but we might speculate that, holding all else equal, there is greater food security and/or lower rates of infectious disease in rural areas.

The coefficients on child age and squared-age show that HFA z-scores (stunting) follow a U shape (inverted-U) pattern, deteriorating in the early months followed by a modest recovery. This is similar to z-score patterns observed worldwide and in South Asia in particular (Victora, de Onis, Hallal, Blössner, & Shrimpton, 2010). Contributing factors include the poor feeding practices that have been documented in Pakistan, such as low rates of breastfeeding in the first hour after birth, and low rates of exclusive breastfeeding, as well as deficiencies in the diversity of complementary foods (Torlesse & Raju, 2018).

Before we conclude this section, we would like to discuss the role of parental height and its absence from the analysis here. Genetic endowment, especially through parental height, has a strong relationship with a child's adult height, and while we would have liked to control for parental height in our regressions, the data is not collected by the MICS. On the other hand, WHO guidelines suggest that children under the age of five, when adequately nourished, will have a common distribution of height-for-age. Our main variable of interest here has been the incidence of stunting, determined by children falling at least two standard deviations below the median height for their gender and age, a measure that is substantially more representative of child nutritional status (and consequently less related to parental height) according to the WHO (de Onis & Blossner, 2003).

On the other hand, where we look at the average HFA of the family's under-five children, we admit that the parental height may be considered an omitted variable. However, bias is only a concern to the extent that the omitted variable is correlated with the explanatory variables. It is plausible that mother's height is positively correlated with her educational attainment and therefore the coefficient on maternal education may be biased upwards. However, we cannot think of a reason *a priori* why a mother's height should be related to our main variables of interest, that is the gender mix of the children, and therefore we remain confident of the results regarding son-biased fertility (i.e., when there is a larger share of children without an elder brother).

As a robustness check, we ran the regressions separately for 2008, 2011, and 2014. While there are some minor changes in the magnitude and statistical significance of a few coefficients (in particular for the 2014 sample, which is much smaller than the other years), the results do not change qualitatively from those presented in Table 4 (see Appendix Tables 2-4).

(ii) Child-level HFA with (or Without) an Elder Brother

In the second part of the analysis, we consider the impact on child-level HFA of gender and of not having an elder brother. For this analysis, we use the individual HFA data on more than 145,000 children (summary statistics at the household level were presented in Table 2). We start with an OLS analysis, first with only the gender variables, and then including a large number of household and child-level controls (Table 5, col 1-2).

Finally, in order to control for other relevant unobservable factors that are constant within neighbourhoods and households, we control for cluster fixed effects (CFE) and household fixed effects (HFE) in Table 5 (col 3-4). Eldest sons have an advantage of 0.09 to 0.21 z-score points. For girls without an elder brother, this advantage is reduced by 0.04-0.05 z-score points, although this effect disappears in the HFE specification. Female children on average are taller by 0.06-0.07 standard deviations for the first three specifications, which rises slightly in the HFE regression. Overall, however, girls without an elder brother have better nutritional outcomes than eldest brothers since the positive coefficient on *Female* overpowers the negative coefficient on the interaction term *Female*No Elder Brother* in all but the HFE specification, as revealed by the F-statistic on the significance of the test *Female+ Female*No elder brother* = 0.

Table 5

Correlates of Child-level HFA z-score of Children under Age 5, 2008-2014

Variables	(1) OLS no Controls	(2) OLS with Controls	(3) CFE	(4) HFE
Female	0.069***	0.062***	0.065***	0.087***
	(0.012)	(0.011)	(0.011)	(0.016)
No Elder Brother	0.210***	0.086***	0.093***	0.203***
	(0.012)	(0.011)	(0.012)	(0.017)
Female* No Elder Brother	–0.044***	–0.040**	–0.045***	0.027
	(0.017)	(0.016)	(0.017)	(0.024)
Observations	146,083	145,817	145,817	146,030
R-squared	0.004	0.121	0.089	0.112
Number of Households				92,074
Number of Clusters			15,588	
F-test: *Female+ Female*No Elder Brother* = 0	F=3.38 Prob > F=0.0659	F=4.52 Prob > F=0.0335	F=2.66 Prob > F=0.1030	F=37.58 Prob > F= 0.0000

Source: Authors' calculations based on MICS 2008, 2011, 2014. Robust standard errors clustered at the mother, cluster, and household levels respectively. Controls include mother's education, household head education, household landholding, wealth, urban dummy, child age-in-months fixed effects, district fixed effects, year-of-birth fixed effects, and month-of-birth fixed effects.

(iii) The Finite Mixture Model

Lastly, we apply the finite mixture model technique on the sub-sample of couples in Punjab that have at least one child of each gender under the age of five (summarised in Table 3), using a set of controls resembling those used in Morduch and Stern (1997)[8] to see if there is a latent group of households with a pro-son bias. The dependent variable we use to measure latent gender discrimination is defined at the couple-level as the difference in the average HFA for sons and the average HFA for daughters: (average

[8]Morduch and Stern (1997) controlled for: age of woman head of household, income per capita, Hindu religion, rural location, household size, mother's education, distances to medical facilities and regional centres, and gender of first born.

HFA of sons - average HFA of daughters). Since development is associated with greater gender equality in a variety of settings, we predict that discrimination will be lower for families that are wealthier, urban, and more educated, but higher for families with son-biased fertility preferences, the latter being consistent with Jayachandran and Pande (2017).

As a first step, before applying the mixture model, we run an OLS regression on the full (pooled) sample of around 19,000 couples to see the how the population average gender gap in HFA varies with household characteristics.[9] According to the OLS regression results, girls have an average *advantage* of 0.132 standard deviations in height-for-age z-score over their brothers when we control only for household characteristics, which rises to 0.208 standard deviations when we control for gender composition (Table 6, col 1-2).

Table 6

Finite Mixture Model Results

Dependent variable: Male average less female average of height-for-age in family (Children Aged 0-5 years)

Variables	(1) Pooled Sample (OLS)	(2) Pooled Sample (OLS)	(3) Group 1 (FMM)	(4) Group 2 (FMM)
Residual Difference in HFA (Boys - Girls)	**-0.132***	**-0.204***	**-0.144**	**-0.329**
	(0.080)	(0.118)	(0.159)	(0.380)
Share of Male Children		-0.219**	-0.141	-0.379
		(0.108)	(0.151)	(0.345)
Share of Children without Elder Brother		0.217***	0.090	0.484***
		(0.055)	(0.075)	(0.184)
Urban (dummy)	0.028	0.034	-0.014	0.138
	(0.036)	(0.036)	(0.048)	(0.115)
Landholding (dummy)	-0.029	-0.033	0.009	-0.121
	(0.031)	(0.031)	(0.043)	(0.102)
Wealth Score	-0.014	-0.023	0.008	-0.087
	(0.019)	(0.020)	(0.028)	(0.066)
Number of Children under 5 Years in HH	0.004	0.009	0.023	-0.023
	(0.015)	(0.015)	(0.020)	(0.046)
Mother Educated to Secondary or Higher (dummy)	-0.035	-0.045	-0.067	0.002
	(0.039)	(0.039)	(0.050)	(0.123)
HH Head Educated to Secondary or Higher (dummy)	-0.025	-0.024	0.019	-0.114
	(0.034)	(0.034)	(0.044)	(0.112)
Mother's Average Age at Birth	0.003	0.005**	0.003	0.009
	(0.002)	(0.002)	(0.004)	(0.008)
Observations		19,123	19,123	19,123
Classification Based on Likely Latent Class Membership			16641	2482

Source: Authors' calculations based on MICS 2008, 2011, 2014.

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

[9]Given that the dependent variable in the mixture model is the *difference* in height-for-age between male and female siblings, the effect of parental height drops out as long as parental height affects both genders to roughly the same extent.

The female advantage in our sample is reinforced when there is a larger share of sons in the household but is reduced in families where the share of children without an elder brother is higher; in other words, the female advantage in HFA falls when the first son is born at a later birth order (Table 6, col 2). Therefore, when the eldest son is born at a later birth order, either the son(s) are doing better nutritionally, daughter(s) are doing worse, or both. This might happen if some families increase their fertility beyond the number of children they can support, to have a son, harming the nutritional status of the elder daughters, known as a son-biased fertility pattern. However, a more benign possibility is that if the boy is the youngest he will naturally have a higher HFA because, as noted in Figure 1, younger children (especially less than 15 months) tend to have higher HFA z-scores than older children do.

Next, in order to test whether a latent sub-population of couples with a pro-son bias exists, we apply the finite mixture model to divide the sample into two groups. When we do this, however, we do not find a higher height-for-age for boys in either group. In fact, we identify one group where girls have a statistically insignificant advantage in their height-for-age of 0.14 z-score points (Table 6, col 3), and a second group where girls have a larger but still statistically insignificant advantage of 0.329 z-score points over their brothers (Table 6, col 4). Group 1, identified by the mixture model, encompasses 87 percent of the observations. As a robustness check, we carried out the FMM estimation separately for households with two children and for households with three or more children. In both cases, the constant term, which is the measure for latent discrimination, is statistically insignificant (Appendix Table 7). As another robustness check, we included district fixed effects; again, the results did not change qualitatively from those reported in Table 5 (Appendix Table 8).

Therefore, we do not find evidence of the same kind of latent discrimination against girls as was found in Bangladesh by Morduch and Stern (1997) using the mixture model approach, where they found sons to have 7 percent higher HFA z-scores on average than daughters in one group of households.[10] Morduch and Stern (1997) also found that mothers' education at the primary level and rural households benefited boys over girls, but we do not find the same in our results. Another result of Morduch and Stern (1997) was that the height advantage of boys was greater when the first-born child was a girl. This is similar to our result that the height advantage of boys was greater when the share of children without an elder brother was higher (that is, the first-born children were girls).

Concluding this section, we found that the male-female gap was statistically insignificant in our FMM specification. In addition, the diagnostic tests on the FMM cast doubt that our model can identify two distinct classes of families (Appendix Table 6).[11] Putting these together, we are not confident that we can classify a latent group of families discriminating based on gender.

[10]Given that there were some outliers for the dependent variable, as seen in the summary statistics in Table 3, we re-estimate the mixture model excluding those households for which the difference in HFA z-scores between male and female children is less than 6 in absolute value. The results, shown in Appendix Table 5, do not change substantially from Table 6.

[11]Diagnostics of the finite mixture model results are in Appendix Table 6. We see that average probability of a household being assigned to a latent class if they are actually a member of that group is nearly 74 percent, which appears promising. However, as the entropy measure is only around 0.2 (on a scale of 0 to 1), the mixture model has less explanatory power than we would expect if there were in fact two distinct classes of households; typically, the entropy measure should take a value at least 0.5.

5. CONCLUSIONS

Child nutritional status has improved in Punjab, Pakistan over the period 2008 to 2014, as severe stunting rates have declined by 8.6 percentage points and average HFA has increased by 0.19 standard deviations. However, the nutritional status of its children is still quite poor in comparison to a number of Sub-Saharan African countries. Studies in India and Bangladesh have found evidence pointing to potential latent gender discrimination (Barcellos et al. 2014; Jayachandran & Pande, 2017; Morduch& Stern, 1997).

Barcellos et al. (2014) had found that youngest-born girls had an advantage of 0.181 standard deviations over youngest-born boys using DHS data from 58 developing countries spanning 1986 – 2009, although this advantage was 0.034 deviations smaller for Indian girls. Replicating their analysis using our sample, in unreported results, we find that youngest girls have an advantage of 0.127 standard deviations over youngest boys, in other words an advantage even smaller than Barcellos et al. (2014) observed for Indian girls.

We find that girls in Punjab have a smaller HFA advantage over boys as seen in other studies in developing countries. Yet we do not find evidence of latent discrimination against girls using the finite mixture model, unlike what Morduch and Stern (1997) found in Bangladesh. We do find, however, that when a larger share of children is born before the eldest son, that is, a son is born after many daughters that the share of children stunted is higher and the average HFA of the children is lower. This suggests that families extend their fertility quite possibly beyond the number of children they can support in pursuit of sons. Current evidence does not suggest that this has led to sex-selective abortions (Zaidi & Morgan, 2016). We conclude that couples' preferences regarding the gender composition of their offspring (in particular, pursuit of a son) can lead to excess fertility, which can have subsequent effects on the long-term nutritional status of their children, especially (and ironically) sons. These effects are concentrated in the second (from bottom) and third (middle) quintiles of wealth.

Fertility preferences driven by son-bias are attitudes that are unlikely to change in the short term, but have scope to change as the status of women in the household improves through higher rates of educational attainment, participation of women in the labour force, and greater empowerment of women. Increasing education of mothers also has a direct impact on children's nutritional status.[12]

Arif, Farooq, Nazir, & Satti (2014, p. 115) note that child malnutrition is a difficult problem to tackle, as it is "deeply rooted in child illness, environmental factors and a weak health system", further finding that it will not be fixed simply through economic growth or poverty alleviation. Even so, there are many useful interventions available to improve nutrition in the near term, in particular early and exclusive breastfeeding and a diverse complementary diet as children age (Torlesse and Raju, 2018). Raju and D'Souza (2017) note that Pakistan's expenditures on nutrition programmes are low, and this is an area where targeted improvements can be made, especially in lagging areas.

[12]In a related analysis of the correlates of child-level HFA carried out in a separate study, we find that child nutritional status is positively related to mother's and household head's education, household wealth and land ownership, and negatively related to birth order, child age-in-months, and living in urban areas (Chaudhry, Khan, & Mir, 2018).

Raju and D'Souza's literature review also summarises some evidence that cash transfer programs like BISP can improve the nutritional status of girls. The lady health worker (LHW) program has proven to be effective in some areas of child nutrition such as growth monitoring, and can be further improved in other aspects, including encouraging early and exclusive breastfeeding and proper complementary feeding. Isolated pilot programs to improve child nutrition by LHWs have shown much promise for future scaling up (Raju & D'Souza, 2017). Finally, given that son-biased fertility (that is, having too many children in order to bear a son) appears to be a significant factor in child stunting, family planning and birth spacing should also be strongly encouraged.

Appendix Table 1

Correlates of Share of Children Stunted a Couple's Children under Age Five, 2008-2014, by Wealth Quintile

Variables	Lowest Quintile	Second Quintile	Middle Quintile	Fourth Quintile	Highest Quintile
Male Share of under-5 Children	0.021	0.036***	0.035***	0.028***	0.020**
	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)
Share of Children without Elder Brother	0.016	0.037**	0.038**	0.004	0.008
	(0.017)	(0.016)	(0.015)	(0.014)	(0.014)
Number of Children	0.004	0.010***	0.013***	0.008***	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Urban (dummy)	-0.007	0.018*	0.036***	0.035***	0.017*
	(0.016)	(0.011)	(0.008)	(0.007)	(0.009)
Landholding (dummy)	-0.033***	-0.035***	-0.027***	-0.043***	-0.038***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Wealth Score	-0.059***	-0.086***	-0.104***	-0.102***	-0.053***
	(0.013)	(0.019)	(0.019)	(0.017)	(0.009)
Number of Children under 5 Years in HH	-0.017***	-0.005	-0.003	0.001	0.000
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Mother Educated to Primary School (dummy)	-0.032**	-0.045***	-0.030***	-0.029***	-0.009
	(0.014)	(0.009)	(0.008)	(0.009)	(0.014)
Mother Educated to Middle School (dummy)	-0.032	-0.040***	-0.057***	-0.036***	-0.039***
	(0.030)	(0.015)	(0.011)	(0.010)	(0.013)
Mother Educated to Secondary or Higher	-0.053	-0.086***	-0.082***	-0.078***	-0.079***
(dummy)	(0.043)	(0.017)	(0.010)	(0.008)	(0.011)
HH Head Educated to Secondary or Higher	-0.051***	-0.024**	-0.032***	-0.032***	-0.026***
(dummy)	(0.014)	(0.009)	(0.007)	(0.006)	(0.007)
Mother's Average Age at Birth	-0.001	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Data year=2011 (dummy)	-0.048***	-0.056***	-0.077***	-0.072***	-0.098***
	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
Data year=2014 (dummy)	-0.035***	-0.063***	-0.102***	-0.097***	-0.135***
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)
Average Child Age (months)	0.014***	0.013***	0.011***	0.009***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Squared Avg. Child Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.253***	0.223***	0.249***	0.325***	0.393***
	(0.034)	(0.032)	(0.028)	(0.028)	(0.031)
Number of Observations	15,838	16,579	17,923	19,101	16,801
R-Squared	0.030	0.033	0.044	0.041	0.041

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 2

Correlates of Share of Children Stunted and Average HFA z-score of a Couple's Children under Age Five, 2008

Variables	(1) Share of under-5 Children Stunted (All)	(2) Share of under-5 Children Stunted (Males)	(3) Share of under-5 Children Stunted (Females)	(4) Avg HFA (All)
Male Share of under-5 Children	0.019**	0.059***	-0.043**	-0.127***
	(0.009)	(0.018)	(0.021)	(0.033)
Share of Children without Elder Brother	0.017	0.032*	-0.019	-0.105**
	(0.011)	(0.016)	(0.019)	(0.043)
Number of Children	0.007***	0.009**	0.009***	-0.017*
	(0.002)	(0.004)	(0.003)	(0.009)
Urban (dummy)	0.048***	0.041***	0.052***	-0.167***
	(0.008)	(0.010)	(0.010)	(0.030)
Landholding (dummy)	-0.017***	-0.018**	-0.015*	0.060***
	(0.006)	(0.008)	(0.008)	(0.023)
Wealth Score	-0.077***	-0.072***	-0.081***	0.307***
	(0.004)	(0.005)	(0.006)	(0.016)
Number of Children under 5 Years in HH	-0.010***	-0.006	-0.013***	0.044***
	(0.003)	(0.004)	(0.004)	(0.011)
Mother Educated to Primary School (dummy)	-0.038***	-0.045***	-0.028***	0.133***
	(0.008)	(0.010)	(0.010)	(0.029)
Mother Educated to Middle School (dummy)	-0.041***	-0.037***	-0.039***	0.143***
	(0.010)	(0.014)	(0.013)	(0.037)
Mother Educated to Secondary or Higher (dummy)	-0.061***	-0.077***	-0.040***	0.261***
	(0.009)	(0.011)	(0.012)	(0.033)
HH Head Educated to Secondary or Higher (dummy)	-0.015**	-0.013	-0.020**	0.077***
	(0.006)	(0.008)	(0.008)	(0.024)
Mother's Average Age at Birth	-0.002***	-0.002***	-0.003***	0.007***
	(0.000)	(0.001)	(0.001)	(0.002)
Average Child Age (months)	0.009***	0.009***	0.008***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.003)
Squared Avg. Child Age	-0.000***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.324***	0.255***	0.368***	-1.000***
	(0.022)	(0.039)	(0.030)	(0.086)
Number of Observations	30,547	18,879	17,962	30,547
R-Squared	0.052	0.045	0.048	0.070

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3

Correlates of Share of Children Stunted and Average HFA z-score of a Couple's Children under Age Five, 2011

Variables	(1) Share of under-5 Children Stunted (All)	(2) Share of under-5 Children Stunted (Males)	(3) Share of under-5 Children Stunted (Females)	(4) Avg HFA (All)
Male Share of under-5 Children	0.035***	0.071***	-0.025	-0.104***
	(0.007)	(0.015)	(0.018)	(0.023)
Share of Children without Elder Brother	0.026***	0.027*	0.011	-0.083***
	(0.010)	(0.014)	(0.016)	(0.031)
Number of Children	0.008***	0.011***	0.008***	-0.018***
	(0.002)	(0.003)	(0.003)	(0.006)
Urban (dummy)	0.017***	0.024***	0.020***	-0.069***
	(0.006)	(0.008)	(0.008)	(0.019)
Landholding (dummy)	-0.043***	-0.039***	-0.046***	0.149***
	(0.005)	(0.007)	(0.007)	(0.017)
Wealth Score	-0.076***	-0.075***	-0.079***	0.287***
	(0.003)	(0.004)	(0.005)	(0.011)
Number of Children under 5 Years in HH	-0.001	-0.001	-0.001	0.007
	(0.002)	(0.003)	(0.003)	(0.008)
Mother Educated to Primary School (dummy)	-0.038***	-0.036***	-0.034***	0.094***
	(0.006)	(0.008)	(0.008)	(0.019)
Mother Educated to Middle School (dummy)	-0.050***	-0.050***	-0.047***	0.144***
	(0.008)	(0.011)	(0.011)	(0.025)
Mother Educated to Secondary or Higher (dummy)	-0.093***	-0.094***	-0.096***	0.325***
	(0.007)	(0.009)	(0.009)	(0.022)
HH Head Educated to Secondary or Higher (dummy)	-0.040***	-0.040***	-0.039***	0.149***
	(0.005)	(0.007)	(0.007)	(0.016)
Mother's Average Age at Birth	-0.001***	-0.002***	-0.001***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
Average Child Age (months)	0.011***	0.012***	0.010***	-0.050***
	(0.001)	(0.001)	(0.001)	(0.002)
Squared Avg. Child Age	-0.000***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.203***	0.168***	0.221***	-0.759***
	(0.018)	(0.033)	(0.025)	(0.060)
Number of Observations	39,219	24,741	23,532	39,219
R-Squared	0.083	0.067	0.080	0.118

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 4

Correlates of Share of Children Stunted and Average HFA z-score of a Couple's Children under Age Five, 2014

Variables	(1) Share of under-5 Children Stunted (All)	(2) Share of under-5 Children Stunted (Males)	(3) Share of under-5 Children Stunted (Females)	(4) Avg HFA (All)
Male Share of under-5 Children	0.029***	0.073***	-0.022	-0.028
	(0.011)	(0.022)	(0.027)	(0.034)
Share of Children without Elder Brother	0.016	0.019	0.017	-0.056
	(0.015)	(0.021)	(0.024)	(0.046)
Number of Children	0.008***	0.009**	0.012***	-0.004
	(0.003)	(0.004)	(0.004)	(0.008)
Urban (dummy)	0.012	0.007	0.006	-0.040
	(0.009)	(0.012)	(0.011)	(0.027)
Landholding (dummy)	-0.052***	-0.060***	-0.044***	0.150***
	(0.007)	(0.010)	(0.010)	(0.024)
Wealth Score	-0.093***	-0.084***	-0.097***	0.319***
	(0.005)	(0.007)	(0.007)	(0.016)
Number of Children under 5 Years in HH	0.002	0.004	-0.003	-0.009
	(0.003)	(0.005)	(0.005)	(0.011)
Mother Educated to Primary School (dummy)	-0.029***	-0.017	-0.029**	0.089***
	(0.010)	(0.013)	(0.013)	(0.027)
Mother Educated to Middle School (dummy)	-0.062***	-0.059***	-0.064***	0.191***
	(0.012)	(0.016)	(0.016)	(0.036)
Mother Educated to Secondary or Higher (dummy)	-0.092***	-0.088***	-0.098***	0.345***
	(0.011)	(0.014)	(0.014)	(0.033)
HH Head Educated to Secondary or Higher (dummy)	-0.044***	-0.053***	-0.037***	0.156***
	(0.007)	(0.010)	(0.010)	(0.023)
Mother's Average Age at Birth	-0.001***	-0.002***	-0.001	0.004***
	(0.000)	(0.001)	(0.001)	(0.001)
Average Child Age (months)	0.012***	0.011***	0.012***	-0.048***
	(0.001)	(0.001)	(0.001)	(0.003)
Squared Avg. Child Age	-0.000***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.173***	0.154***	0.149***	-0.810***
	(0.027)	(0.049)	(0.035)	(0.085)
Number of Observations	16,476	10,325	9,926	16,476
R-Squared	0.118	0.090	0.119	0.155

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 5

Mixture Model Results on Restricted Sample (|Dependent variable| <6

Dependent variable: Male average less female average of height-for-age in HH (Children Aged 0-5 years)

Variables	(1) Pooled Sample	(2) Group 1	(3) Group 2	(4) Pooled Sample	(5) Group 1	(6) Group 2
Residual Difference in HFA (Boys - Girls)	-0.198*	0.087	-0.322	-0.204*	-0.006	-0.291
	(0.115)	(0.299)	(0.200)	(0.114)	(0.285)	(0.188)
Share of Male Children	-0.196*	0.018	-0.286	-0.198*	-0.020	-0.271
	(0.105)	(0.323)	(0.193)	(0.105)	(0.314)	(0.186)
Share of Children Born before Eldest Son	0.193***	-0.036	0.294***	0.191***	-0.040	0.290***
	(0.053)	(0.131)	(0.088)	(0.053)	(0.132)	(0.087)
Urban (dummy)	0.032	-0.016	0.057	0.026	-0.038	0.056
	(0.034)	(0.096)	(0.060)	(0.034)	(0.085)	(0.057)
Landholding (dummy)	-0.016	0.010	-0.027	-0.017	0.020	-0.032
	(0.030)	(0.080)	(0.051)	(0.030)	(0.077)	(0.050)
Wealth Score	-0.025	0.040	-0.054	-0.022	0.042	-0.051
	(0.019)	(0.054)	(0.034)	(0.019)	(0.055)	(0.034)
Number of Children under 5 Years in HH	0.012	0.015	0.010	0.012	0.017	0.009
	(0.014)	(0.030)	(0.023)	(0.014)	(0.031)	(0.023)
Mother Educated to Secondary or Higher (dummy)	-0.048	-0.071	-0.037	-0.048	-0.064	-0.041
	(0.037)	(0.084)	(0.061)	(0.037)	(0.082)	(0.059)
HH Head Educated to Secondary or Higher (dummy)	0.001	0.022	-0.008	0.000	0.028	-0.012
	(0.032)	(0.077)	(0.054)	(0.032)	(0.076)	(0.053)
Mother's Average Age at Birth	0.005**	-0.000	0.007	0.005*	-0.001	0.007*
	(0.002)	(0.007)	(0.004)	(0.002)	(0.007)	(0.004)
Data year=2011 (dummy)	-0.046	-0.146	-0.008			
	(0.031)	(0.227)	(0.104)			
Data year=2014 (dummy)	0.031	-0.145	0.106			
	(0.036)	(0.221)	(0.105)			
Observations	18,987	18,987	18,987	18,987	18,987	18,987

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 6

Average Posterior Probabilities

Mean	LC1	LC2
p1	**0.738**	0.262
p2	0.264	**0.736**
Entropy	**0.201**	

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.

Appendix Table 7

FMM Estimation, Splitting Sample by Number of Children

	Two Child Families			Families with 3+ Children		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Pooled Sample	Group 1	Group 2	Pooled Sample	Group 1	Group 2
Residual Difference in HFA (Boys - Girls)	-0.260*	0.067	-0.951*	-0.045	-0.147	0.242
	(0.153)	(0.215)	(0.531)	(0.183)	(0.259)	(0.693)
Share of Male Children	-0.180	-0.366	0.221	-0.255*	0.042	-0.997*
	(0.154)	(0.227)	(0.533)	(0.151)	(0.197)	(0.514)
Share of Children Born before Eldest Son	0.269***	0.050	0.738***	0.137	0.139	0.115
	(0.072)	(0.095)	(0.252)	(0.088)	(0.125)	(0.324)
Urban (dummy)	0.049	0.059	0.038	0.020	-0.083	0.262
	(0.046)	(0.062)	(0.150)	(0.056)	(0.078)	(0.199)
Landholding (dummy)	-0.030	0.005	-0.110	-0.032	-0.011	-0.085
	(0.040)	(0.055)	(0.134)	(0.048)	(0.066)	(0.166)
Wealth Score	-0.033	-0.016	-0.073	-0.004	0.021	-0.057
	(0.026)	(0.036)	(0.085)	(0.030)	(0.044)	(0.110)
Number of Children under 5 Years in HH	-			-0.013	0.047	-0.152
				(0.024)	(0.033)	(0.100)
Mother Educated to Secondary or Higher (dummy)	-0.073	-0.131**	0.052	-0.008	0.054	-0.154
	(0.051)	(0.064)	(0.167)	(0.060)	(0.078)	(0.217)
HH head Educated to Secondary or Higher (dummy)	0.003	0.075	-0.139	-0.065	-0.049	-0.111
	(0.044)	(0.056)	(0.147)	(0.053)	(0.072)	(0.189)
Mother's Average Age at Birth	0.005*	0.006	0.004	0.005	-0.003	0.025*
	(0.003)	(0.005)	(0.011)	(0.004)	(0.006)	(0.014)
Data year=2011 (dummy)	-0.029	-0.176**	0.240	-0.033	-0.069	0.035
	(0.042)	(0.079)	(0.181)	(0.052)	(0.095)	(0.220)
Data year=2014 (dummy)	0.054	-0.146*	0.449**	0.030	0.038	-0.013
	(0.050)	(0.083)	(0.194)	(0.060)	(0.098)	(0.236)
Observations	12,107	12,107	12,107	7,016	7,016	7,016
R-squared	0.003			0.002		

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 8

FMM Regression including District Fixed Effects

Variables	(1) Pooled Sample	(2) Group 1	(3) Group 2
Residual Difference in HFA (Boys - Girls)	-0.055	-0.081	-0.581
	(0.137)	(0.218)	(0.515)
Share of Male Children	-0.218**	-0.122	-0.384
	(0.108)	(0.155)	(0.350)
Share of Children Born before Eldest Son	0.215***	0.079	0.494***
	(0.055)	(0.075)	(0.181)
Urban (dummy)	0.025	-0.031	0.141
	(0.037)	(0.051)	(0.119)
Landholding (dummy)	-0.035	-0.010	-0.092
	(0.031)	(0.043)	(0.101)
Wealth Score	-0.006	0.038	-0.097
	(0.022)	(0.031)	(0.070)
Number of Children under 5 Years in HH	0.009	0.024	-0.022
	(0.015)	(0.020)	(0.048)
Mother Educated to Secondary or Higher (dummy)	-0.049	-0.061	-0.017
	(0.039)	(0.050)	(0.124)
HH Head Educated to Secondary or Higher (dummy)	-0.028	0.011	-0.105
	(0.034)	(0.045)	(0.111)
Mother's Average Age at Birth	0.005**	0.003	0.010
	(0.002)	(0.004)	(0.008)
Data year=2011 (dummy)	-0.030	-0.122*	0.137
	(0.034)	(0.065)	(0.140)
Data year=2014 (dummy)	0.036	-0.065	0.227
	(0.040)	(0.070)	(0.149)
2.districtcode	-0.211**	0.019	0.545
	(0.092)	(0.159)	(0.396)
3.districtcode	-0.148	0.085	-0.253
	(0.090)	(0.155)	(0.386)
4.districtcode	-0.024	0.184	-0.240
	(0.128)	(0.167)	(0.399)
5.districtcode	-0.203*	0.166	0.165
	(0.105)	(0.243)	(0.553)
6.districtcode	-0.133	0.006	-0.053
	(0.108)	(0.162)	(0.402)
7.districtcode	-0.038	0.036	0.085
	(0.122)	(0.202)	(0.463)
8.districtcode	-0.121	0.155	0.151
	(0.084)	(0.207)	(0.472)
9.districtcode	-0.093	-0.059	0.333
	(0.097)	(0.149)	(0.372)
10.districtcode	-0.079	0.160	-0.033
	(0.109)	(0.161)	(0.406)
11.districtcode	-0.253***	-0.080	0.501
	(0.095)	(0.172)	(0.431)
12.districtcode	-0.185*	-0.102	0.011
	(0.101)	(0.157)	(0.403)
13.districtcode	-0.127	-0.017	0.050
	(0.122)	(0.156)	(0.398)
14.districtcode	-0.075	-0.081	0.366
	(0.122)	(0.180)	(0.480)
15.districtcode	-0.264**	0.231	-0.145
	(0.112)	(0.184)	(0.440)

Continued—

Appendix Table 8—(*Continued*)

16.districtcode	-0.288***	0.105	-0.455
	(0.107)	(0.177)	(0.430)
17.districtcode	-0.175*	-0.385**	0.455
	(0.099)	(0.181)	(0.448)
18.districtcode	-0.206**	0.092	-0.144
	(0.099)	(0.168)	(0.409)
19.districtcode	-0.220**	-0.126	0.203
	(0.111)	(0.172)	(0.419)
20.districtcode	-0.071	0.260	-0.628
	(0.107)	(0.187)	(0.435)
21.districtcode	-0.088	0.017	0.321
	(0.112)	(0.169)	(0.454)
22.districtcode	-0.076	-0.185	0.608
	(0.102)	(0.259)	(0.557)
23.districtcode	-0.140	-0.061	0.433
	(0.118)	(0.227)	(0.482)
24.districtcode	-0.233**	0.109	-0.048
	(0.115)	(0.213)	(0.496)
25.districtcode	-0.077	0.005	-0.143
	(0.126)	(0.183)	(0.454)
26.districtcode	-0.236**	-0.084	0.478
	(0.118)	(0.246)	(0.540)
27.districtcode	-0.240**	-0.070	-0.010
	(0.102)	(0.174)	(0.456)
28.districtcode	-0.190*	0.002	-0.169
	(0.101)	(0.170)	(0.414)
29.districtcode	-0.224*	0.034	-0.069
	(0.133)	(0.157)	(0.414)
30.districtcode	-0.081	0.254	-0.528
	(0.118)	(0.245)	(0.596)
31.districtcode	0.022	-0.002	0.357
	(0.109)	(0.172)	(0.456)
32.districtcode	-0.021	0.113	0.431
	(0.093)	(0.160)	(0.432)
33.districtcode	-0.084	0.058	0.425
	(0.111)	(0.149)	(0.380)
34.districtcode	-0.084	0.158	0.003
	(0.117)	(0.196)	(0.444)
35.districtcode	-0.280**	0.305*	-0.366
	(0.131)	(0.165)	(0.429)
36.districtcode	-0.188	-0.127	-0.000
	(0.133)	(0.174)	(0.462)
Observations	19,123	19,123	19,123
R-squared	0.004		
Adjusted R-squared	0.000285	0.00180	0.00180

Source: Authors' calculations based on data from MICS 2008, 2011 and 2014.
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

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