Gender differences in mathematics performance: Evidence from rural India

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Abstract

The paper examines gender gap in performance in mathematics among rural children at an all-India level. Our findings show significant gap in mathematics which is not observable for reading skills or writing skills. The results remain consistent across various types of households. While exploring the possible reasons behind the gender gap, we find indicative evidences of: worse health outcomes for girls in early childhood, possible higher participation of boys in petty works outside home or in sports, and economic aspirations along with gender role stereotyping emanating from family and society as (one or multiple) possible explanations. The policy recommendations include research in form of systematic evaluations to identify the instruments including the psychological interventions which can help in reducing the gender gap in mathematics. This is especially necessary in states that do not show significant improvement in performance of girls with respect to boys over the years.

Keywords: Gender gap; mathematics; rural; India; learning outcomes

JEL Classification: I21, I28, J16

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I. Introduction

Gender has been one of the most pervasive forms of inequality across all classes, social groups and communities especially in developing countries. Along with glaring gender bias in health inputs like immunization, women tend to be deprived in the labor market as well as job opportunities, and wages are found to be substantially lower than that for males **(Weichselbaumer and Winter-Ebmer, 2005; Sengupta and Das, 2014).** Much of this gender wage gap can be explained by the significant gender bias that is prevalent in education since learning outcomes play a major role in shaping up individual development and earnings **(Hanushek and Woessemann, 2008; Stiglitz, Sen and Fitoussi,2010).** In particular, difference in performance in mathematics is found to be at least partly responsible in enhancing the gender wage gap and reduction of opportunities in the labor market **(Murnane, Willet and Levy,1995; Altonji and Blank, 1999)**.

This paper draws motivation from this aspect and attempts to examine gender disparity in test scores in mathematics among rural children at an all-India level. The paper also looks at the association of gender of the child and learning outcomes in reading and writing to explore if gender gap is evident in other subjects apart from mathematics. Our findings show significant chances of a rural female child scoring poorly in mathematics as compared to a similar male child. We find our inferences to hold for households of different socio-economic structure and also observe evidence of girls performing poorly than boys belonging to the same households.

In trying to understand the persistent gender gap, we find differences in innate abilities (or biological differences across gender) not likely to be the reason as we find urban females to score similarly in comparison to the urban males. This leaves us with four potential reasons in the context of rural India which might explain these differences: gender stereotyping emanating from households (mainly parents), society or from school; comparatively lower nutrition level among female children as younger ages, economic aspiration in the household and more involvement of boys in activities (such as petty work and sports) or chores which involve simple mathematical skills like identification of numbers, addition and subtraction at an early age. Our findings are only indicative of a possible role of one or several of these reasons to explain the gender gap in mathematics performance. In the absence of exogenous variation, further research is necessary to establish the exact causal channel(s).

One of the recent and important works in this area has been that by **Bharadwaj et al. (2016)**, who found significant gender gap in mathematics scores in Chile, which tends to increase at higher ages even after controlling for a host of relevant factors that may affect mathematical performance. Our paper examines this gender gap in rural India, which holds importance for various reasons. Firstly, data suggests that gender inequality in India is substantially higher than that in Chile. For example, Gender Inequality Index (GII) in Chile is found to be 0.325 and 0.322 in 2014 and 2015 respectively, whereas for India, it is as high as 0.544 and 0.530 and this figure is likely to be higher in rural India.[1] Very recently, it is found that India has slipped 21 places in terms of Global Gender Gap Index brought out by the World Economic Forum.[2] Likewise, this inequality is spread across health dimension, labour market and education as well. Secondly in this paper, we examine the nutrition and health in the early childhood and its role in explaining the gender gap in mathematics performance. This is because studies have found gender difference in nutrition to be prevalent in India **(Pande 2003)**. The case of India is also unique in terms of various underlying sociological factors related to gender that emanates from the society, family members and schools. In this context, our paper attempts to evaluate the significance of gender role stereotyping in explaining the differences in scores. Additionally, we also attempt to relate the gap with activities in which rural children in India might typically be involved which are often gendered themselves (for example, boys are more likely to carry out activities outside the home). Although the broad objectives remain same as that by **Bharadwaj et al. (2016)**, our paper examines the social underpinnings that are typical to India and attempt to associate those with the gender gap in mathematical scores and open up further related research questions.

The structure of the paper is as follows. Section 2 discusses the literature related to differences in mathematics learning among females. Section 3 talks about the data used in the paper and then discusses about the

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[1] The data can be retrieved from http://hdr.undp.org/en/data (last accessed on September 28, 2017). Description of the GII can be obtained from the website.

[2] Please refer to the article: http://www.thehindu.com/news/national/india-slips-21-slots-occupy-108th-rank-on-wef-gender-gap-index-2017/article19966894.ece (last accessed on November 4, 2017)

variables used in the paper. Section 4 presents the econometric methodology used in the paper. Section 5 discusses the results obtained from the econometric exercise and discusses the possible mechanisms of the observable gender gap. Limitations of the paper are discussed in section 6 and section 7 presents the conclusion.

II. Gender gap in mathematics scores

One of the earliest works which analysed differences across gender in terms of mathematical scores is by **Benbow and Stanley (1980)** who found ‘sex differences’ in mathematics using the math component of the SAT examination, which is a standardized test for college admission in the United States. Another major work in this direction is the one by **Fryer and Levitt (2010),** who find no difference in math scores between boys and girls in the United States upon entry to school but an emergence of gender gap is found in early years of schooling. They find parental expectations with regards to math to be lower for girls and even for girls whose mothers are in math-related professions, the results do not change. As discussed earlier, **Bharadwaj et al. (2016)** also find the existence of gender gap in mathematics in Chile. Similar results were found in Baltimore **(Entwisel, Alexander and Olsen,1994)** and across other low and middle income countries as well **(Bharadwaj et al. 2012).** Female children of various ages also tend to report higher levels of mathematical anxiety (**Devine et al. 2012**). This anxiety arises not just due to the subject but to the way math is presented and/or taught in school where often teachers with that anxiety might pass it on to their students (Stuart, 2000).

This paper examines gender gap in mathematics scores among rural children at an all-India level. Literature on this issue from India is limited to papers that have attempted to analyse the possible set of factors that may be responsible for the gender gap in multiple cognitive skills and not mathematics alone **(Jain, 2016; Singh and Krutikova, 2017)**. Our paper looks closely to the persisting gender gap in mathematics which does not seem to be strongly evident in other cognitive skills and the possible specific reasons thereof pertaining to the outcome in mathematics scores. Particular to mathematics, **Muralidharan and Seth (2016)** found girls to be likely to score at par with boys in mathematics at the end of first grade but perform significantly worse by the end of 5 grade. Though their primary interest was to look at the role of teacher gender to reduce gender gaps in learning and focussed on the state of Andhra Pradesh. While the **National Curriculum Framework (NCF)** set up by the National Council of Educational Research and Training (NCERT) in India acknowledges the possibility of difference in the learning experience between males and females and higher mathematical phobia or anxiety among female children **(NCERT, 2005),** empirical evidence in this issue is very limited. Hence this paper is among the first attempts to empirically examine if girl children score significantly lesser in mathematics than a similar boy child at the primary level and explore the possible reasons, in the Indian context.

III. Data and variables

We use data from the **Indian Human Development Survey** conducted in 2011-12, conducted jointly by National Council of Applied Economic Research (NCAER) and University of Maryland. The dataset covered over 40,000 households gathered data on education, health, economic wellbeing, social status, and various other domains. Short tests capturing learning outcomes on reading, math and writing for children aged 8-11 years were also administered in the survey. These simple tests were conducted in 14 languages (where children could choose to write the test in a language that they chose) and each test was successfully administered to over 11,500 children (over 8000 children belonged to rural households) at their homes. These test scores serve as the outcome variables of the paper. While our main variable of interest is mathematics scores, we also look at scores in reading and writing to gain a better understanding of differences (if any). We also utilise the earlier round of the same survey conducted in 2005 to study the improvements in test score performance, and utilise neo-natal child-specific health indicators.

Outcome Variable

Outcomes on reading skills have been coded into five categories from 0 to 4, which includes those who cannot read at all (=0), those who can recognise letters but not words (=1), those can read words but not a paragraph (=2), those who can read a paragraph but not a story (=3) and those who can read a story (=4). Math scores are coded into four categories from 0 to 3 which includes those who are unable to recognise numbers (=0), those who recognise numbers but are unable to do arithmetic (=1), those who can do a subtraction problem but not division

(=2)and those who can solve a division problem (=3).Writing has been coded into 3 categories ranging from 0 to 2, which includes those who cannot write (=1), those who can write a sentence but make one or two mistakes (=1) and those who write without mistakes (=2).

The reading and mathematics tests have been widely used by Pratham (a non-governmental organisation) which conducts assessment tests across the country for their widely popular Annual Status of Education Report (ASER).[3] The highest level of reading corresponds to what a child learns in grade 2. The highest level in the mathematics test corresponds to what a child learns in grade 3 or 4, depending on the curriculum board followed at the school (difficulty level may vary across states).

Variable of interest and other controls

The main explanatory variable of interest is the gender of the child, which would indicate gender based differences arising independently after controlling for other factors. Drawing from the vast literature on determinants of learning outcomes and factors that influence education for children in the Indian context (**Chudgar and Quin, 2012; Dreze and Kingdon 2001; Govinda and Bandyopadhyay 2008; Chudgar, 2011; Singh, Gaurav and Das,2013, Gangopadhyay and Sarkar, 2014, Dongre and Tewary, 2015**), we include a number of controls such as birth order, age and the grade of the child, caste and religion, household size, the state where household resides in, age, gender and level of education of household head. Household economic factors like yearly per capita consumption expenditure, main income source (which also captures the primary occupational category), television ownership and type of walls (whether concrete or not) has been added as controls.

In the regression model, we also control for direct inputs like time spent in school, private coaching and for doing home works. Further school management (private or government run schools) is also controlled for following a number of studies which have seen the impact of attendance in private schools for the children on their learning outcomes **(Desai et al., 2008; French and Kingdon, 2010; Chudgar and Quin 2012; Muralidharan and Sundararaman 2015; Singh 2015; Singhal and Das 2017)**. Following **Banerjee et al. (2007),** access to computers has been incorporated as a control. Other independent variables include whether the child has suffered from short-

[3] An overview about Pratham and ASER can accessed from http://www.pratham.org/programmes/aser (last accessed on September 28, 2017)

term illness or fever in the last 30 days prior to the survey, medium of instruction in the school, distance of the school and gender of the teacher since all these variables can directly influence learning outcomes. Children having major morbidity problems such as mental illnesses, cancer, paralysis and heart diseases, and children who are not attending any schools have been dropped from the analysis due to limited number of observations. We have also added education of the mother and whether she is involved in household chores or other activities as control variables in the regressions.

A significant factor that could deter spending time with school related activities is that girls could be spending more time cooking at home or doing chores within the house which has not been captured directly. There are two variables that capture household chores- whether the child is involved in collecting fuel from outside the household and whether it is usual practice for the household to send their girl (or boy) under the age of 15 to collect water. The first variable is not taken due to the limited number of observations (under 1% of the sample) and the second variable is not included as it does not correspond directly to the studied child. This means that even if the household admits to sending boys (or girls) below 15 to fetch water outside of the house, it still may be the case that the child aged 8-11 years may not be the one doing the activity. We have controlled for the time spent on doing various activities such as tuition, homework and school which should serve as suitable proxies. However, due to paucity of data, we are unable to control for involvement in other chores- where it could be that boys do more activities that require application of basic mathematical concepts like going to the store to purchase goods or involving in sports.

One of the possible limitations of the study might be the inability to control for school characteristics that might affect learning abilities as pointed out by **Bharadwaj et al. (2016)** and others due to paucity of data. However some of the controls including medium of instruction, time spent in doing homework and school management (private managed or not) might be highly correlated with school infrastructure. Hence to some extent we would be able to capture the influence of school infrastructure. Further the fact that we are controlling for household economic variables might also partially capture the impact of school infrastructure since richer households would be more likely to send their children to schools with better amenities even after controlling for the three factors mentioned above.

IV. Methods and Empirical Analysis

As mentioned earlier, the dependent variables are learning outcomes namely reading, writing and mathematics skills for rural children of 8 to 11 years. In the survey these variables have multiple levels which are ordered. Hence to find the association of gender of the child with the learning outcomes, we use ordinal logistic (or ordered logit) models separately for the three outcomes.

Let us consider that the number of children is N. Since for each level of outcome of the *N* children, we have *J* achievement levels ordered in a meaningful way (ranked) for the ordinal dependent variable, we model them using ordinal logistic regression (Maddala 1986). Consider y_i is the observed ordered variable (scores in tests designed to measure reading skills, mathematics skills and writing skills) for child, i. The model can be specified as below:

$$y_i^* = \lambda FEMALE + \beta X_i + \varepsilon_i \qquad (1)$$

where y_i^* is the continuous unmeasured latent variable, whose value determine the level of y_i. In equation (1), X is the matrix of corresponding household and child level control variables pertaining to child, i (as listed in Table 1) and β is the vector of coefficients associated with these child and household specific characteristics. The variable $FEMALE$ is a dummy to indicate if the child, i is a female or not and λ is the coefficient. The random error term, ε_i follows a standard logistic distribution. Estimation of the ordered logit models is done by maximum likelihood **(Woodridge, 2015)**.

One limitation of the above estimation strategy is the assumption of the gender of the child being exogenous. One may argue that the variable might be endogenously determined in countries where sex selection is prevalent. In such a scenario the estimates from the model might be biased ones. However our assumption is likely to be valid since sex selection may be less prevalent as availability of sex screening technology is limited in the rural parts, though not uncommon. Further the Government of India passed the Pre-natal Diagnostic Techniques Act (PNDT) in

1994, which was further amended into the Pre-Conception and Pre-natal Diagnostic Techniques (PCPNDT) Act in 2004 to deter as well as punish prenatal sex screening and sex selective abortion. **Nandi (2015)** finds the law to significantly increase the likelihood of female birth and hence our assumption should remain valid. Even if there is sex selective abortion, the extent should be too less to cause substantial bias in the estimates.

V. Results

A. Descriptive Statistics

Table 1 presents the mean levels of scores in reading, writing and mathematics across gender.[4] It is found that the average score for all subjects including mathematics is higher for boys than girls. Figures 1, 2 and 3 give the breakup of these scores in terms of proportion among the rural children of both the genders. Quite clearly, a strong gender gap is evident especially in mathematics where we find the difference of proportion to be substantial for higher mathematical ability like subtraction and division.

TABLE 1: DESCRIPTIVE STATISTICS

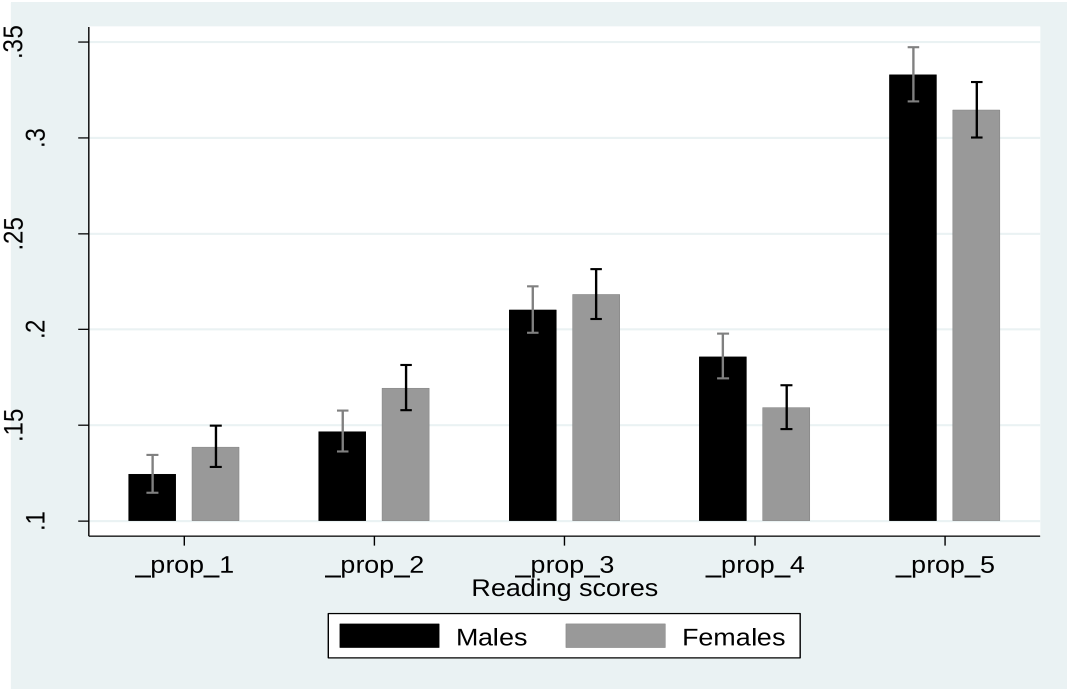
	Reading	Writing	Math
Total	2.40	1.06	1.39
Male children	2.46	1.09	1.46
Female children	2.34	1.02	1.31
Difference	0.12*	0.06*	0.15*
Observations	8176	8100	8140

Note: The numbers in the first three rows represent the mean value. Difference gives the difference between male and female children.
* Significant at 5%.

Please see Table 1A in Appendix for the complete table

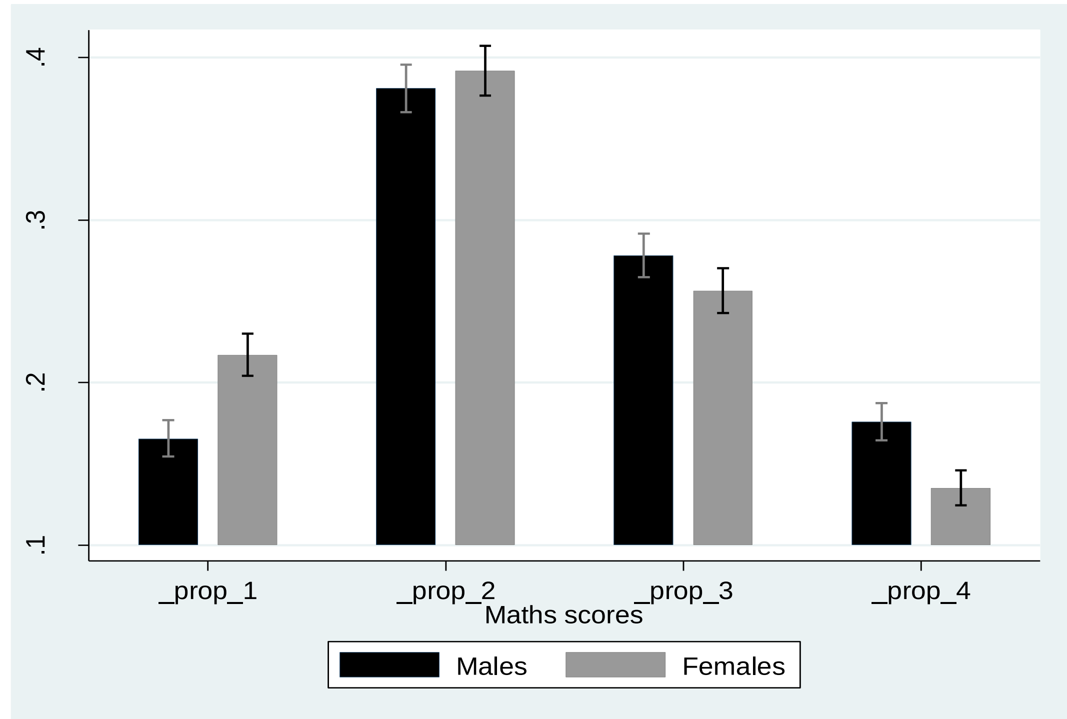
[4] For descriptive statistics of other variables, refer appendix table 1A.

FIGURE 1: BREAK UP OF READING SCORES BY GENDER.



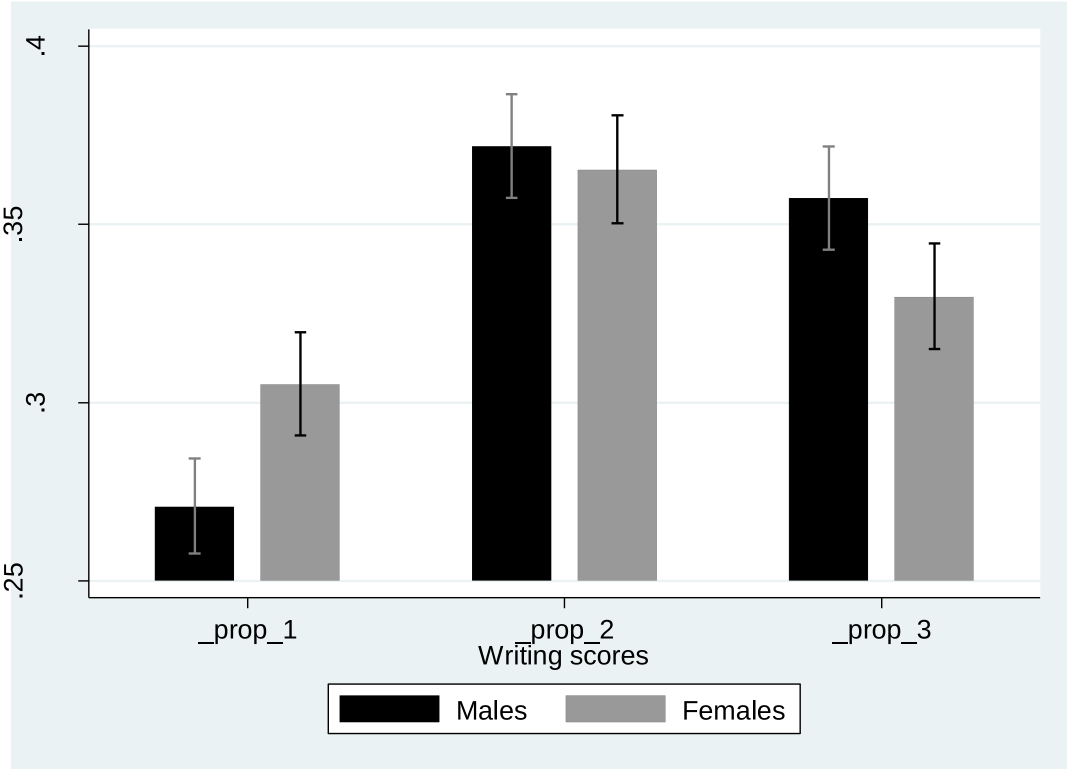
Note: "_prop_" represents proportion of rural children. The numbers represents the scores. 1: Those who cannot read at all, 2: those who can recognise letters but not words, 3: those can read words but not a paragraph, 4: those who can read a paragraph but not a story, and 5: those who can read a story. The lines represent the 95% confidence intervals.

FIGURE 2: BREAK UP OF MATHEMATICS SCORES BY GENDER.



Note: "_prop_" represents proportion of rural children. The numbers represents the scores. 1: those who are unable to recognise numbers, 2: those who recognise numbers but are unable to do arithmetic, 3: those who can do a subtraction problem but not division and 4: those who can solve a division problem. The lines represent the 95% confidence intervals.

FIGURE 3: BREAK UP OF WRITING SCORES BY GENDER



Note: "_prop_" represents proportion of rural children. The numbers represents the scores. 1: those who cannot write, 2: those who can write a sentence but make one or two mistakes and 3: those who write without mistakes. The lines represent the 95% confidence intervals.

B. Regression analysis

As indicated earlier we run ordered logistic regression for reading, writing and mathematics scores on a dummy to indicate whether the child is male or female. A host of controls as discussed have been incorporated in the regressions. Table 2 shows the odds ratio from regression results for reading, writing and mathematics scores. An odds ratio greater than 1 indicates a positive relationship (implying a greater chance of achieving a higher outcome as against other outcome level than the reference group) and that less than 1 indicates a negative relationship (a lower chance of achieving a higher outcome level as against other outcome level than the reference group). In terms of estimates, an odds ratio of “x” would imply that chances of achieving the highest outcome level as against the lower outcomes is “x” times than that for the reference group.

For reading scores, we find females performing worse than male children but the level of significance is 10%. For writing as well, we find similar significant results at 5% level of significance. However for mathematics we find the strongest negative association at 1% level of significance. The odds ratio values suggest that the odds for scoring highest in mathematics versus other lower scores is about 0.77 times for females than that for male children, controlling for other factors. For reading and writing scores, these odds of scoring highest for girls is 0.9 times that for boys indicating performance in mathematics for the former is substantially worse than the latter. The extent of scoring lower is reading or writing is much lesser as against mathematics. The coefficients of the control variables behave as expected: age and standard of the child, attendance in private schools, ownership of television and homework hours per week are positively correlated with test scores in all subjects.

TABLE 2: OVERALL REGRESSIONS

	Reading level	Writing level	Math level
Ref: Male			
Female	0.919*	0.912*	0.772***
	(0.044)	(0.044)	(0.036)
State fixed effects	Yes	Yes	Yes
N	6651	6602	6630
Pseudo R^2	0.115	0.120	0.140

Note. Standard errors clustered across PSU in parenthesis. Please see Table 2A in Appendix for the complete table.
* Significant at 10%
** Significant at 5%
*** Significant at 1%

It should be noted that dropping some of the independent variables from the regression can increase the number of observations. We tried out the regressions without the independent variables indicating mother characteristics and hours spent on private tuitions since the number of missing observations are higher for these variables. However the findings remain same.

To see whether the results hold for earlier years as well, we run similar regressions using IHDS data that was collected in 2004-05 **(IHDS I).**[5] Table 3 presents the regression results. Gender gap is found to be prevalent not only in mathematics but also in reading and writing skills. This indicates that our finding of lower mathematics score for females in comparison to the male children is robust not only across specifications but also across time. In this context, we also run a regression with the 2004-05 and 2011-12 data pooled together to find if performance in mathematics over these two rounds has improved for females. Table 3, which also presents the regression results, indicates that there has been a significant improvement for girls. [Table 3 here]

What is apparent from these regressions is the consistently poorer performance in mathematics especially for girls and this opens up a question whether this relationship holds in general for all females or whether this holds only for certain types of households. Therefore, in the next section of our analysis, we examine if gender gap in mathematics is prevalent across households and children of different groups using the 2011-12 dataset.

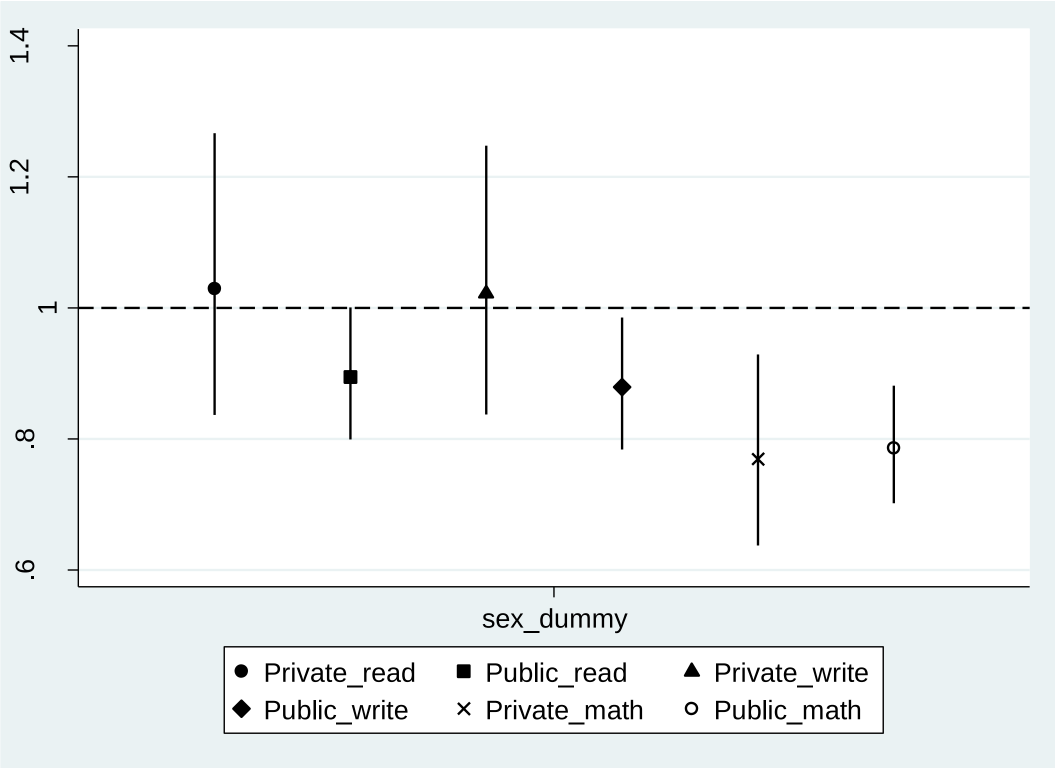
(i) Private and Government Schools[6]

As discussed earlier, we found schools to be a significant predictor of scores for children as those studying in private schools may fare better than those studying in government schools. We extend this further to explore if females studying in private or government run schools perform better or are at par with the males studying in private or government run schools respectively. Figure 4 shows the odds ratio along with the 95% confidence intervals for both these types of regressions.

For children studying in government run schools, our results are similar to results in table 2. Females tend to score lesser in all the subjects but the negative relationship is strongest in mathematics. For those from private schools, we find insignificant difference between boys and girls in reading and writing, but for mathematics the disadvantage for females holds at 1% level of significance.

[5] Please refer to https://ihds.umd.edu/ for more details (last accessed on September 28, 2017)
[6] Here 'private' refers to private-unaided schools that do not receive any support from the government. Those attending schools that belong to other than these two categories such as convents, *madrassas*, and private-aided, among others, have been excluded from the analysis owing to heterogeneity among these groups and very low observations for these categories.

FIGURE 4: REGRESSIONS ACROSS TYPES OF SCHOOL ATTENDANCE



Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Sex_dummy takes the value of "1" if the child is a female and "0" otherwise.

(ii) Social groups

As discussed, social groups which categorize households into different caste and religion constitute an important dimension in the Indian society. A plethora of literature has suggested households belonging to backward castes including Scheduled Caste (SC), Scheduled Tribe (ST) and Muslim religion suffer from deprivation, discrimination and subsequently face inequality in opportunities in terms of health, education and employment **(Thorat and Neuman, 2012; Banerjee et al. 2009)**. Accordingly, we run separate regressions for children belonging to the following:

(a) *Brahmin* caste, Christian religion and other forward caste

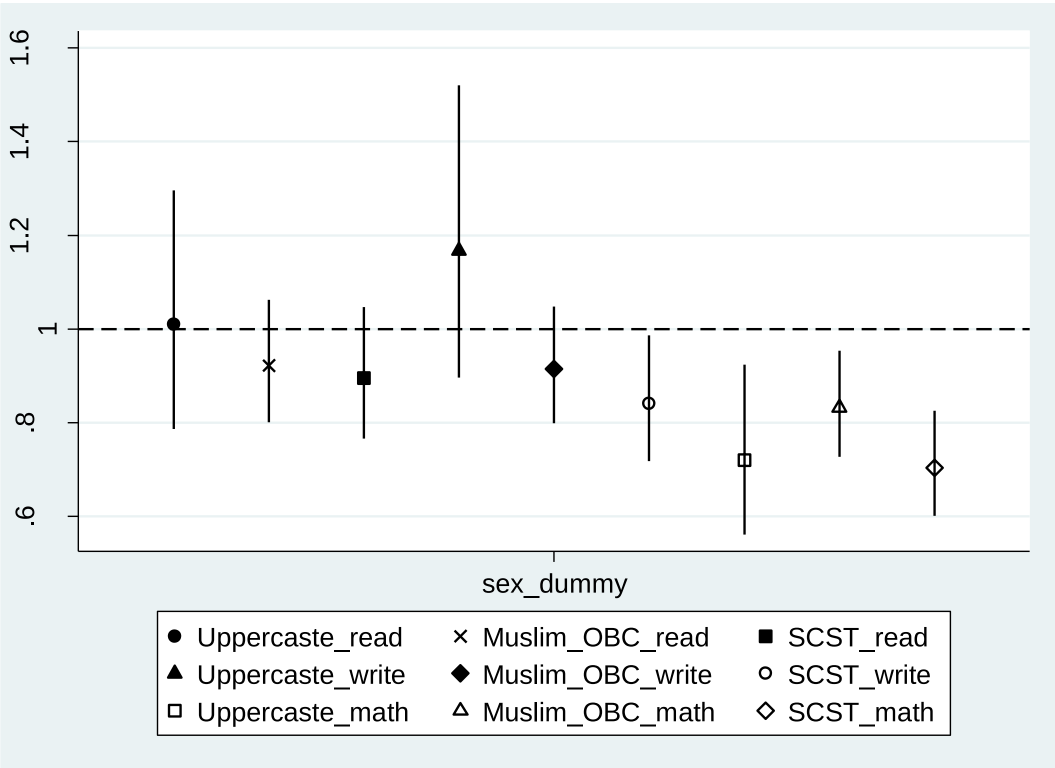
(b) Muslim and "Other Backward Classes" (OBC)

(c) *Dalits* (Scheduled Castes) and *adivasis* (Scheduled Tribes)[7]

Individuals belonging to the first group on average are economically and socially better off as compared to those belonging to the other two groups. *Dalits* and *adivasis* form arguably the worst off group both socially as well as economically and lag behind the upper castes in different indicators of welfare **(Sundaram and Tendulkar 2003)**

Figure 5 presents the odds ratio from the regressions run separately for these three groups. Our findings again seem to suggest female children from all these groups performing significantly worse in mathematics than their male counterparts. In terms of reading, no significant difference is found between boys and girls cross all social groups. We observe similar findings for writing except for dalits and adivasis, where girls seem to score significantly lesser than boys.

FIGURE 5: REGRESSION ACROSS SOCIAL GROUPS



Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Uppercaste includes Brahmin caste, Christian religion and other forward caste. Sex_dummy takes the value of "1" if the child is a female and "0" otherwise.

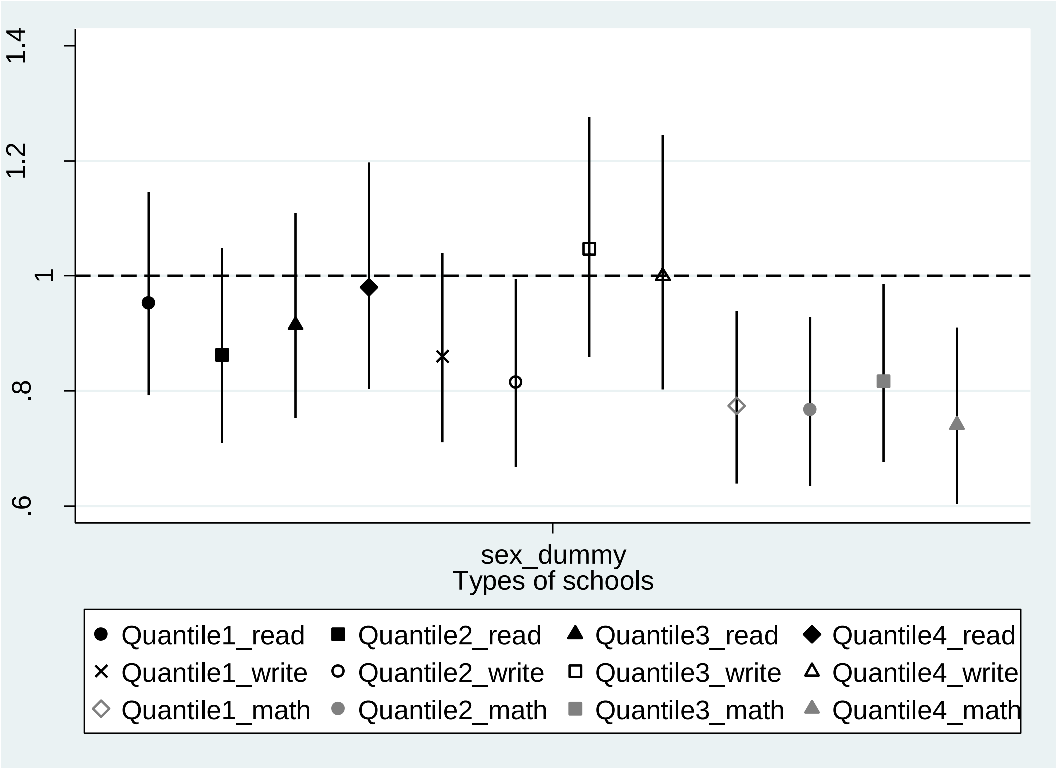
[7] Individuals belonging to the Dalit and Adivasi group have suffered severe social exclusion and discrimination and lag behind the upper castes in different indicators of welfare **(Sundaram and Tendulkar 2003)**

(iii) Economic groups

Arguably one of the best indicators of economic wellbeing is household Monthly Per-capita Consumption Expenditure (MPCE), which has also been used to estimate official poverty levels in India **(Planning Commission, 2014)**. In the context of this paper, it might be argued that the difference in mathematics scores across gender is heterogeneous for households of different economic position. In poorer households, males might be treated better than females since the former can be seen as the source of future economic support and the latter a source of financial liability. Since parents might perceive numeracy or mathematical skills to be important pre-requisite for getting jobs in the future, education investment in terms of money and time might be relatively more for boys than that for girls especially when resources to meet educational needs is scarce.

We test if at all there is a heterogeneous association of girls scoring lesser in mathematics across different households in terms of their economic position. For this purpose, we divide the distribution of household yearly per-capita consumption expenditure into four equally divide quantiles and run similar but separate regressions for each of these four groups of households. Figure 6 gives the results from the regressions. Interestingly, contrary to our hypothesis, we find girls from all the type of households score significantly lesser than male children (at 1% or 5% level of significance). In fact, for girl children from the richest 25% of the households, the odds ratio of scoring highest mathematics as against lower scores is 0.74 times lower than that for male children. For poorer households, this value varies from 0.77 to 0.82.

FIGURE 6: REGRESSIONS ACROSS ECONOMIC GROUPS

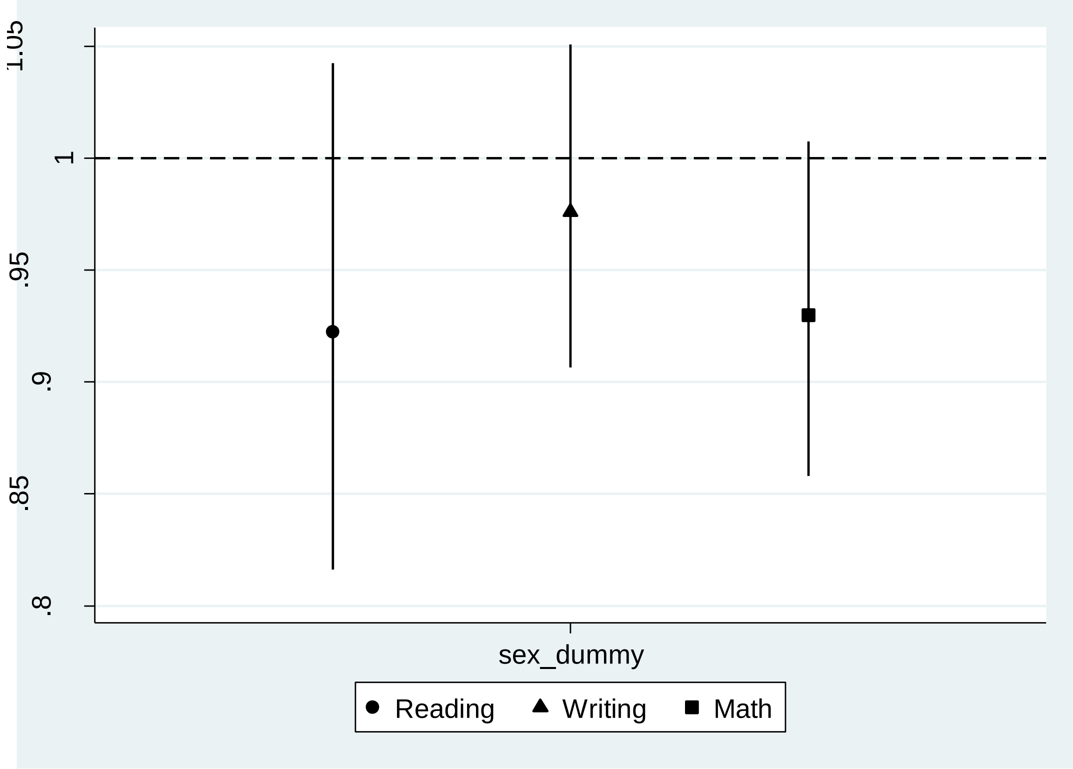


Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Households in the Quantile 1 are the poorest 25% in terms of yarly consumption expenditure and those in Quantile 4 are the richest . Sex_dummy takes the value of "1" if the child is a female and "0" otherwise.

(iv) Households with at least one boy and one girl

In the next set of analysis, we separate out households with at least one boy and one girl aged between 8 to 11 years (which was the test taking criteria) and run similar regressions to examine the mathematical performance of girls from such households. For this we use household fixed effects wherein all the household level unobserved as well as observed variables would be controlled for automatically, and thus, in our model, only include individual characteristics pertaining to the child (such as age, school management, homework hours, etc.). Household level factors like social groups, MPCE, household head's gender and education or main income source of the household among others that are invariant across children within a household would be automatically controlled in the regression. Hence, this enables us to capture purely the effect of factors which vary across the children within households. Figure 7 shows the odds ratio from the regression.

FIGURE 7: REGRESSIONS FOR HOUSEHOLD WITH AT LEAST TWO TEST-TAKERS (AT LEAST ONE BOY AND ONE GIRL)



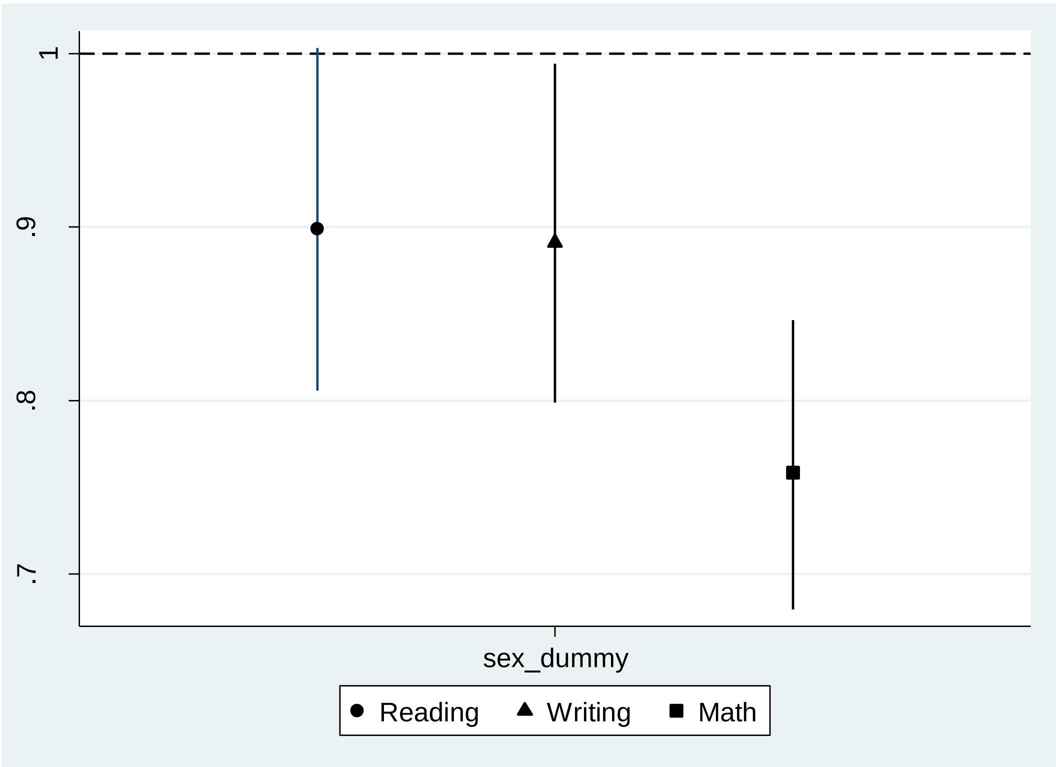
Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Sex_dummy takes the value of “1” if the child is a female and “0” otherwise.

Our findings again suggest that differences in scores in reading and writing are insignificant across girls and boys. However, in mathematics girl children are found to score lesser on average than boys. Interestingly, the strength of this relationship is weaker as the odds for females to score high in mathematics as against other lower scores is about 0.92 times than that for males. In other cases, we have seen this value ranging from about 0.77 to 0.80. Further the results are found to be significant at 5% level as against 1% in other cases. It should be noted that **Bharadwaj et al. (2016)** examined the gender gaps in twins as well since it would naturally control for most of the household, parental and child level factors. We are unable to do the same from our dataset, since the number of observations would be too less to obtain credible estimates.

(v) Households with only male or female children

Similarly to the last section where we concentrated only on households with at least one male and one female child, in the next set of regressions, we separate out households with only male or female children and compare them. Figure 8 which presents the odds ratio from the regression show the odds for females to score highest in mathematics as against all other scores are found to be only 0.76 times than that for male children. This holds at 1% level of significance. Interestingly, we find similar results for reading and writing as well though the level of significance is higher at 10% and 5% respectively.

FIGURE 8: REGRESSIONS FOR HOUSEHOLD WITH ONLY BOY(S) OR GIRL(S) TEST TAKER

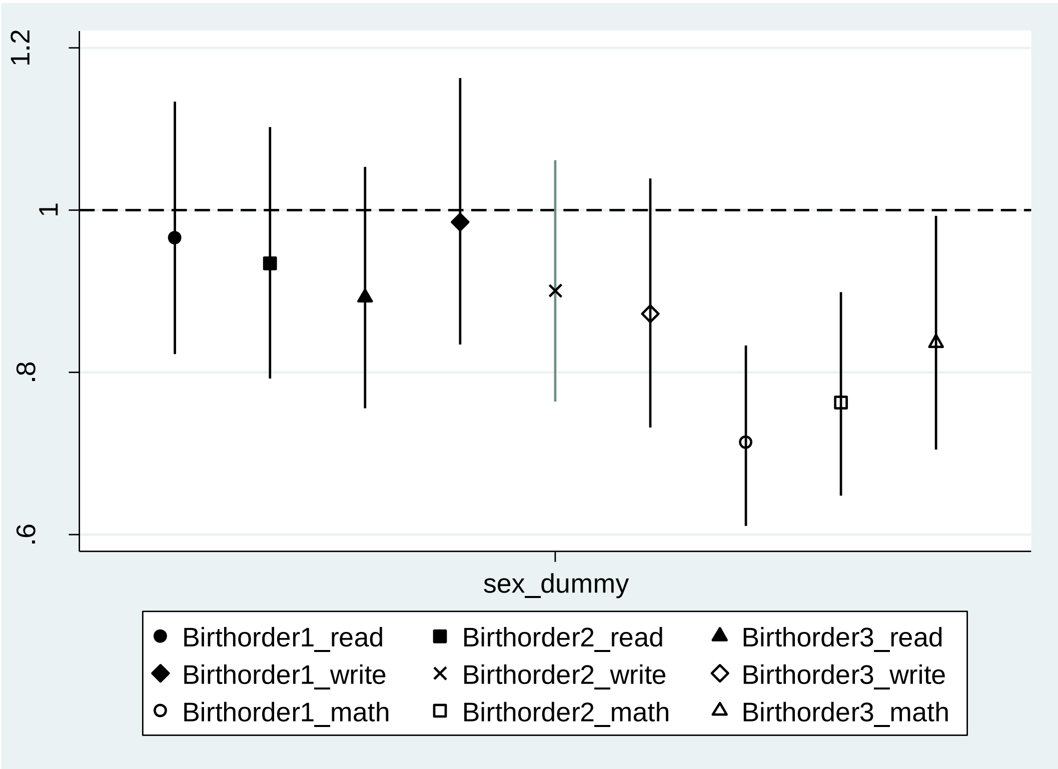


Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Sex_dummy takes the value of “1” if the child is a female and “0” otherwise.

(vi) Birth order

Literature indicates various hypotheses about the impact of birth order on educational expenditure and achievements of children. Those predicting a negative hypothesis suggest reasons such as greater parental involvement and responsibility towards children of lower birth order. The parents also get older when they rear children of higher birth order. However, those predicting a positive relationship put forward reasons like growth of family income over the life cycle, experience gained by parents towards child rearing and assistance provided by the older children in terms of finance and caring **(Booth and Kee 2009).** Accordingly, we examine if the phenomenon of difference in mathematics scores for female children is heterogeneous across children of different birth order. For this purpose we categorize children into three groups: those with birth order of one, those with birth order of two and those with birth order of three and above. Figure 9 presents the odds ratio from ordered logistic regression for these three types of children.

FIGURE 9: REGRESSION ACROSS BIRTH ORDERS



Note: The graph presents the odds ratio from ordered logit regression with all controls listed in Table 2. Sex_dummy takes the value of “1” if the child is a female and “0” otherwise.

Our findings seem to suggest that mathematics scores for girls across children of different birth order is lower than that for boys and the difference is significant at 1% level. The odds for females to score high in mathematics as against obtaining lower scores increase with higher birth order. For females of the first birth order, the odd is 0.71 times than that for boys of same birth order, controlling for other relevant factors. It goes up to 0.76 and then for females of higher birth order, the value stands at about 0.84 times than that for boys of similar birth order.

C. Possible Mechanisms

Our analysis finds a substantial gap in learning outcomes among females, which is evident with respect to mathematics and to a much lesser extent in other subjects. The findings show that the gap is significant across all types of households and the inferences even hold for children of different groups. This raises a question as to why is this so?

(i) Biological Differences

The first reason that we inquire into is the biological or exogenous differences across males and females. Some have argued that there is an innate difference in ability, brain development, hormone levels and that higher order thinking is much superior for male children **(Witelson 1976; Johnson and Meade 1987; Gur et al 1999; Davison and Susman 2001; De Bellis et al 2001; Cahill 2005; Gallagher and Kaufman 2005; Lawton and Hatcher 2005).** The above differences get reflected in mathematics which is more analytical than other subjects such as language (and the skills associated with it such as reading and writing). We tried to explore this hypothesis by running the same regressions on the urban children, the data for which is taken from the same survey. If there exists a systematic difference between boys and girls, it should come up in the urban specifications as well. Table 4 presents the odds ratio for the regressions.

The findings from the regression results reveal that there is no significant difference in mathematics scores between urban boys and girls. This holds true for reading scores as well. In fact girls are found score higher with respect to writing scores. We repeat the same exercise for children from urban metropolitan cities and the results remain similar. Hence, we rule this mechanism out as one of the explanations.

TABLE 4: REGRESSIONS FOR URBAN CHILDREN

	Urban areas			Metro cities		
	Reading level	Writing level	Math level	Reading level	Writing level	Math level
Ref: Male						
Females	1.094	1.253***	0.996	0.993	1.531**	0.873
	(0.077)	(0.097)	(0.072)	(0.164)	(0.290)	(0.149)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2893	2862	2879	570	568	567
Pseudo R^2	0.131	0.113	0.164	0.155	0.155	0.204

Note. Standard errors clustered across PSU in parenthesis. Please see Tables 4A in Appendix for the complete table

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

(ii) Gender stereotyping

Literature also suggests societal factors, which lead to gender stereotyping can explain this difference. For example, **Gneezy, Niederle and Rustichini(2003)** argue males are more competitive, which leads to better performance in mathematics, often perceived to be an indicator of intelligence and is important in the job market. Explanation on this ground emphasizes on how girls are made to believe mathematics is not useful and is not a part of a girl's identity **(Wilder and Powell, 1989)**.

Studies have shown that gender role stereotypes emanating from parents is prevalent **(Eccles and Jacobs 1986; Eccles, Jacobs and Harold 1990; Parsons, Adler and Kaczala1982; Muller 1998; Bouffard and Hill 2005; Bhanot and Jovanovic 2005)**. It is also found that in naturally occurring conversations, parents are three times more likely to discuss science and related issues to boys in comparison to girls **(Crowley et al. 2001)** and females are found to report higher levels of anxiety over mathematics **(Devine et al. 2012)**. In fact a very recent paper finds gender gap in mathematics among students in Italy increases for those who are assigned to teachers with stronger gender stereotypes **(Carlana, 2017)**. In India as well, studies have shown gender stereotyping is deeply rooted in families and gender bias at home is a key element of the socialization process for girls **(Mishra, Behera and Babu2012).**

To get an indication of this, we divide the states based on the rural sex ratio as enumerated in Census 2011. Gender stereotyping from states with high rural sex ratio is expected to be lower that for those with lower sex ratio. Table 5 presents results from separate regression for the seven states with highest sex ratio and seven with lowest figures.[8] The results indicate that gender difference in mathematics scores is insignificant for the states with higher sex ratio. For states with lower sex ratio, similar to previous results, girls are found to score significantly lower as compared to boys. While we are unable to directly prove or disprove the argument of gender stereotyping due to paucity of data, this result could be indicative that societal factors and parental role leading to gender stereotyping may play an important role within the society and family. However, to establish this, further research is essential. It

[8] States with lower sex ratio include Jammu Kashmir, Punjab, Haryana, Bihar, Uttar Pradesh, Sikkim and Rajasthan. Those with highest sex ratio include Uttarkhand, Orissa, Chhattisgarh, Andhra Pradesh, Tamil Nadu, Kerala and Goa.

should also be noted that the heterogeneous estimates we obtain from states of varying sex ratio might again help us eliminate innate gender differences as a possible explanation/ mechanism for this gap.

TABLE 5: REGRESSIONS ACROSS STATES (FOR MATH SCORES)

	States with high sex ratio	States with low sex ratio
Ref: Male		
Females	0.874	0.662***
	(0.108)	(0.045)
Controls	Yes	Yes
State Fixed Effects	Yes	Yes
N	1143	2837
Pseudo R^2	0.131	0.182

Note. Standard errors clustered across PSU in parenthesis. Please see Table 5A in Appendix for the complete table

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

(iii) Early childhood nutrition

Another argument often put forward by development scholars is the lack in nutrition level in early childhood, which may have detrimental effects on brain development and learning capacity for children **(Popkin and Lim-Ybanez, 1982; Glewwe, Jacoby and King 2001)**. One major reason for female children scoring lower than the male children in mathematics might be accrued to lack of nutrition for these females. This is especially important since a number of studies have observed intra-household inequality in health condition and nutrition in early childhood and worst health outcomes for girls in India (Behrman, 1988). Lack of nutrition which affects educational performance may show up in mathematics since the level of mathematics test is higher than reading as mentioned earlier.

To get an indication if this is true, we exploit the individual level panel data of IHDS. The first round of survey was conducted in 2004-05 and the second round in 2011-12. In the 2005 survey, anthropometric measures like weight and height of the children were collected using which the zscores including the Height for Age (HAZ), Weight for Age (WAZ), Weight for Height (WHZ) and Body Mass Index (BMIZ) have been calculated.[9] From the matched sample of 5377 children, children with a zscore below -6 or above 6 are dropped from the sample after which the sample size reduces to 4547.[10] Each of the zscores is then classified as 0 if the value is below the median and 1 if the value is above the median. After that we categorize the merged sample of children into three groups: (i) the ones with poor scores, defined as those for whom each of the zscores is below the median or only one of them is above median; (ii) the ones with middle scores defined as those for whom either two of the zscores or three are above median and (iii) the ones for whom all the four zscores lie above the median value.

First we run separate regressions using the sample of children with the three categories of anthropometric measures. Table 6 presents the results from the regressions. The findings suggest that among children with poor zscores, the gender gap in mathematics scores seems insignificant. However for better off children in terms of anthropometric scores, the gap becomes significant at 1% level. Even when the female children are taken care of from the childhood and are similarly healthy in comparison to the boys, differences at higher level of z scores, point to the probable prevalence to gender role stereotyping.

TABLE 6: REGRESSIONS FOR DIFFERENT ANTHROPOMETRIC MEASURE CATEGORIES (FOR MATH SCORES)

	Low scores: none or one above median	Middle scores: two or three above median	High sco
Ref: Male			
Females	0.850	0.764***	
	(0.091)	(0.068)	
Controls	Yes	Yes	
State Fixed Effects	Yes	Yes	
N	1340	1777	
Pseudo R^2	0.131	0.148	

Note. Standard errors clustered across PSU in parenthesis. Please see Table 6A in Appendix for the complete table
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

[9] These scores have been calculated using the command "zscore06" in STATA, which calculates the anthropometric z-scores using the 2006 World Health Organisation (WHO) child growth standards.

[10] These cut off points are arrived at by the WHO as such z-scores are considered implausible. http://www.who.int/nutgrowthdb/software/Differences_NCHS_WHO.pdf (last accessed on September 28, 2017)

We use these zscores obtained to also find whether there is gender gap in mathematics scores comparing females with better scores to males of lower zscores. Table 7 presents the results from these regressions. In the first column, we compared females in the second category (two or three scores above median) with males in the first category (at most one score is above median). In the second column, we compare females with highest zscores (all above median) with the male children in the first category. In the third, females in the third category are compared with males in the second category. The results suggest females with better anthropometric score as a kid are likely to score equally well as males with a worse score. This probably indicates an independent role of nutrition and health during childhood which might manifest as better scores in mathematics. However to establish this, further research which controls the unobservable factors affecting mathematics scores can be pursued.

TABLE 7: REGRESSIONS COMPARING GIRLS WITH BETTER ZSCORES WITH BOYS OF LOWER VALUES (FOR MATH SCORES)

	Girls with middle scores vs. boys with low scores	Girls with high scores vs. boys with low scores	Girls with high scores vs. boys with middle scores
Ref: Male			
Females	1.076	0.905	0.900
	(0.155)	(0.092)	(0.119)
Controls	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
N	1048	1612	1213
Pseudo R^2	0.148	0.141	0.148

Note. Standard errors clustered across PSU in parenthesis. Please see Table 7A in Appendix for the complete table.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

(iv) Non-household activities and sports

Entwisel et al. (1994) find learning outcomes in mathematics for boys are more sensitive to environment (particularly resources) available and accessed outside the home than for girls. Studies have also found that playing games outside or getting more exposure to the outside environment may positively impact the development of numerical and also spatial abilities, and could benefit from activities such as carrying out transactions in stores or paying for the bus **(Bing, 1963)**. In the Indian context, household chores are mostly carried out by girls whereas it is likely that boys are involved in non-household activities like helping the father in agriculture or working as a help in a local shop. Further, playing and watching sports (for example cricket which the most popular sport in the country) may help the boys learn basic mathematics and develop numeracy at a faster pace than girls. While paucity of the relevant data does not enable us to directly find the impact of these activities on learning outcomes for children, we use the levels of mathematics captured in the existing data to get some indicative results.

In this regard, we run separate regressions for children scoring 0 or 1 (cannot identify numbers compared to those who can), 1 or 2 (those who can identify numbers compared to those can subtract) and 2 or 3 (those who can subtract to those who can divide) in mathematics, from the dataset. For the first regression, the dependent variable is whether the child 0 or 1. Similarly, in the second regression, the probability of children scoring 2 as compared to 1 for all children is modelled and for the third regression, we estimate the probability of children scoring 3 as compared 2. The odds ratio obtained from these regressions is given in table 8.

TABLE 8: REGRESSIONS FOR SEPARATE MATH LEVELS

	Level 0 to 1 (Those who cannot and can recognise numbers)	Level 1 to 2 (Those who can recognise numbers and those can subtract)	Level 2 to 3 (Those who can subtract and those can divide)
Ref: Male			
Females	0.791^{***}	0.851^{**}	0.924
	(0.062)	(0.059)	(0.078)
Controls	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

N	3717	4313	2841
Pseudo R^2	0.118	0.114	0.100

Note. Standard errors clustered across PSU in parenthesis. Please see Table 8A in Appendix for the complete table
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Our findings reveal that in the first \ regression, the odds for females to score '1' in mathematics against zero are 0.79 times lesser in comparison to male children. For the other regression, a girl child is less likely to score '2' in mathematics in comparison to boys of similar characteristics. However this association fades away when children scoring '2' or higher is taken into consideration. Here we find no significant association of gender of the child and scores in mathematics. This can be seen in the light of the previous argument. It is possible that once a boy child starts spending time outside playing and involving himself in petty works like agriculture or running a petty shop in the village, they would have an advantage over the basic mathematics involving identification of numbers or basic arithmetic like addition or subtraction. For higher levels, which involve division, no such significant gain is found for boy children.

Further, to establish this, we separated out girl children of birth order one and compared their performance in mathematics with male children of higher birth orders. The reason is it is possible that petty non-household activities are carried out mostly by the eldest child (sometimes irrespective of their gender). Hence a girl of birth order 1 is likely to carry out these activities more than her siblings and of other girls belonging to a higher birth order. The regression results that enable us to draw comparisons of these children with boys of higher birth order are presented in table 9. We find significant gender gap in mathematical scores between girls of the first birth order and boys of the first and second birth order. However when we compare them with boys of birth order above two, the difference is insignificant. This indicates that involvement in non-household activities might help in acquiring mathematical skills. Again, as mentioned earlier these are the indicative findings that might be suggestive of a role of differential daily activities on explaining the gender gap in mathematical abilities. However to establish this robustly, further research is required.

TABLE 9: REGRESSIONS FOR CONTRASTING BIRTH ORDERS

	Female of first birth order and males of higher birth order (two and above)	Female of first birth order and males of higher birth order (three and above)
Ref: Male		
Females	0.808***	0.881
	(0.065)	(0.098)
Controls	Yes	Yes
State Fixed Effects	Yes	Yes
N	3402	2253
Pseudo R^2	0.141	0.136

Note. Standard errors clustered across PSU in parenthesis. Please see Table 9A in Appendix for the complete table
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

(iv) Economic aspirations and nurturing

Research has shown the gender difference in nurturing from the household members may as well play an important role to widening gender gap in cognitive abilities **(Hoffman, Gneezy and List 2011)**. Nurturing of a female child may be higher for households which already have women working in better jobs that the society accepts. Furthermore in such households, one major economic contribution comes from the women who work in these jobs. Hence female children from these households are likely to be relatively well nurtured and have higher aspirations.

Since less than 4 percent of the households in our sample of rural children (8 to 11 years) have at least one woman working as professionals or in salaried jobs or organized business, we test this aspect by separating all households consisting of these women and representing them with a dummy. We interacted this dummy with the gender dummy of the child to get four categories: male children from households consisting of at least one of its female members working as professionals or in salaried jobs or organized business (taken as reference), female children from similar households and male and female children from households with no females working in these jobs. The interaction variable was incorporated in the regression of mathematics scores along with other controls.

Table 10 which presents the results indicated that girls from households having at least one female member working as professionals or in salaried jobs or organized business do not score significantly worse in comparison to the boys in similar households.

TABLE 10: REGRESSIONS FOR HOUSEHOLDS WITH AT LEAST ONE WOMAN WORKING IN SALARIED JOBS OR ARE PROFESSIONALS OR RUN BUSINESS UNITS.

	Maths scores
Ref: Male	
Females	0.735
	(0.215)
Controls	Yes
State Fixed Effects	Yes
N	6621
Pseudo R^2	0.140

Note. Standard errors clustered across PSU in parenthesis. Please see Table 10A in Appendix for the complete table.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

It should be noted that the evident gender gap in mathematical learning outcomes might be explained by all the four possible reasons outlined in the paper and not necessarily limited to one or two. In other words, the gap might be a manifestation of all the four explanations possible in the rural Indian context. However, as mentioned earlier, further research is necessary to establish the correct causal mechanism(s).

VI. Limitations

It is as important to mention some of the limitations of the study that we identified. The first and foremost limitation is the fact that in the absence of exogenous variation, we are unable to give causal channels that lead to the evident gender difference. However we give indicative evidence of the possible channels which may help to propagate further research. Further limitations include the paucity of panel data with learning outcomes, which would have enabled us to track the improvement of the children in terms of learning outcomes. Apart from this, the available data is not administered for children below 8 years and those above 11 years, which makes it impossible to gauge the age where the scores converge or diverge across gender. The other important limitation is that the mathematical ability is coded into identification of numbers or performing subtraction or division without information on the ability to add or multiply. A finer variable capturing the mathematical abilities instead of various ordered levels (which may not be spread across equal intervals), would have helped us to decipher the point of convergence or divergence. Further, it is difficult to understand specific psychological and sociological underpinnings that might affect the development of cognitive abilities (in numeracy) with the data we use.

The final limitation we identify is the way the survey is conducted. Despite this rigorous training of surveyors to ensure that the child feels comfortable while writing the tests, there remains a possibility that the way of testing generates a bias which is not uniform across the subjects.. The presence of the surveyor, who is in all likelihood a stranger to the child might have a differential impact on the girl child. Since literature suggest that mathematical anxiety is likely to be higher for girls (Devine et al. 2012), which might get enhanced with the presence of the supervisor, the whole process can lead to the evident gender gap in mathematics[11].

VII. Conclusion

In the light of studies finding strong correlation in acquiring mathematical skills and its importance in getting employed and earning better in future, this paper examines if there are any differences in mathematics scores based on gender in rural India. Using nationally representative data for 2011-12 and applying standard econometric techniques to control for observable characteristics and a battery of checks, we find performance of rural females to be worse than similar male children in mathematics. The findings hold across households of different types (across social group, economic classification and household composition), children of different birth orders as well as school management.

[11] One of the authors of this paper has trained surveyors and conducted these learning assessments on children (6-8 years) for a different study in Ahmedabad (Gujarat) in 2016. It was observed that some of the girls tested took longer to become comfortable with the surveyor (especially with male surveyors) and some were observed to be shy when compared to boys.

These findings corroborate with the limited and scattered evidence which examines the prevalence of higher mathematical anxiety among girl students in other countries and schooling levels. We explore many mechanisms which can explain the gender gap but are unable to isolate a single one due to the paucity of data. While we reject the hypothesis of innate difference between a girl and a boy child as a possible explanation of the evident gender gap, a common mechanism that might explain these differences is due to the stereotyping and "systematic devaluation" of girls in schools, society and household. Due to this, girls might develop higher anxiety towards mathematical subjects, which may affect the learning outcomes. Further, better health in childhood among male children and their participation of daily activities and involvement in sports may partly explain the differences in mathematics scores across gender. Nevertheless, further research to attribute the exact reasons explaining the gender difference needs to be carried out. These may include systematic evaluations and psychological interventions that can help in understanding the gender gap vividly.

It should be noted that over the two years of IHDS, we found heterogeneous results for different states. In Haryana, Uttar Pradesh, Madhya Pradesh and Gujarat, there is a significant gender gap, however it isnot declining over the years. The situation in Tamil Nadu seems even worse as the gender gap is found to be insignificant but over the years, this is increasing as well. In Maharashtra, Bihar, Karnataka and all the North eastern states except Assam, female performance is found to be significantly increasing. This is evident from table 11. Hence higher efforts to improve performance of female children should be concentrated more in states like Haryana, Madhya Pradesh, Gujarat and Tamil Nadu among others.

TABLE 11: STATEWISE REGRESSION (SIGN AND LEVEL OF SIGNIFICANCE) ON MATHEMATICS SCORES ON GENDER AND INTERACTION OF GENDER AND TIME (POOLED 2011-12 AND 2004-05)

	Gender		Interaction	
State	Sign	Level of significance	Sign	Level of significance
Himachal Pradesh	Negative	Insignificant	Positive	Insignificant
Punjab	Negative	Insignificant	Negative	Insignificant
Haryana	Negative	At 10 percent	Positive	Insignificant
Rajasthan	Negative	Insignificant	Negative	Insignificant
Uttar Pradesh	Negative	At 1 percent	Positive	Insignificant
Bihar	Negative	At 1 percent	**Positive**	**At 10 percent**

West Bengal	Negative	Insignificant	Negative	Insignificant
Jharkhand	Negative	Insignificant	Positive	Insignificant
Orissa	Negative	Insignificant	Positive	Insignificant
Chhattisgarh	Negative	Insignificant	Positive	Insignificant
Madhya Pradesh	Negative	At 1 percent	Positive	Insignificant
Gujarat	Negative	At 1 percent	Positive	Insignificant
Maharashtra	Negative	At 1 percent	**Positive**	**At 1 percent**
Andhra Pradesh	Positive	Insignificant	Negative	Insignificant
Karnataka	Negative	At 1 percent	**Positive**	**At 1 percent**
Kerala	Positive	Insignificant	Negative	Insignificant
Tamil Nadu	Positive	Insignificant	**Negative**	**At 1 percent**
Assam	Negative	Insignificant	Negative	Insignificant
Other North Eastern states	Negative	Insignificant	**Positive**	**At 5 percent**

Note: Standard errors of odds ratios are in parenthesis and have been clustered at the village level. All the regressions are run with the discussed controls and a dummy for the survey time period. Other north eastern states include Sikkim, Meghalaya, Arunachal Pradesh, Manipur, Mizoram, Nagaland and Tripura.

Though systematic interventions are needed to understand what instruments can help reduce these gaps, in terms of immediate policy prescriptions, addressing the lack of reference to female mathematicians in text books, female names and characters in word problems among other simple tweaks might be a good place to start in order to address at least some of these issues **(NCERT, 2005)**. Given that these differences start out at very early ages , government must prioritize policies related to removing this stigma which would include sensitization of teachers, and a more inclusive pedagogy and syllabus (as discussed above).

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