A vaccination for education - the ICDS and the education of older girls in rural India*

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Abstract

Girls lag behind boys in education in India. They also appear to provide significant amount of childcare at home. Thus, I investigate if provision of childcare services by India's largest child development program - Integrated Child Development Scheme (ICDS) - helps to reduce gender education gap by releasing girls from home responsibilities. There are several mechanisms by which the ICDS provides childcare directly and could reduce its cost. Using logit, covariate matching and conditional logit (village and mother fixed-effects), I find that the girl 6-14 years, having a younger sibling below 5 years receiving any of the ICDS services intensely, increases her odds of attending school by at least 44% in rural India. The effect on boys 6-14 years is positive, but not robust. Further evidence suggests that younger age girls seem to be benefiting relatively more, and the effect is driven mainly by positive health benefits of vaccinations of younger children, and perhaps of supplementary feeding. The bigger and more robust effect on girls seems to be consistent with evidence from time-use of children 6-14. In comparison to boys, relatively many more girls spend time on childcare, especially those with very young siblings of ages 0-23 months, and significantly lesser number combine childcare and education.

Keywords: child development program, educations of girls.

1 Introduction

Primary education gender gap exists across many developing countries, including India, even though it is declining over time (Dreze and Kingdon (2001), Alderman et al. (1996)). Research indicates that older siblings, especially girls, provide child care in developing countries (Pitt and Rosenzweig (1990), Connelly et al. (1996)). Research also indicates that part of the gender gap in education is driven by differentials in child care responsibilites between girls and boys (Lincove (2009), Lokshin et al. (2004)). In this paper I analyze if the reduction in the child care costs can reduce the gender gap in primary school attendance in rural India. I study the reduction in child care costs through the "indirect" or "unintended" benefits of India's biggest early childhood development program - the Integrated Child Development Scheme (ICDS). The ICDS program provides various services from non-formal preschool education to supplementary feeding to

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vaccinations to health check-ups to children 0-6 years. To my knowledge, there is no study which has looked at the impact of an integrated child development program for children ages 0-6 years, on the education of their older siblings. Lokshin et al. (2004) study for Kenya is similar, but unlike the ICDS, the Kenyan child development program's targeted age-group is older (3-7 years) and provides for only daycare and preschooling.

There are two big challenges for this study. Firstly, because of the package of services provided by the ICDS, it is difficult to disentangle the effect of individual components. Secondly, only non-experimental data is available for the analysis, with inherent difficulty in controlling for selection on unobservables. For the main analysis, I use the latest round of demographic health survey data for India - National Family Health Survey3 for 2005-6 - which for the first time collected information on utilization of the ICDS program services at the child level. I further substantiate my findings with another data set - Time Use Survey 1998-99 - which has detailed time use information of children above 5 years old through 24 hour recall.

In non-experimental survey data, the children who are receiving various ICDS services have not been selected randomly. For example, children from poorer families are more likely to use the ICDS services and less likely to go to school. Therefore, to "identify" the effect of any of the ICDS services, observable differences between the girls (boys) aged 6-14 years, whose younger sibling below 5 years is receiving them and those whose sibling is not, need to be accounted for. To do this I start with logit with controls. To minimize the selection bias on observables that may remain with simple technique like logit, because of misspecification in functional form, I then use matching technique like covariate matching. This technique also helps in better balance of unobservables to the extent that they are correlated with observables. To further control for unobservables, like the local access to schools, village-fixed effects using conditional logit is estimated. In addition, to control for mother specific unobservables, like her motivation level, mother fixed-effects model is estimated. To disentangle the effect of preschooling from other ICDS services, the highly collinear preschooling and supplementary feeding components are combined and so are less frequent services like immunization and health check-ups. I also bundle up the whole package of ICDS services together to examine their combined effect on schooling of older siblings.

The results indicate that the girls 6-14, whose sibling is receiving any of the ICDS services intensely, increases her odds of attending school by at least 44% in rural India. The effect seems to be driven mainly by those, whose younger sibling is receiving most vaccinations at the ICDS center. The effect remains robust to better control for selection on observables (using covariate matching) and on unobservables at the village level and mother-level (using village fixed-effects and mother fixed-effects). In addition, it seems that the effect is concentrated among younger age girls, and they are more likely to repeat grade. It seems that the boys are also benefiting from having a sibling receiving similar services, but the effect is smaller and not robust across different specifications. Like girls, the younger age boys seem to be benefiting more, and are more likely to repeat a grade. Evidence also suggests that there is a weak positive impact of the combination of daily supplementary feeding and preschooling/ECC on schooling of girls 6-14, which seems to be driven by the health benefits of daily supplementary feeding, and not by the daycare implicit in regular preschooling/ECC or implicit income subsidy.

Overall, the results suggest that the benefits on education of older girls, seem to be driven by improvement in health of younger children because of vaccinations, and perhaps because of supplementary feeding. The benefits could also be driven by their positive externalities on health of older children (Miguel and Kremer (2004)). The bigger and more robust effect on girls seems to be consistent with evidence from time-use of children 6-14. I find that in comparison to boys, relatively many more girls spend time on childcare, especially those with very young siblings of ages 0-23 months, and significantly lesser number combine childcare and education. The results also seem to be consistent with the findings from the scant literature on

relationship between childcare and education of older siblings. Mostly the findings suggest that the presence of younger sibling has a negative effect on education of older girl siblings.

The remainder of the paper is organized as follows. Section 2 briefly summarizes the literature on childcare and education of older siblings. Section 3 gives a description of the ICDS program and the potential mechanisms of reduction in child care costs. Section 4 discusses the empirical strategy. Section 5 describes the data used in the analysis. Section 6 presents the evidence from time use survey. Section 7 presents empirical results, Section 8 summarizes and discusses the empirical results, and Section 9 concludes.

2 Child Care and Education of Older Siblings

There is a scant literature on the effect of child care duties on the education of older siblings and the findings generally indicate a significant negative effect, especially for girls. Lincove (2009) found that girls in Nigeria are less likely to attend school if there are infants at home, and Psacharopoulos and Arriagada (1989) found a significant negative effect of presence of younger siblings, on school attendance of older children aged 7-14 years in Brazilian households. Similarly, Deolalikar (1998) found that the presence of a child below three years had a significantly negative effect on primary and secondary school enrolment of girls, but not of boys in Kenya. In another study on relationship between child care costs and schooling in Kenya, Lokshin et al. (2004) found that higher price of child care had no significant effect on schooling of boys but significantly decreased the probability of girls being at school.

To my knowledge, there is no study which looks at the effect of an integrated child development program for younger children, on education of their older siblings, and my study aims to do this. Lokshin et al. (2004) study for Kenya is similar, but unlike the ICDS, the Kenyan child development program's targeted age-group is older (3-7 years) and provides for only daycare and preschooling.

3 The ICDS program services and their impact on child care costs

The ICDS program was launched in 1975, and since then it has expanded and matured from 33 blocks to 6,284 blocks in India and now has more than one million centers. In 2009-10 the ICDS program was allocated a budget of 1.5 billion USD (Rs 6.7 billion). The program offers various services, from supplementary nutrition to health check-ups to preschooling to immunization, as detailed in Appendix Table A.1. These services are supposed to be delivered in an integrated manner at the anganwadi, or childcare center, located within the village itself. Each center is run by an anganwadi worker (AWW) and one helper (AWH), who undergo three months of institutional training and four months of community-based training.

The services provided directly and exclusively through the ICDS program to children 0 to 6 years of age are: supplementary nutrition to children 0-6[1] for 25 days in a month, and preschooling to children ages 3-6 years for about 3 hours daily for 28 days in a month. Besides these services, children also receive immunization, health check-up and referral services through the ICDS, which are delivered in collaboration with the public health officials. The Anganwadi worker helps the public health officials in identification and mobilization of the target group of children and mothers for immunization and health check-up.

As the ICDS program provides various services, the program can reduce child care costs through several mechanisms and their combinations:

[1] Children below age three receive "take home rations" that last for a week or a month depending on the frequency of distribution. Children 3-6 receive feeding at the center itself.

1. Provision of supplementary nutrition and immunization is likely to have positive health benefits on children, which is likely to lead to reduce morbidity and mortality, leading to reduction in resources and time required for child care. Healthier young children can also have positive externalities on the health of older children, further reducing child care time and monetary costs.

2. Time spent in Anganwadis for preschooling releases the older siblings, especially girls, from supervision duties and allows them to engage in other activities.

3. Increase in household resources because of implicit income subsidy through supplementary nutrition.

Because of the above mechanisms, I would be analyzing the impact of all ICDS services directly provided to the young children.

4 Empirical Strategy

To analyze the impact of each of the ICDS services received by the children below 5 years on education of older siblings, I estimate the following logit (probit) regression equation for boys and girls 6-14 years old who have at least one younger sibling below 5 years:

$$AtnSch_i = \alpha Presch_i + \beta Dailyfd_i + \gamma Mhcheck_i + \delta Immun_i + \eta X_i + \lambda_i + u_i \tag{1}$$

where $AtnSch_i$ is a dummy variable with value of one for a child who has attended school in the current academic year. $Presch_i$ is a dummy variable with the value of one for a child, who has at least one younger sibling who received preschooling/early child care through ICDS *regularly*. $Dailyfd_i$ is a dummy variable with the value of one for a child, who has at least one younger sibling who received supplementary nutrition through ICDS *daily*. $Mhcheck_i$ is a dummy variable with the value of one for a child, who has at least one younger sibling who received health check-up through ICDS *monthly*. $Immun_i$ is a dummy variable with the value of one for a child, who has at least one younger sibling who received most vaccinations at the ICDS center. X_i is a vector of control variables composed of the *children characteristics*: age of the child in years, age-square, age-cube; *mother specific characteristics*: mother's age in years, mother's highest number of years of completed education, mother's height in cms; *spouse specific characteristics*, that is spouse's age, spouse's education; *household head specific characteristics*, or household head's age and household head's education; *socio-economic characteristics* (caste, religion, wealth score); and *environmental factors* (water source, toilet facility, cooking fuel). λ_i captures unobservable or observable but unaccounted state-specific[2] or village-specific fixed effects. u_i is an error term. α, β, γ and δ are the parameters of interest and capture the effect of having a younger sibling receiving the various ICDS services.

The above specification estimates the impact of each ICDS service controlling for receipt of other ICDS services by children below 5 years. However, because of likely collinearity between the receipt of various ICDS services, estimates can have lower precision. Therefore, to assess the impact of each ICDS service individually with higher precision, other specifications are also estimated in which the impact of each ICDS services is examined independently of other services. In another specification highly collinear services or similar frequency services are bundled together to improve precision of estimates. Also, to examine the impact of the package of ICDS services put together, another specification is estimated in which the girls and boys 6-14, whose sibling below 5 years is receiving different ICDS benefits intensely are combined

[2]For rural India as a whole some states were combined into two regions because of small sample size. One region contained Jammu&Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Delhi and Goa. Another region contained Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya and Assam.

into one single variable called "Any ICDS intensely." This dummy variable takes the value of one for boys and girls 6-14, having at least one sibling below 5 years receiving any of the following benefits: regular preschooling/early childhood care or monthly supplementary feeding or monthly health check-up or most vaccinations at the ICDS center; and zero otherwise.

I use non-experimental survey data in which the children who are receiving different ICDS services have not been selected randomly. For example, children from poorer families are more likely to use the ICDS services and less likely to go to school. Therefore, to "identify" the effect of ICDS services on schooling of older siblings, I need to take account of the observable differences between the two groups of children, like their economic status, in order to get to the pure effect of ICDS services on their schooling. With logit, I can control for observable characteristics related to children 6-14 with the addition of control variables X_i.

There also might be some unobserved factors (unobserved heterogeneity), or observed but unaccounted factors at the state level, like higher political commitment and/or better administrative structure, which could result in better provision of ICDS services and hence greater use of those services. Or, there might be income shocks at the state level that affect the number of women who go to the ICDS center. In such cases, the logit regression probably suffers from omitted variable bias. To account for within-state differences, I use state fixed-effects model which adds λ_i in the equation above. Similar rationale holds for carrying out village fixed-effects, which controls for village level unobservables such as local access to schools. In this case the λ_i in the equation accounts for village fixed-effects, which is estimated using conditional logit regression. Further to control for mother level unobservables, such as her motivation level, I carry out mother fixed-effects, using conditional logit regression. I estimate the following equation for mother fixed-effects:

$$AtnSch_i = \alpha ICDS_i * Girl_i + \beta Girl_i + \gamma Age_i + \delta Age_i * Girl_i + u_i \tag{2}$$

where $AtnSch_i$ is a dummy variable with value of one for a child who has attended school in the current academic year. $ICDS_i$ is a dummy variable with the value of one for a child 6-14, who has at least one younger sibling below 5 years receiving most vaccinations at the ICDS center ("Any ICDS intensely"); $Girl_i$ is a dummy variable with the value of one for a girl 6-14; Age_i is the age in years of child 6-14; u_i is an error term; α is the parameter of interest.

Unbalanced distribution of covariates could yield biased logit estimates because of their sensitivity to functional form. With covariate matching one seeks to better "balance out" the groups being compared in terms of their covariates. Also, if the observables are correlated with the unobservables, then one may be able to balance out the latter by doing a better job of balancing the former. Thus, I use covariate matching (CVM) to minimize the selection bias on observables. In CVM, measures like the Mahalanobis distance are used to calculate the similarity of two girls (boys) in terms of covariate values and the matching is done on these distances. This method, developed by Abadie and Imbens (2006), adjusts for bias when matching is not perfect, makes no assumption about functional form, and provides the standard errors for matching estimators.

5 Data

The data come from the National Family Health Survey (NFHS), a nationwide cross-section demographic health survey for India. So far three rounds have been conducted in the years 1992-3, 1998-9, and 2005-6. For this paper, I use the third round covering 2005-6 because this is the only one with detailed information on usage of ICDS services. It also provides information on demographics and education of children 5-14 years;, demographic characteristics, work status, and reproductive behavior of women ages 15-49; and

important aspects of nutrition and health care of children aged 0-5 years. It also provides the anthropometric measurements of height and weight for children 0-5 and women 15-49.

In NFHS-3, there are 19,665 children in the age-group 6-14 years with at least one sibling below 5 years. Out of these 46% are boys and 54% are girls. The percentage of children in the sample declines with age. In this paper a boy or girl having attended school[3] in the current academic year includes the following cases: children who are enrolled into school currently but not in the previous year; have advanced to a higher level; are repeaters. Using this definition, around 69% boys and 66% girls aged 6-14 years, with sibling below 5 years, attended school in 2005-06. The percentage is lowest for those from the poorest families and it increases with wealth quintile (Figure 1). There is a difference of around 25 percentage points in school attendance of both girls and boys between those from the poorest and the richest quintile. Compared to boys, a lower percentage of girls attended school in the poorest quintiles: 8% less among the "poorest" quintile, and 5% less among those in the "poorer". This differential disappears for those in the middle quintile and above. In fact in the topmost wealth quintiles, a higher percentage of girls attended school (Figure 1) than boys.

NFHS survey collects information on utilization of various ICDS services by women and children 0-5 in the household. For the ICDS services which are directly benefiting the children below 5 years, the information on intensity of usage is also collected.[4] Among all these different ICDS services, immunization is the most accessible: 19% of children received most of their vaccinations at the ICDS center (Figure A.1). The percentage is relatively similar across different age-groups. The percentage of young children receiving monthly health check-up through the ICDS is also high, and it increases with age of children, though rather slowly. For supplementary feeding and preschooling/early childhood care, the access is relatively lower and it picks up for older children , especially from 2 years onwards. In the NFHS-3 questionnaire the information on access and intensity of preschooling is collected with that on early childhood care. The preschooling component of ICDS is officially only for children from 3-6 years. It seems from the data that the question is most likely picking up information on preschooling as very low percentage of children below 2 years are going to ICDS center regularly for either "early childhood care (ECC)" or "preschooling." Significant regular ICDS attendance of children for either of these services is seen only starting at age of 24 months or 2 years and then it picks up substantially from 3 year onwards (Figure A.1).

Summary statistics in Table 1 show that there are significant unconditional mean differences between characteristics of girls (boys) with at least one sibling below 5 years, who is receiving any of the ICDS services intensely, from those whose sibling is not. Compared to the girl with none of her younger siblings receiving any of the ICDS services intensely, the one who does have such a sibling, is more likely to be younger in age, has a mother younger in age, slightly more educated and taller, to be poorer, from schedule caste/tribe, to be a hindu, to have drinking water coming from piped water and wood being used as cooking fuel and living in states like Haryana, West Bengal, Jharkhand, Orissa, Gujarat or Maharashtra. The patterns are mostly similar for boys 6-14.

Additional dataset used in the paper is Time Use Survey (TUS) Data. This survey was canvassed during July 1998 to June 1999 with a sample size of 18600 households spread over six states namely, Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu and Meghalaya. The survey estimates are representative at national and state level. Out of the total households interviewed, 12,750 are from rural areas with 53,981 respondents in total, and there are 1308 boys and 1317 girls in the age-group 6-14 years with a sibling below 5 years. The TUS asked about the time use of all household members above 5 years during the previous 24

[3]The question asks if the child attended school at any time during the present and previous academic year.

[4]For immunization of children, the information on "most vaccinations at the ICDS center" (the measure of intensity of immunization used in this paper) is collected in the section under vaccination of children. Therefore, unlike other ICDS services, the reference period for this information is not "last 12 months," but age of the child.

hours. Description of activities in the time diary section was open-ended and so was the time allocated to them, allowing for reporting of multiple (simultaneous) activities. I analyze time use of data corresponding to "normal" days only (excluding, for example, holidays).[5]

The main variables of interest are the amount of time spent on childcare and study by girls and boys 6-14 years, with siblings below 5 years. I combine the time spent on all activities classified as childcare: physical care of children (washing, dressing, feeding); teaching, training and instruction of own children;[6] accompanying children to places (schools, sports, lessons, doctor); supervising children needing care; and travel related to care of children. To calculate study time I combine the following activities classified under "learning": general education - school/university/other educational institutions attendance; studies, homework and course review related to general education; additional study, non-formal education under adult education programmes; non-formal education of children; other training/education; learning not classified elsewhere; and travel related to learning. Some of the limitations of the data are that it is not possible to identify families or the child/children who are being taken care of in the data and there is age heaping. To identify families, I use the information only on "children" of the household head; "grandchildren" if there is only one daughter/daughter-in-law; and children below 5 years categorized as "other relative" if there is only one adult women also categorized as "other relative." There is age heaping on even numbers for boys and girls 6-16 years.

Summary statistics in Table 2 compare the characteristics of boys and girls 6-14 years with at least one younger sibling 0-5 years between TUS and NFHS surveys. Mother and household head's characteristics seem to be similar in the two surveys, however, the TUS sample has relatively more children from schedule tribes and hindus.

6 Evidence on time spent on childcare and study by boys and girls 6-14 years from Time-Use Survey

Among girls 6-14, with a younger sibling below 5 years, 22% report spending time on childcare, while only 9% boys do so (Figure 2). This proportion increases for those with very young siblings of ages 0-23 months: 13% of boys and 34% of girls spend time on childcare (Figure 3).[7] The percentage remains largely similar across different ages of boys, but for girls it generally increases with age .

Both boys and girls report spending about two hours on average on childcare, though it differs with age. For girls, it jumps from 55 minutes per day for six year old girls to 136 minutes for 7-8 year old girls, and then it does not change much (Figure 4). For boys on the other hand, 6 year old boys also spend an average of 55 minutes on childcare, and it increases more or less steadily with age. The time spent does not seem to differ much by age of the youngest sibling for either girls or boys (Figure 5).

The two most important components of childcare on which about half (on each) the girls report spending time are a) physical care of children: washing, dressing and feeding; and b) supervising children needing care. Among boys also these two activities are important (about 40% boys spend time on each of these activities), but there is an additional important component: accompanying children to places (schools, sports, lessons, doctor) - about 20% boys[8] report spending time on it, and a larger proportion of older boys do so.

[5] Time-use information is collected on three type of days: normal, abnormal and weekly. Saturday and Sunday are generally reported as "weekly variant," and festival days or when someone is sick are "abnormal" days. All household members are interviewed for at least one normal day.

[6] A few children report spending time on this activity.

[7] In comparison 7% of boys and 19% of girls with a sibling in the age-group 24-59 months spend time on childcare.

[8] 6% girls report spending time on this activity.

Among the boys who spend time on childcare, 60% also report spending time on education. On the other hand, only 40% girls report spending time studying along with childcare. There is a negative relationship between studytime and childcare time (Figure 6), and it is sharper for boys than girls.[9]

To summarize, both boys and girls 6-14 spend time on childcare, and significantly more so if their youngest sibling is 0-23 months old. However, relatively many more girls spend time on childcare, and significantly lesser number combine childcare and education.

7 Empirical Results

Figure 7 indicates that for girls 6-14, whose younger sibling is not receiving any ICDS service or not receiving it intensely, have a lower unconditional likelihood of school attendance at all ages. For boys, the pattern is similar for those at younger ages, although difference is smaller in magnitude, and disappears for those who are older (Figure 8).

Using the logit regression, Table 3 provides the impact of having a younger sibling below 5 years receiving different ICDS services, on education of older boys and girls 6-14. Columns A and G present estimates for all the ICDS services taken together in one regression. Columns B and H shows impact of regular preschooling/ECC exclusively. Similarly columns C and I provide estimates for daily supplementary feeding exclusively; columns D and J for monthly health check-up; and columns E and K for most vaccinations at the ICDS center. Results for "Any ICDS intensely" are provided in columns F and L.

The results indicate that the girls 6-14 years, who have a sibling receiving any of the ICDS services intensely, and exclusively, are more likely to have attended school. For boys 6-14, the direction of effects is similar to girls, but the magnitudes are lower and the effect is generally weaker in statistical significance.[10] When all the ICDS services are taken together, the effect is statistically significant for daily supplementary feeding and most vaccinations at the ICDS center for girls. For boys the effect of monthly health check-up and most vaccinations at the ICDS center is statistically significant.

Table 4 provides effect of having a younger sibling receiving "Any ICDS intensely" or most vaccinations at the ICDS center with covariate matching (CVM). In CVM I allow for bias adjustment when matches are not exact and for heteroscedasticity-consistent standard errors. I start with one match and then increase the number of matches to three to take advantage of more information without also incorporating observations that are not sufficiently similar. The precision of estimates remain largely similar between the one and three matches, but the magnitude changes. Abadie et al. (2004) point out that it is not clear which estimate is more reliable in these cases. I choose to go with three matches estimates for both boys and girls because I am using more information. For children who have a younger sibling receiving most vaccinations at the ICDS center, the results indicate that the CVM estimates increase somewhat for boys and decrease somewhat for girls, suggesting that there is not much selection on observables, over and above as accounted by logit regression. For those who have a sibling receiving any of the ICDS services intensely, for girls estimates decrease substantially (from 10 to 6 percentage points), for boys the estimates are the same.

With CVM one can analyze the effect of individual ICDS services, but not their combination separately. Thus, to analyze the mechanisms of impact I have to rely on logit regression. Because of the collinearity between various ICDS services (Appendix Table A.2 & Figure A.1), I estimate another logit specification with a combination of ICDS services. One of the two dummy variables takes value of one if the boys and girls 6-14 have at least one younger sibling below 5 years, who receives either regular preschooling/ECC

[9] Because of small sample size, the graph combines boys and girls of all ages. The graphs largely remain the same for age-groups 6-10 and 11-14 taken separately.

[10] Using the chi-square statistic the pooling of girls and boys models is rejected at 1% level of significance for all specifications.

or daily supplementary feeding services. The other dummy variables takes a value of one for those who have a younger sibling receiving less frequent services, i.e. either most vaccinations at the ICDS center or monthly health check-up. For this specification, the estimates in Table 5 (column F) indicate that for the girls 6-14 having a younger sibling receiving either regular preschooling/ECC or daily supplementary feeding, increases her odds of attending school by 32%. Similar effects for boys are insignificant. In addition, for girls the effect of having a younger sibling receiving either immunization or monthly health check-up, is significant and positive and indicates an increase in odds by 51%. For boys also this effect is significant, but lower in magnitude indicating a 38% increase in odds of schooling.

Controlling for village level unobservables (village fixed-effects), such as local access to schools, the effect of having a younger sibling receiving daily supplementary feeding or regular preschooling, on schooling of girls 6-14, remains statistically significant when taken exclusively (Table 5, Column F), but becomes insignificant when taken in combination with other services (Column E).[11] On the other hand, the effect of most vaccinations at the ICDS center or monthly health check-up remains statistically significant for them in either case. For boys the effect of all services, whether taken exclusively or in combination with other services, is insignificant. The results remain mostly similar even with logit estimation on the village-fixed effects sample (Table 5) accounting for both within and across village variation.

Significance of positive effects on girls schooling of having a younger sibling receiving most vaccinations at the ICDS center or any of the ICDS services intensely, remain robust to controls for mother level unobservables (mother fixed-effects), such as her motivation level (Table 6, Column C and Rows III and VI respectively).

The age-specific marginal effects (from probit regression) for girls and boys in Figure 9 suggest that in comparison to 6 year old girls, the effect increases for those who are older till age 9, and then decreases, becoming negative after age 11. The pattern is similar for boys, although unlike girls where the effect is positive for ages 7-10, it is positive only for ages 9-10. The age-specific heterogeneous effects, of having at least one younger sibling receiving most vaccinations at the ICDS center or monthly health check-up, suggest that for both boys and girls 6-14 there is a decrease[12] in impact on schooling with age. These results suggest that the effect is relatively larger on the schooling of girls and boys who are younger in age.

Also, I examine the effect of ICDS services on grade repetition, drop-outs and being in the right grade-for-age. I find that boys and girls, having a sibling receiving any of the ICDS services intensely, are more likely to repeat a grade (Table 7). I find no significant effect of ICDS services on drop-out (Table 7) or right grade-for-age.[13]

8 Summary and Discussion of Empirical Results

To summarize, I find significant positive effect on schooling of girls 6-14, who have a younger sibling receiving most vaccinations at the ICDS center or any of the ICDS services intensely. The effect remains robust to better control for selection on observables (using covariate matching) and on unobservables at the village level and mother-level (using village fixed-effects and mother fixed-effects). In addition, it seems that the effect is concentrated among younger age girls, and they are less likely to repeat grade. It seems that the boys are also benefiting from having a sibling receiving similar services, but the effect is smaller and not robust across different specifications. Like girls, the younger age boys seem to be benefiting more, and are

[11] The huge drop in sample size in village fixed-effects regression is due to the fact that in a large number of villages all boys and girls 6-14 years are attending school.

[12] The magnitudes are small, but coefficients are jointly significant. Results not presented but are available

[13] Results not presented.

more likely to repeat a grade.

8.1 How important is daily supplementary feeding and preschooling/ECC service?

I find positive significant impact of the combination of daily supplementary feeding and regular preschooling/ECC on schooling of girls 6-14, although it is not robust across different specifications. I analyze over here the possible mechanisms of this impact.

In my earlier paper Jain (2012), I find that daily supplementary feeding has a positive impact on the height of the children in the age-group 0-2 years but no impact on those ages 3-5. Less malnourished children are less likely to be sick, thereby requiring less child care time which helps older siblings redirect their time and energy to other activities. If the health benefits of daily supplementary feeding were driving the impacts on education of older siblings, then I should see the impact on the children with the youngest sibling in the 0-2 age-group children, rather than those whose youngest sibling is above 2 years of age. To check this hypothesis, I separate the girls and boys 6-14 whose youngest sibling is 0-23 months old from those of 24-59 months.[14]

Estimates in Tables 8 and 9 suggest that the health benefits of daily supplementary feeding might be driving the impact on schooling of girls 6-14. I find significant positive effect of daily supplementary feeding, whether taken exclusively or with other ICDS services, for those having the youngest sibling 0-23 months old. For boys having a youngest sibling 0-23 months receiving this service, I find no significant effect. The positive significant effect on girls is unlikely due to preschooling/ECC service as very low percentage of their very young siblings of ages 0-23 months are receiving it regularly (Appendix Figure A.2). Also, my calculations indicate that the income subsidy through daily supplementary feeding is too small in magnitude to have a significant effect - daily supplementary nutrition transfer for a month is equivalent to only a little more than one day wage of female casual laborer wage.[15]

Given that I find weak significant impact on schooling of girls 6-14, having youngest sibling 24-59 months old receiving daily supplementary feeding or regular preschooling (Table 9), it seems that the impact is not coming from either of these services to this age-group children. The bigger and significant impact on the girls with very young siblings of ages 0-23 months is consistent with the evidence from the TUS, which shows that a much higher proportion of such girls spend time on childcare, in comparison to girls with older siblings of ages 24-59 months and also to boys.

To summarize, the results suggest that the positive impact of the combination of daily supplementary feeding or preschooling/ECC, seems to be driven by the health benefits of daily supplementary feeding, and not by the regular preschooling/ECC or implicit income subsidy.

9 Conclusion

Girls are less likely to attend school than boys in India. Various public policies have been formulated to bring the girls to school, including increase in construction of schools, provision of mid-day meals, free books and free uniforms, and adult literacy campaigns. This paper analyzes the impact of a child development program (ICDS) for children below 5 years on the schooling of older girls.

[14] I take 24 months children in the older group because the percentage of children reporting regular preschooling/ECC increases substantially for children starting from 24 months of age (Appendix Figure A.2).

[15] In 2005-6, the norm for expenditure on supplementary nutrition was Rs 2 per child. If the program is performing well and the normative expenditure is fully transferred to the household, then the maximum amount the household would receive it Rs 50 (USD 1) per month (for 25 days per month). In 2005-06, the female casual laborer earned around Rs 38 in a day (USD 0.8). Thus, monthly daily supplementary nutrition transfer is equivalent to 1.3 times daily female casual laborer wage.

One of the important inhibiting factor in girls education is the household work responsibilities, including care of younger siblings. This paper finds that receiving any of the ICDS services intensely by younger sibling, can have significant positive effects on education of older girl sibling in rural India. The effect seems to be driven mainly by those receiving most vaccinations at the ICDS center. The results suggest that public programs such as immunization of children could have "unintended" positive effects, which need to be accounted for in evaluation of benefits of such programs.

One of the mechanism, which I could not explore in this study because of lack of data, is positive externalities of improvement in health of younger children, on health of older children. Miguel and Kremer (2004) found positive externalities of deworming on school participation of untreated children in primary schools. It is possible that the time spent on child care is a lesser inhibiting factor in a girl's education, than the negative health externalities of taking care of the younger sibling who is constantly sick. This is an important area of future research, which can have important policy implications for public policies on girls education.

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Figure 1: Percentage of boys and girls 6-14 years currently in school by wealth quintile - Rural India (Base - with at least one sibling below 5 years)

Table 1: Summary statistics NFHS; Base - Boys and girls 6-14 years with at least one sibling below 5 years

	Boys 6-14 years					Girls 6-14 years				
	Any ICDS intensely†		No ICDS intensely			Any ICDS intensely†		No ICDS intensely		
	Mean	Std. Dev.	Mean	Std. Dev.	p-value	Mean	Std. Dev.	Mean	Std. Dev.	p-value
% attending school	0.74	0.44	0.68	0.47	(0.000)**	0.75	0.44	0.62	0.48	(0.000)**
Age in years	8.5	2.3	8.8	2.4	(0.000)**	8.7	2.3	8.9	2.4	(0.003)**
Mother's age in years	30.4	5.1	31.4	5.3	(0.000)**	30.6	4.8	31.4	5.2	(0.000)**
Mother's education in years	1.8	3.2	1.5	3.2	(0.013)*	1.9	3.3	1.7	3.3	(0.010)*
Mother's height in cms	151.3	5.5	151.3	5.7	(0.63)	151.6	5.8	151.3	5.8	(0.037)*
Spouse's age	36.0	6.2	37.0	6.5	(0.000)**	36.3	6.1	36.9	6.2	(0.000)**
Spouse's education in years	4.1	4.4	4.3	4.7	(0.34)	4.4	4.5	4.6	4.8	(0.09)
Household head's age	40.7	12.0	41.3	12.0	(0.10)	40.9	11.9	41.4	12.4	(0.10)
Household head's education in years	3.3	4.0	3.4	4.4	(0.27)	3.6	4.2	3.6	4.5	(0.95)
Wealth score	-1.0	0.6	-0.9	0.6	(0.000)**	-0.9	0.6	-0.9	0.7	(0.000)**
Caste - Scheduled caste	0.23	0.42	0.22	0.41	(0.27)	0.23	0.42	0.21	0.41	(0.016)*
Caste - Scheduled tribe	0.21	0.41	0.10	0.31	(0.000)**	0.19	0.39	0.10	0.30	(0.000)**
Caste - Other backward cste	0.36	0.48	0.44	0.50	(0.000)**	0.37	0.48	0.45	0.50	(0.000)**
Caste - Others	0.17	0.38	0.21	0.41	(0.001)**	0.17	0.38	0.21	0.41	(0.001)**
Religion - Hindu	0.80	0.40	0.73	0.45	(0.000)**	0.83	0.38	0.75	0.43	(0.000)**
Religion - Muslim	0.16	0.36	0.24	0.43	(0.000)**	0.13	0.34	0.21	0.41	(0.000)**
Religion - Christian	0.02	0.13	0.02	0.13	(0.37)	0.01	0.11	0.02	0.12	(0.24)
Religion - Sikh/Budd/Jain/Parsi	0.01	0.09	0.01	0.09	(0.83)	0.02	0.13	0.01	0.11	(0.13)
Water - Piped	0.19	0.39	0.10	0.30	(0.000)**	0.24	0.43	0.12	0.33	(0.000)**
Water - Tubewell	0.59	0.49	0.72	0.45	(0.000)**	0.52	0.50	0.70	0.46	(0.000)**
Water - Unprotected well, etc.	0.20	0.40	0.15	0.36	(0.000)**	0.21	0.41	0.15	0.36	(0.000)**
Toilet - Flush	0.08	0.27	0.11	0.31	(0.001)**	0.10	0.30	0.13	0.34	(0.000)**
Toilet - Pit latrine & others	0.04	0.20	0.05	0.22	(0.07)	0.04	0.20	0.05	0.22	(0.046)*
Toilet - No facility	0.87	0.34	0.82	0.38	(0.000)**	0.86	0.35	0.80	0.40	(0.000)**
Cooking fuel - Wood	0.70	0.46	0.52	0.50	(0.000)**	0.71	0.45	0.54	0.50	(0.000)**
Cooking fuel - Others	0.28	0.45	0.44	0.50	(0.000)**	0.26	0.44	0.42	0.49	(0.000)**
State - Haryana	0.02	0.14	0.01	0.11	(0.005)**	0.03	0.18	0.01	0.12	(0.000)**
State - Rajasthan	0.04	0.20	0.10	0.30	(0.000)**	0.05	0.22	0.10	0.30	(0.000)**
State - Uttar Pradesh	0.13	0.34	0.35	0.48	(0.000)**	0.09	0.29	0.32	0.46	(0.000)**
State - Bihar	0.08	0.27	0.20	0.40	(0.000)**	0.06	0.24	0.19	0.39	(0.000)**
State - West Bengal	0.10	0.29	0.05	0.23	(0.000)**	0.09	0.28	0.06	0.24	(0.000)**
State - Jharkhand	0.07	0.25	0.03	0.18	(0.000)**	0.06	0.24	0.03	0.18	(0.000)**
State - Orissa	0.07	0.26	0.02	0.13	(0.000)**	0.07	0.25	0.02	0.13	(0.000)**
State - Chhatisgarh	0.07	0.25	0.01	0.10	(0.000)**	0.06	0.24	0.01	0.10	(0.000)**
State - Madhya Pradesh	0.12	0.33	0.05	0.22	(0.000)**	0.15	0.36	0.06	0.24	(0.000)**
Observations	2331		6014			3061		6882		

* significant at 5%; ** significant at 1%; NFHS - National Family Health Survey; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS center); State specific statistics are presented only for some states

Table 2: Summary statistics TUS & NFHS; Base - Boys and girls 6-14 years with at least one sibling below 5 years

	TUS		**NFHS**	
	Boys	**Girls**	**Boys**	**Girls**
Mother's age in years	32	32	31	31
TUS - Mother not literate (%) / NFHS - Mother cannot read at all (%)	72	68	78	76
Household head age in years	39	39	41	41
TUS - HH head not literate (%) / NFHS - HH head never attended school (%)	45	37	54	51
Caste - Scheduled Caste (%)	19	21	22	22
Caste - Scheduled Tribe (%)	22	21	13	13
Religion - Hindu (%)	91	92	75	78
Religion - Muslim (%)	6	5	22	19
Religion - Christian (%)	1	2	2	2

TUS - Time Use Survey; NFHS - National Family Health Survey; HH - Household

Figure 2: Percentage of boys and girls 6-14 years spending time on childcare - by Age (Base - with at least one sibling below 5 years)

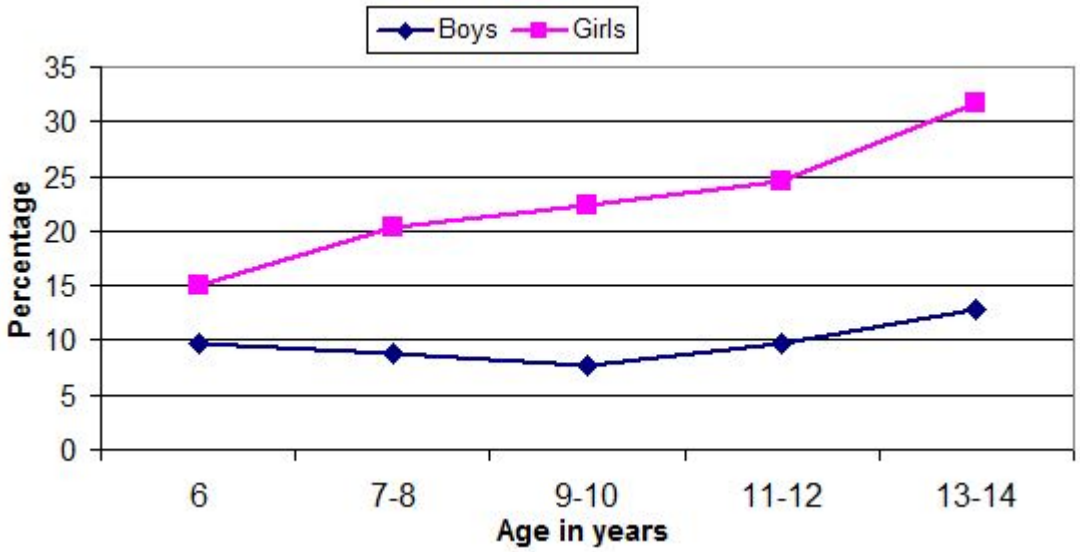
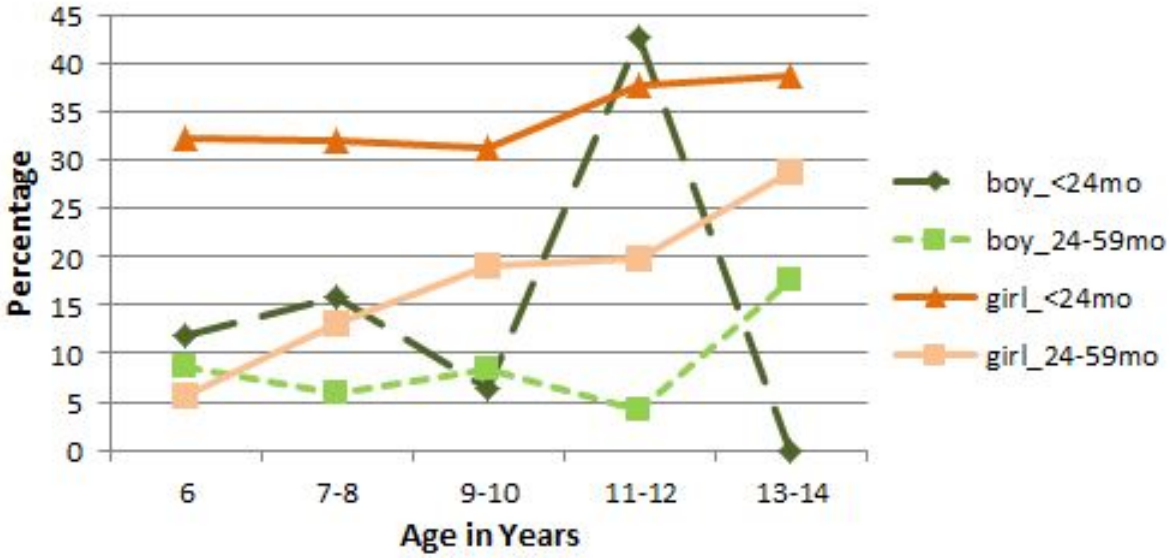


Figure 3: Percentage of boys and girls 6-14 years spending time on childcare - by Age of Youngest Sibling (Base - with at least one sibling below 5 years)



$boy < 24mo$ refers to boy 6-14 years with youngest sibling 0-23 months; $boy24 - 59mo$ refers to boy 6-14 years with youngest sibling 24-59 months. Similar labeling holds for girls

Figure 4: Average time spent on childcare (in minutes) by boys and girls 6-14 years - by Age (Base - with at least one sibling below 5 years and spending positive childcare time)

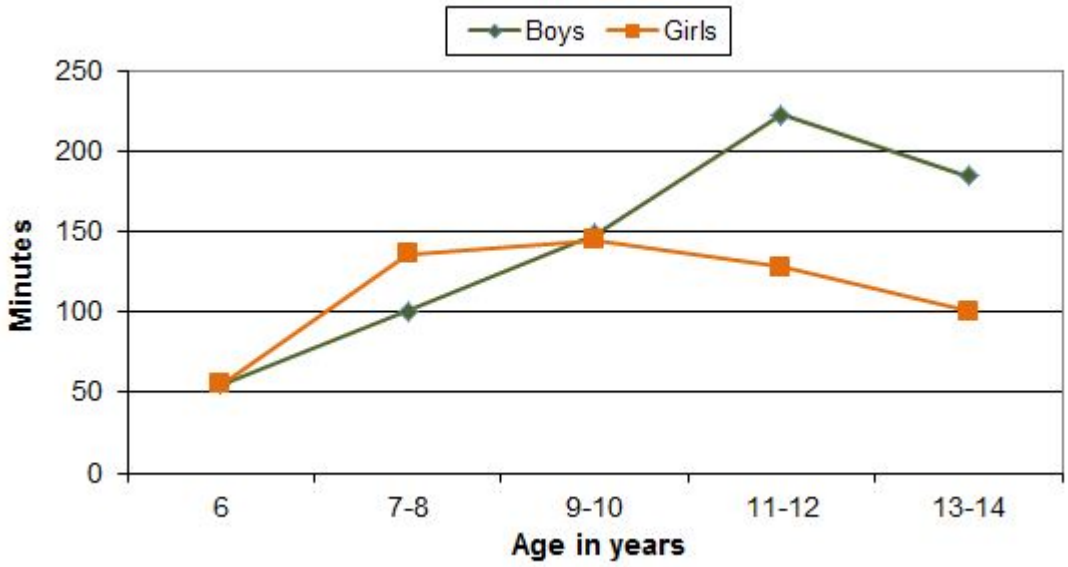
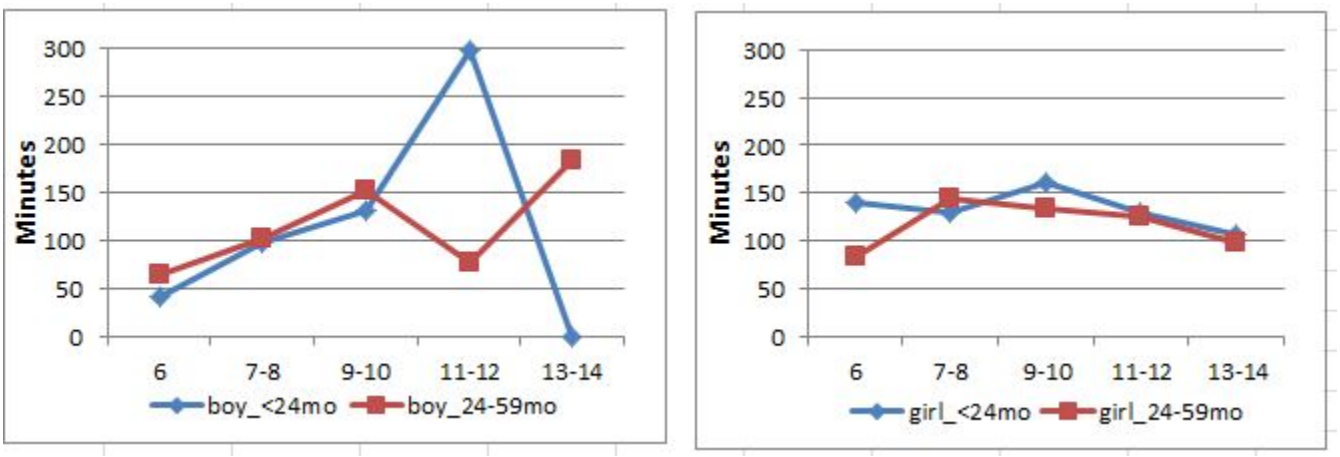


Figure 5: Average time spent on childcare (in minutes) by boys and girls 6-14 years - by Age of Youngest Sibling (Base - with at least one sibling below 5 years and spending positive childcare time)



$boy < 24mo$ refers to boy 6-14 years with youngest sibling 0-23 months; $boy24 - 59mo$ refers to boy 6-14 years with youngest sibling 24-59 months. Similar labeling holds for girls

Figure 6: Relationship between childcare time and study time for boys and girls 6-14 years (Base - with at least one sibling below 5 years and reporting positive childcare time and study time)

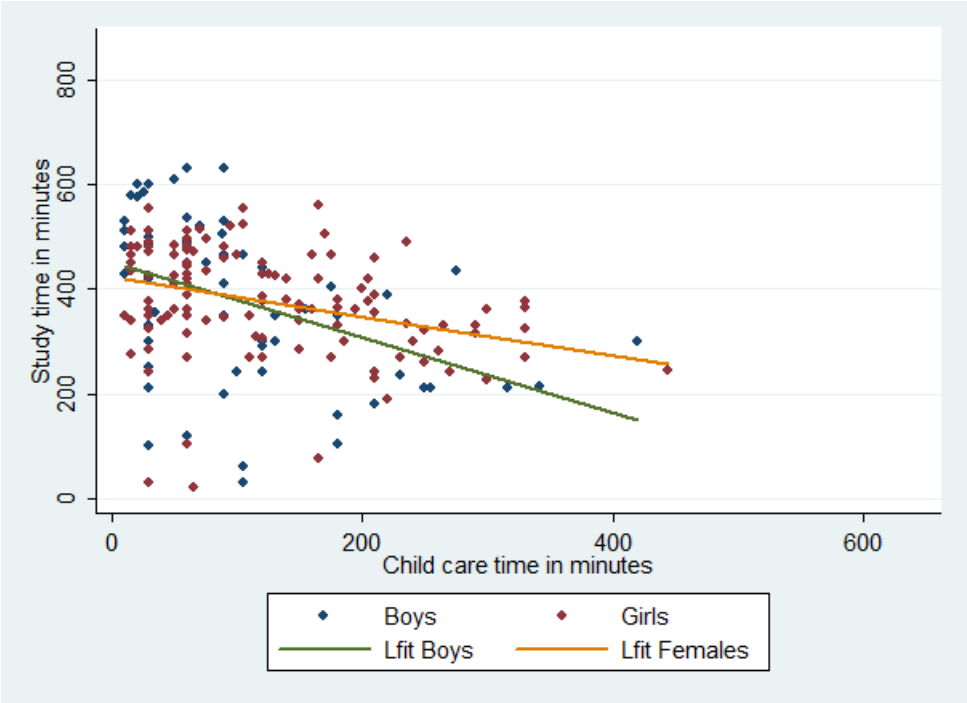


Figure 7: Percentage of girls 6-14 years currently in school having a younger sibling below 5 years receiving different ICDS services - Rural India

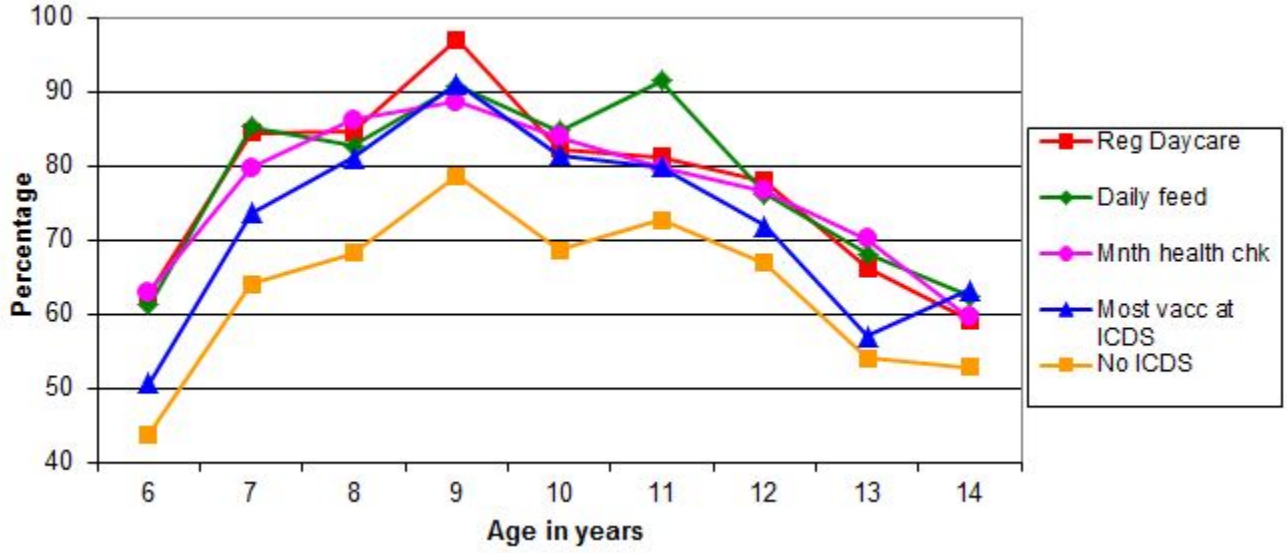
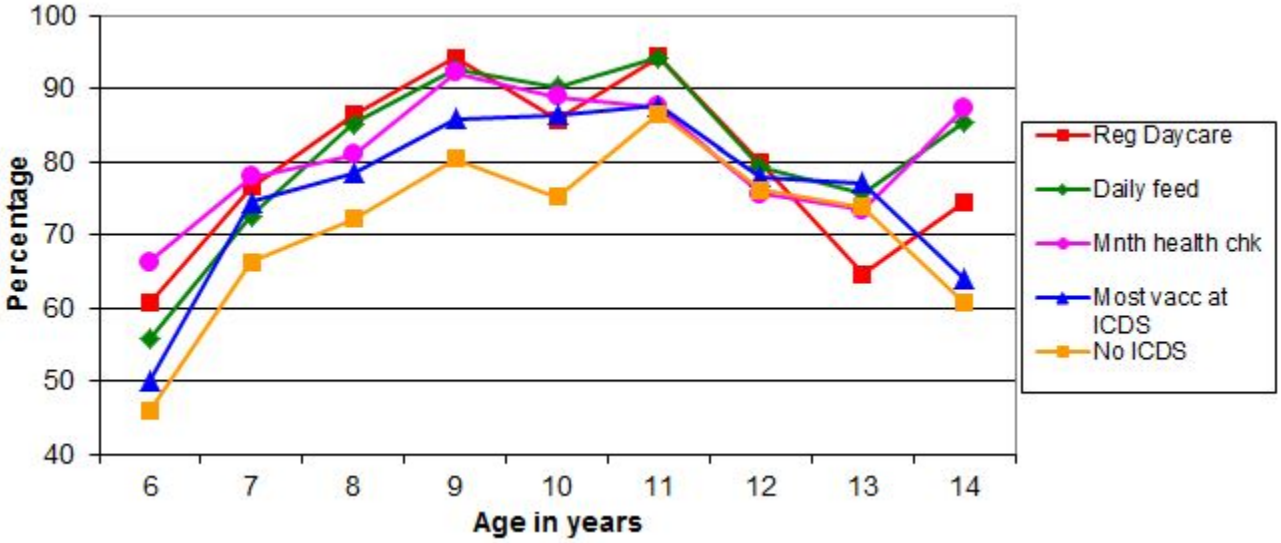


Figure 8: Percentage of boys 6-14 years currently in school having a younger sibling below 5 years receiving different ICDS services - Rural India



Reg Daycare - Regular Daycare/ECC; Daily feed - Daily supplementary feeding; Mnth health chk - Monthly health check-up; Most vacc at ICDS - Most vaccinations at ICDS center;

Table 3: Logit: Effect of different ICDS services on current schooling of children 6-14 years (Base: with at least one sibling below 5 years)

	Boys 6-14 years						**Girls 6-14 years**					
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Regular preschool / ECC	1.07	1.25					1.14	1.52				
	(0.43)	*(1.74)**					*(0.95)*	*(3.86)****				
Daily supplementary feeding	1.10		1.31				1.35		1.56			
	(0.63)		*(2.24)***				*(2.31)***		*(4.38)****			
Monthly health check-up	1.30			1.47			1.16			1.50		
	*(1.90)**			*(3.06)****			*(1.39)*			*(4.19)****		
Most vaccinations at ICDS	1.26				1.29		1.37				1.48	
	*(2.37)***				*(2.72)****		*(3.84)****				*(5.00)****	
Any ICDS intensely†						1.35						1.63
						*(3.67)****						*(6.86)****
Observations	8166	8297	8321	8204	8341	8345	9723	9889	9917	9762	9938	9943
MeanY	0.69	0.69	0.69	0.69	0.69	0.69	0.66	0.66	0.66	0.66	0.66	0.66
P-value: all ICDS components=0	0.00						0.00					
P-value: Dailyfd=Preschool=0	0.53						0.00					

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odd ratios; Robust z-statistics in parentheses; ECC - early childhood care; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each column is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies;

Table 4: Logit, Probit & CVM: Effect of combination of ICDS services on current schooling of children 6-14 years (Base: with at least one sibling below 5 years)

	Boys 6-14 years					**Girls 6-14 years**				
			Covariate Matching					**Covariate Matching**		
	Logit	**Probit**	**1 mtch**	**3 mtch**	**Obs**	**Logit**	**Probit**	**1 mtch**	**3 mtch**	**Obs**
Any ICDS intensely†	1.35	0.06	0.08	0.06	8345	1.63	0.10	0.06	0.06	9943
	(3.67)***	(0.01)***	(0.02)***	(0.02)***		(6.86)***	(0.01)***	(0.01)***	(0.01)***	
Most Vaccinations at ICDS	1.29	0.05	0.06	0.07	8341	1.48	0.08	0.06	0.06	9938
	*(2.72)****	*(0.01)****	*(0.02)****	*(0.02)****		*(5.00)****	*(0.01)****	*(0.02)****	*(0.02)****	

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate marginal effects for probit and covariate matching (CVM), and odd ratios for logit; Robust standard errors in parentheses for probit and CVM, and robust z-statistics for logit; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each cell is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies.

Table 5: Logit/Clogit: Effect of combination of ICDS services on current schooling of children 6-14 years - with and without village fixed-effects (Base: with at least one sibling below 5 years)

	Logit: No village fixed-effects							
	Boys 6-14 years				**Girls 6-14 years**			
	(A)	(B)	(C)	(D)	(F)	(G)	(H)	(I)
Regular preschool/ECC or Daily supp feeding	1.13	1.24			1.32	1.52		
	(1.08)	*(1.98)***			*(2.93)****	*(4.54)****		
Most vaccinations at ICDS or Monthly health check-up	1.38		1.42		1.51		1.62	
	*(3.57)****		*(3.96)****		*(5.36)****		*(6.42)****	
Any ICDS intensely†				1.35				1.63
				*(3.67)****				*(6.86)****
Observations	8328	8331	8342	8345	9927	9929	9941	9943
	Clogit: Village fixed-effects							
	Boys 6-14 years - VFE				**Girls 6-14 years - VFE**			
Regular preschool/ECC or Daily supp feeding	1.12	1.16			1.24	1.32		
	(0.70)	*(0.95)*			*(1.58)*	*(2.12)***		
Most vaccinations at ICDS or Monthly health check-up	1.25		1.28		1.39		1.44	
	(1.43)		*(1.55)*		*(2.58)****		*(2.93)****	
Any ICDS intensely†				1.23				1.44
				(1.50)				*(3.12)****
Observations	5856	5861	5870	5875	7162	7164	7165	7167
	Logit: VFE Sample							
	Boys 6-14 years - VFE sample				**Girls 6-14 years - VFE sample**			
Regular preschool/ECC or Daily supp feeding	1.04	1.10			1.25	1.42		
	(0.32)	*(0.79)*			*(2.12)***	*(3.41)****		
Most vaccinations at ICDS or Monthly health check-up	1.21		1.22		1.47		1.54	
	*(1.87)**		*(2.03)***		*(4.54)****		*(5.28)****	
Any ICDS intensely†				1.19				1.51
				*(1.96)**				*(5.32)****
Observations	5856	5861	5870	5875	7162	7164	7165	7167

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odds ratio; Robust z-statistics in parentheses; ECC - early childhood care; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each column is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies.

Table 6: Logit/Clogit: Effect of most vaccinations at the ICDS center and "Any ICDS intensely" on current schooling of children 6-14 years in pooled sample (Base: with at least one sibling below 5 years)

	Estimation method	**Conditional logit**	**Logit**	**Conditional logit**	**Logit**
	Sample	**Pooled - VFE**	**VFE sample**	**Pooled - MFE**	**MFE sample**
		(A)	(B)	(C)	(D)
I	Any ICDS intensely†	1.10	1.26		0.81
		(0.93)	*(2.70)****		*(1.57)*
II	Girl	0.01	0.02	2.14	0.00
		(1.21)	*(1.13)*	*(2.48)***	*(1.83)**
III	**Girl * Any ICDS** intensely†	**1.39**	**1.24**	**1.65**	**1.41**
		(2.90)***	***(1.86)****	***(3.42)******	***(1.94)****
	Observations	15109	15109	6249	5851
	P-value: AnyICDS=Girl*AnyICDS=0	0.00	0.00		0.15
IV	Most vaccinations at ICDS	1.22	1.32		0.78
		(1.58)	*(2.86)****		*(1.62)*
V	Girl	0.01	0.02	2.34	0.00
		(1.18)	*(1.13)*	*(2.77)****	*(1.88)**
VI	**Girl * Most Vaccinations at ICDS**	**1.24**	**1.18**	**1.48**	**1.67**
		(1.64)	***(1.28)***	***(2.41)*****	***(2.57)*****
	Observations	15092	15092	6242	5851
	P-value: Immun=Girl*Immun=0	0.00	0.00		0.03

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odds ratios; Robust z-statistics in parentheses; VFE - Village fixed effects; MFE - Mother fixed effects; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each column corresponding to rows I-III and IV-VI is a separate regression with the following controls (and interactions between controls and girl): age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state dummies.

Figure 9: Marginal effect (from probit) of most vaccinations at the ICDS center or monthly health check-up on schooling of older children 6-14 years by age - Rural India (Control group - Age 6 boys and girls)

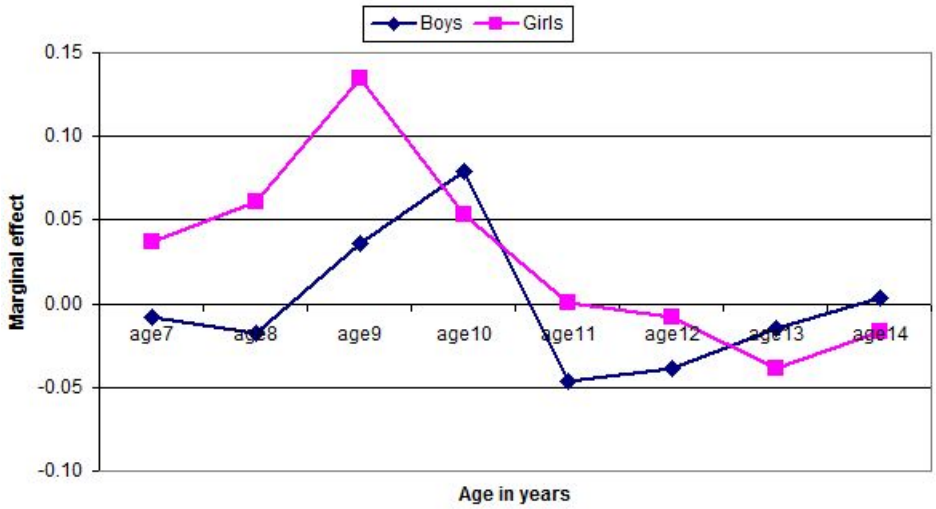


Table 7: Logit: Effect of combination of ICDS services on grade repetition and drop-out among children 6-14 years (Base: with at least one sibling below 5 years)

	Boys 6-14 years				Girls 6-14 years			
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Dependent variable - Grade Repetition								
Regular preschool/ECC or Daily supp feeding	2.01	1.91			1.50	1.80		
	*(2.77)****	*(3.00)****			*(1.60)*	*(2.68)****		
Most vaccinations at ICDS or Monthly health check-up	0.86		1.12		1.46		1.69	
	(0.66)		*(0.57)*		*(1.81)**		*(2.96)****	
Any ICDS intensely†				1.46				1.82
				*(2.18)***				*(3.46)****
Observations	8319	8331	8326	8338	9914	9929	9917	9932
MeanY	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Dependent variable - Dropout								
Regular preschool/ECC or Daily supp feeding	0.98	1.03			0.86	0.80		
	(0.07)	*(0.11)*			*(0.77)*	*(1.18)*		
Most vaccinations at ICDS or Monthly health check-up	1.12		1.11		0.90		0.85	
	(0.62)		*(0.61)*		*(0.70)*		*(1.12)*	
Any ICDS intensely†				1.11				0.84
				(0.66)				*(1.25)*
Observations	8319	8331	8326	8338	9914	9929	9917	9932
MeanY	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odd ratios; Robust z-statistics in parentheses; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); For grade repetition and dropout sections - each column is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies.

Table 8: Logit: Effect of different ICDS services on current schooling of children 6-14 years with the youngest sibling 0-23 months vs with those in the age-group 24-59 months (Base: with at least one sibling below 5 years)

	Boys 6-14 years with 0-23 months sibling						**Boys 6-14 years with 24-59 months sibling**					
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Regular preschool / ECC	1.03	1.00					0.99	1.27				
	(0.09)	*(0.01)*					*(0.03)*	*(1.53)*				
Daily supplementary feeding	0.93		0.97				1.16		1.40			
	(0.26)		*(0.15)*				*(0.79)*		*(2.35)***			
Monthly health check-up	0.96			1.09			1.61			1.74		
	(0.21)			*(0.46)*			*(2.52)***			*(3.24)****		
Immunization	1.44				1.44		1.18				1.23	
	*(2.29)***				*(2.38)***		*(1.34)*				*(1.70)**	
Any ICDS intensely†						1.30						1.38
						*(1.94)**						*(3.00)****
Observations	3111	3127	3135	3125	3144	3144	5055	5170	5186	5079	5197	5201
MeanY	0.64	0.64	0.64	0.64	0.64	0.64	0.72	0.73	0.73	0.73	0.73	0.73
P-value: all ICDS components=0	0.25						0.01					
P-value: Dailyfd=Preschool=0	0.97						0.66					
	Girls 6-14 years with 0-23 months sibling						**Girls 6-14 years with 24-59 months sibling**					
Regular preschool / ECC	1.22	1.73					1.07	1.42				
	(0.87)	*(2.91)****					*(0.40)*	*(2.65)****				
Daily supplementary feeding	1.46		1.82				1.34		1.47			
	*(1.75)**		*(3.31)****				*(1.75)**		*(3.07)****			
Monthly health check-up	1.14			1.63			1.21			1.48		
	(0.82)			*(3.25)****			*(1.32)*			*(3.06)****		
Immunization	1.64				1.78		1.23				1.33	
	*(3.90)****				*(4.79)****		*(1.88)**				*(2.71)****	
Any ICDS intensely†						1.91						1.51
						*(5.68)****						*(4.37)****
Observations	3834	3866	3881	3855	3893	3895	5889	6023	6036	5907	6045	6048
MeanY	0.60	0.60	0.60	0.60	0.60	0.60	0.70	0.70	0.70	0.70	0.70	0.70
P-value: all ICDS components=0	0.00						0.00					
P-value: Dailyfd=Preschool=0	0.03						0.06					

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odd ratios; Robust z-statistics in parentheses; ECC - early childhood care; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each column is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies.

Table 9: Logit: Effect of combination of ICDS services on currently schooling of children 6-14 years with the youngest sibling 0-23 months vs with those in the age-group 24-59 months (Base: with at least one sibling below 5 years)

	Boys 6-14 years with 0-23 months sibling				**Boys 6-14 years with 24-59 months sibling**			
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Regular preschool/ECC or Daily supp feeding	0.94	1.01			1.15	1.29		
	(0.33)	*(0.06)*			*(1.01)*	*(1.89)**		
Most vaccinations at ICDS or Monthly health check-up	1.36		1.38		1.43		1.47	
	*(2.11)***		*(2.19)***		*(2.99)****		*(3.33)****	
Any ICDS intensely†				1.30				1.38
				*(1.94)**				*(3.00)****
Observations	3137	3137	3144	3144	5191	5194	5198	5201
MeanY	0.64	0.64	0.64	0.64	0.73	0.73	0.73	0.73
	Girls 6-14 years with 0-23 months sibling				**Girls 6-14 years with 24-59 months sibling**			
Regular preschool/ECC or Daily supp feeding	1.49	1.76			1.26	1.44		
	*(2.44)***	*(3.58)****			*(1.92)**	*(3.15)****		
Most vaccinations at ICDS or Monthly health check-up	1.61		1.76		1.49		1.57	
	*(3.93)****		*(4.83)****		*(3.82)****		*(4.55)****	
Any ICDS intensely†				1.91				1.51
				*(5.68)****				*(4.37)****
Observations	3885	3885	3895	3895	6042	6044	6046	6048
MeanY	0.60	0.60	0.60	0.60	0.70	0.70	0.70	0.70

* significant at 10%; ** significant at 5%. *** significant at 1%; Coefficients indicate odd ratios; Robust z-statistics in parentheses; ECC - early childhood care; † "Any ICDS intensely" indicates a child 6-14 years with at least one sibling aged 0-5 years receiving any of the ICDS benefits intensely (regular preschooling or early childhood care/monthly supplementary feeding/monthly health check-up/most vaccinations at ICDS); Each column is a separate regression with the following controls: age of child in years, age square, age cube, mother's age in years, mother's highest number of years of completed education, mother's height in cms, caste, religion, wealth score, source of drinking water, toilet facility, cooking fuel, spouse's age, spouse's education, household head's age, household head's education and state/region dummies.

A APPENDIX

Table A.1: Types of services provided by the ICDS program

ICDS Services	Target Group	Service Providers
Supplementary Nutrition	Children <6yrs, Pregnant and lactating mothers (PLM)	Anganwadi Workers (AWW) and Anganwadi Helper (AWH)
Immunization*	Children <6yrs, PLM	Auxilary Nurse Midwife (ANM)/ Medical Officer (MO)
Health Check-ups*	Children <6yrs, PLM	ANM/MO/AWW
Referral	Children <6yrs, PLM	AWW/ANM/MO
Pre-School Education	Children 3-6 years	AWW
Nutrition and Health Education	Women (15-45 years)	AWW/ANM/MO

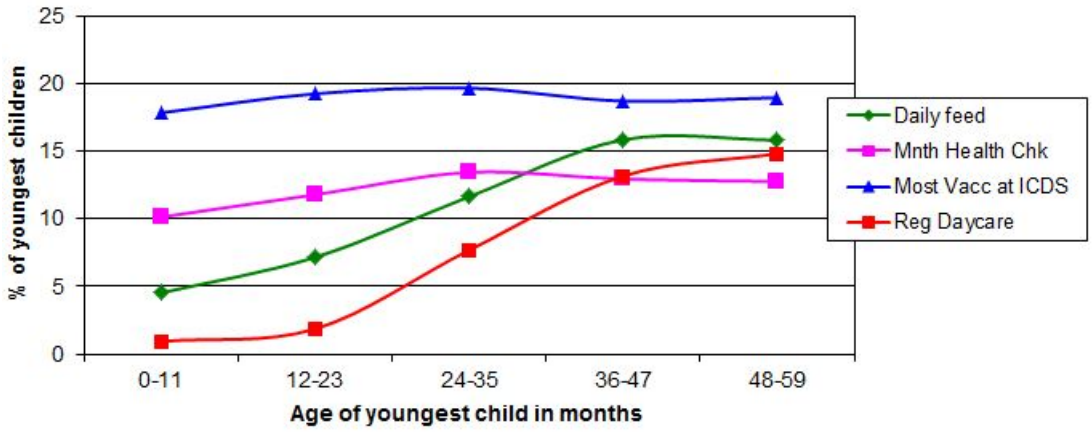
Source: Ministry of Woman and Child Development, Government of India; * AWW assists ANM in identifying and mobilizing the target group;

Table A.2: Correlation between receiving various ICDS services (Base - boys and girls 6-14 years with at least one sibling below 5 years)

	Reg Daycare	Daily feed	Mnth health chk	Most vacc at ICDS
Reg Daycare	1.0			
Daily feed	0.6	1.0		
Mnth health chk	0.4	0.4	1.0	
Most vacc at ICDS	0.1	0.1	0.3	1.0

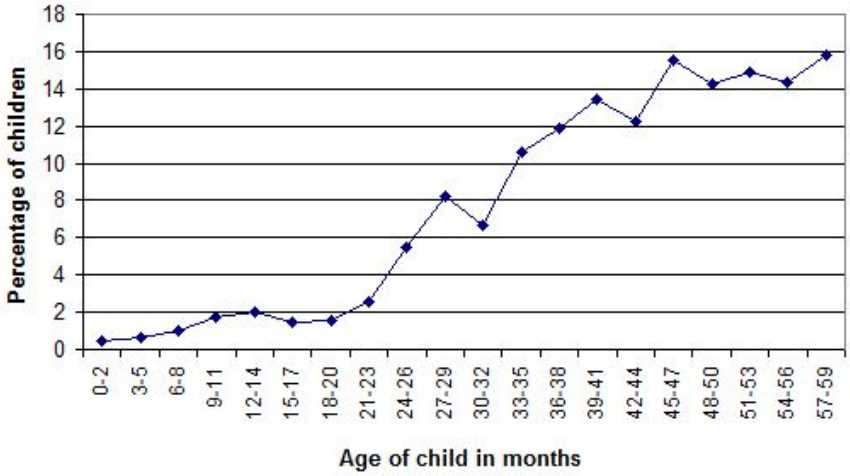
Reg Daycare - Regular Daycare/ECC; Daily feed - Daily supplementary feeding; Mnth health chk - Monthly health check-up; Most vacc at ICDS - Most vaccinations at ICDS center;

Figure A.1: Percentage of children below 5 years receiving different ICDS benefits intensely - Rural India



Daily feed - Daily supplementary feeding; Mnth health chk - Monthly health check-up; Most vacc at ICDS - Most vaccinations at ICDS center; Reg Daycare - Regular Daycare/ECC

Figure A.2: Percentage of children below 5 years receiving regular preschooling/early childhood care by 3 months age intervals - Rural India



Working Draft - Comments Welcome

Bridging the Gender Gap in Developing Country Education: The Role of Female Teachers

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Abstract: Recruiting female teachers is frequently suggested as a policy option for improving girls' education outcomes in developing countries, but there is limited evidence on its impact. We study gender gaps in learning outcomes, and the effectiveness of female teachers in reducing these gaps using a large longitudinal data set (collected annually over five years) on primary school learning outcomes in the Indian state of Andhra Pradesh. We report five main findings in this paper. (1) We find a small but significant negative trend in girls' test scores in both math (0.02σ/year) and language (0.01σ/year); (2) Using five years of panel data and school-grade fixed effects, we find that girls' test scores improve by an additional 0.03σ in years when they are taught by a female teacher relative to a male teacher (with similar effects in both math and language); (3) We find that both males and female teachers are more effective at teaching their own gender, but that boys do not fare worse when taught by female teachers relative to male teachers and the relative increased effectiveness is driven by girls doing worse with male teachers (relative to boys) and better with female teachers (relative to boys). (4) However, we find no effect of having a same-gender teacher on attendance; (5) Finally, regardless of the gender of their own teacher, we find that both boys and girls do better when there are other female teachers in the school (outside their own class), with the marginal positive impact declining in the fraction of female teachers. Thus, a policy of hiring more female teachers will improve overall educational performance due to positive effects to girls and a lack of any offsetting effect on boys.

JEL Classification: I21, O15

Keywords: education gender gaps, female teachers, India, longitudinal data

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1. Introduction

Reducing gender gaps in education attainment has been an important priority for international education policy, and is explicitly listed as one of the Millennium Development Goals (MDGs). This commitment has been reflected in the policies of many developing countries, and substantial progress has been made in the past decade in reducing gender barriers in primary school enrollment (UNESCO 2012). One of the policy innovations credited with increasing girls' education has been the increased recruitment of female teachers. UNICEF has documented the practice in a variety of countries, including Yemen, Nepal, Bangladesh, and Liberia, and the United Nations Task Force for achieving the MDGs has advocated hiring more female teachers as an effective policy mechanism for reaching the goal of universal primary education of girls (UNDG 2010, Rehman 2008, Slavin 2006).

Both these themes (a priority on reducing gender disparities in education and on hiring female teachers) are also reflected in education policy in India, which has the largest primary schooling system in the world (catering to over 200 million children). Numerous Five Year Plans and Sarva Shiksha Abhiyan (SSA), the flagship national program for universal primary education, have called for an increase in female teachers as a policy for increasing girls' education, with SSA requiring 50% of new teacher recruitment to be women, and the 11th Five Year Plan suggesting it be increased to 75% (Government of India 2008). These calls for increased female teachers reflect a belief that through such mechanisms as role model effects, increased safety, reduced prejudices, and greater identification and empathy, female teachers are arguably more effective in increasing girls' achievement in primary school relative to their male counterparts (see Dee 2005 for a discussion on the mechanisms by which shared characteristics between teachers and students could influence educational outcomes).

While the idea that hiring more female teachers can bridge gender gaps is widely prevalent among policy makers, there is very little empirical evidence on testing this hypothesis in developing countries.[1] In this paper, we study the causal impact of having a female teacher on the learning gains of female students, using one of the richest datasets on primary education in a developing country. The dataset was collected as a part of the Andhra Pradesh Randomized

[1] International cross-sectional correlations, using data from UNICEF, suggest a positive relationship between the share of female teachers in a country and female students' enrollment, with a 1% increase in the percentage of female teachers correlated with a .5 percent increase in the female percent of the enrollment rate (Appendix Table 1). However, such a correlation clearly cannot be interpreted causally due to the likely presence of omitted variables correlated with both better female education and having more qualified female candidates to serve as teachers.

Evaluation Studies (AP RESt), and features annual longitudinal data on student learning measured through independent assessments collected over five years across a representative sample of 500 rural schools and over 30,000 students in the Indian state of Andhra Pradesh. The data also includes detailed information on teacher characteristics and on their assignments to specific classrooms in each year.

The combination of panel data and variation in the gender of teachers assigned to cohorts as they pass through grades over time allows us to estimate the causal impact of matching teacher and student gender in a value-added framework. Identification concerns are addressed by showing that our causal estimates of gender matching do not change under an increasingly restrictive set of specifications including school fixed effects, and school-grade fixed effects. We also show that there is no correlation between the probability of being assigned a female teacher and any observable characteristics of the class. Further, the schools only have one section per grade, which precludes the possibility that students may be tracked across sections and that teachers may be assigned to different sections based on unobservables.

We report five main findings in this paper. First, we find a small but significant negative trend in girls' test scores in both math (0.02σ/year) and language (0.01σ/year) over the five years of primary school. Girls start out with higher test scores in language and equal test scores in math relative to boys at the end of grade one, but score on par with boys in language and significantly worse in math by the end of grade five. Thus, the consistent gender gaps in mathematics test score levels at age 15 found in PISA scores (Bharadwaj et al. 2012) probably reflect a culmination of a trend that starts as early as primary school.

Second, using five years of panel data and school-grade fixed effects, we find that girls' test scores improve by an additional 0.03σ in years when they are taught by a female teacher relative to a male teacher (with slightly higher effects in math than language). Third, we find that though both male and female teachers are more effective in teaching to their own gender, this result is driven by girls performing worse with male teachers (relative to boys), and higher with female teachers (relative to boys). Thus, female teachers are overall slightly more effective than male teachers because of the lack of any offsetting effect of teacher gender for boys. Thus, girl students are likely to benefit from a policy of hiring more female teachers and overall educational performance is likely to increase due to the lack of any offsetting effect on male students.

Fourth, we find no effect of having a same-gender teacher on attendance suggesting that the likely mechanism for the 'matching' effect is not on the extensive margin of increased contact time, but rather on the intensive margin of more effective classroom interactions. Finally, regardless of the gender of their own teacher, we find that both boys and girls do better when there are other female teachers in the school (outside their own class), with the marginal positive impact declining in the fraction of female teachers and even becoming negative at very high fractions of female teachers. Thus, there may be an optimal fraction of female teachers across schools.

This paper adds to a limited literature on empirical evidence of the impact of students sharing demographic characteristics with their teacher, most of which is based on data from developed countries. Studies in the US have generally found positive effects of sharing the gender and ethnicity of one's teacher on educational achievement, though these studies usually observe populations older than primary school age. In the US, studies have shown increased test scores, teacher perception, and student engagement of girls when taught by a female teacher in schools (Dee 2007, Dee 2005, Nixon and Robinson 1999, Ehrenberg et al. 1995). However, other studies conducted in European countries have failed to find such an effect (Holmund and Sund 2008, Carrington, Tymms and Merrell 2008, Lahelma 2006). In higher education institutions in the US, female professors have been found to have small effects on female students' course selection, achievement, and major choice (Bettinger et al. 2004, Carrell et al. 2009, Hoffmann and Oreopoulos 2009). Analogous to gender, studies in the United States have also looked at the effect of sharing the ethnicity of a teacher and have generally found positive effects on such educational outcomes as drop outs, pass rates, and grades at the community college level, and teacher perceptions and student achievement in school going children (Dee 2004, Dee 2005, Farlie et al. 2011). In a developing country setting, Rawal and Kingdom (2010) use test score data on 2nd and 4th grade students in the Indian states of Bihar and Uttar Pradesh, and find a positive impact of approximately .03 of a standard deviation on educational achievement in primary schools for students who are taught by teachers who share their gender.

In addition to providing well-identified evidence on the impact of matching teacher and student gender on learning outcomes in a developing country (where the literature is very sparse), our dataset allows us to make advances relative to both the developed and developing country literatures. First, while several existing papers in this literature (especially those looking

at college-level outcomes) use grades or test scores assigned by the students' own teachers, the test scores used in this paper are based on independent assessments and grading. This limits the concern that the measured effects of matching teacher and student characteristics may reflect more generous grading by teachers towards students who share their own characteristics and allows us to be confident that the effects we measure reflect genuine impacts on learning. Second, the best identified papers in the global literature on this question (including Dee 2007 and Rawal and Kingon 2012) use student fixed effects and variation in the gender of teachers across different subjects to identify the impact of the gender match, but they are based on comparing *levels* of test scores as opposed to value added. Thus, it can be difficult to interpret the magnitudes of the estimated effects without knowing the gender composition of the history of teachers (especially because if female teachers are more likely to teach a subject in the grade studied, they are more likely to teach the same subject in earlier grades as well). Our use of five years of annual panel data on test scores allows us to estimate the impact of a gender match on the *value-added in the year that the match occurred*, which has a cleaner interpretation. Third, this is the first paper (to our knowledge) that studies the impact of the gender composition of teachers in the school (outside a student's own class) with credible identification. Finally, we observe students at a younger and more formative age than most of the literature, when the role of matching characteristics may be especially important. This is also the age that is most relevant to policy for reducing education gender gaps in developing countries since the majority of students do not complete more than eight years of school education.

The remainder of this paper is organized as follows: Section 2 describes the dataset and presents summary statistics on students and teachers; Section 3 lays out the estimation and identification strategies; Section 4 presents the main results, and section 5 concludes.

2. The Dataset

The data used in this paper was collected for the Andhra Pradesh Randomized Evaluation Studies (APRESt), which were a series of experimental studies designed to evaluate the impact of various input and incentive-based interventions aimed at improving education outcomes in government-run rural schools in the Indian state of Andhra Pradesh.[2] The project has enabled

[2] These interventions are described and evaluated in Muralidharan and Sundararaman (2010); Muralidharan and Sundararaman (2011); Das, Dercon, Habyarimana, Krishnan, Muralidharan, and Sundararaman. (2012);

the creation of a detailed panel dataset over five years (from 2005-2010) with matched data on students, teachers, and households in a representative sample of 500 government-run primary schools (grades 1 through 5) across 5 districts in Andhra Pradesh. The dataset includes annual data on student learning outcomes as measured by independently conducted and graded tests in language (Telugu) and math, basic data on student and teacher demographics (caste and gender), and detailed household socio-economic data for a subset of households. The test scores are normalized each year within each grade-subject combination and all analysis is conducted in terms of normalized test scores, with magnitudes being reported in standard deviations.

Table 1 presents descriptive statistics on students who have at least one recorded test score in the dataset. We see that female students are not lagging in access, and if anything, have higher enrollment and attendance rates than boys. This does not imply that more girls are going to school than boys since it may be the case that more boys are attending private schools as opposed to public primary schools. However, it does illustrate that on average, girls are well represented in public primary schools. The girls in the sample appear to come from modestly better off socioeconomic backgrounds than the boys, and have parents who are a little more educated and affluent. These differences probably reflect two dimensions of selection into the sample – better off households are more likely to send girls to school, and better off households are more likely to send boys to private schools. However, the magnitudes of these differences are quite small (often in the range of 0-2 percentage points), and the significance reflects the very large sample size. Since the household surveys could only be completed for around 70% of the sample of students for whom we have test score data, our main specifications do not include household controls.[3]

Table 2 presents summary statistics for the teachers in our analysis. Female teachers comprise 46% of the total teacher body, but are less experienced, less likely have completed a college or masters degree, and less likely to hold a head-teacher position. Not surprisingly, their mean salaries are also lower. They also comprise a much greater share of the contract teacher

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Muralidharan and Sundararaman (2012), and Muralidharan (2012). All analysis in this paper includes dummies for the various treatment groups and our main specifications of interest use school-fixed effects thereby using only within school variation to identify the effects of matching teacher and student gender.

[3] While there are a few observable differences between the boys and girls in the sample, including this in the estimation will only matter if there are differential interactions between these household characteristics and teacher characteristics across boys and girls. We verify that our results are robust to the inclusion of household characteristics and that differences appear to be due to the changes in the limited sample used as opposed to the inclusion of household characteristics (not shown).

work-force than that of regular civil-service teachers. Since teacher characteristics vary systematically by gender, we will report our key results on the impact of matching teacher and student gender characteristics, both with and without controls for these characteristics.

Table 3 - Panel A presents summary statistics on gender differences in test scores by subject and grade. We see that girls score as well as boys in math and score 0.05σ *higher* on language in grade 1, and that this result holds both in the overall sample means as well as with school fixed effects. However, there is a steady decline in girls' test scores in both math and language as they advance through the grades and by the end of primary school (grade 5), we see that girls' initial advantage in language scores has declined significantly, and that they do significantly worse than boys on math. Table 3 - Panel B quantifies the annual decline in girls' relative scores with a simple interaction specification and we see a mean decline of 0.02σ/year in math scores and 0.007σ/year decline in language scores for girls relative to boys. Thus, the larger gender gaps between boys and girls documented on internationally comparable test scores such as PISA (administered at age 15) are probably reflecting not just differences in test-score levels between boys and girls at all points in time, but rather also reflecting a trajectory of increasing gender gaps in school performance as students advance to higher grades. [4]

3. Estimation and Identification

Our main estimating equation is based on a standard education production function (Boardman and Murnane 1979, Todd and Wolpin 2003), and takes the form:

$$(1)\ E_{itjk} = \alpha + \beta_1 E_{it-1j-1k} + \beta_2 T_{itjk} + \beta_3 F_{itjk} + \beta_4 M_{itjk} + \beta_5 S_{itjk} + \mu_{itjk}$$

where E_{itjk} are student educational outcomes (i.e., test scores), T_{itjk} are teacher characteristics (including gender), F_{itjk} are student and family characteristics (including student gender), M_{itjk} are matching indicators (in our case, an indicator for whether both the teacher and student are female), S_{itjk} are school inputs, and μ_{itjk} is a stochastic error term. The subscripts *i*, *t*, *j* and *k* represent the student, year, grade, and school respectively. The inclusion of the lagged test score on the right-hand side of the estimation allows us to estimate the impact of the

[4] It is worthwhile to note that achievement differences could be due to educational quality and access being different across genders in schools or to environmental factors that affect education achievement outside of the school's control. Furthermore, lack of differences does not necessarily mean that gender gaps are nonexistent since this is a sample of public schools only – a closing of gender gaps within public schools could be illustrative of more academically superior boys being sent to private schools relative to girls.

contemporaneous inputs (*T*, *F*, *M*, and *S*) in a standard *value-added* framework. Since all test scores are normalized by grade and subject, the estimated coefficients can be directly interpreted as the correlation between the covariate and annual gains in normalized test scores.[5] The same equation is used to assess gender matching on education on attendance, without the inclusion of controlling for attendance in the previous year[6].

The main coefficient of interest in this paper is β_4, which indicates the extent to which being matched with a teacher of the same gender is correlated with an increase in test scores or attendance during the year of the match. Since the indicator variable is based on the interaction of dummies for teacher and student gender, the coefficient is a 'difference in difference' estimate of the impact of female teachers when teaching girls rather than boys *relative* to their male teacher counterparts teaching girls rather than boys. The coefficient on the interaction term therefore reflects the sum of the relative advantage of female teachers when teaching girls (rather than boys) and the relative disadvantage of male teachers when teaching girls (rather than boys). (i.e., β_4 = *(female teachers teaching girls – female teachers teaching boys) – (male teacher teaching girls – male teachers teaching boys)*).

The main identification challenge in interpreting this coefficient causally is that teachers are not randomly assigned to schools, and it is possible that female teachers are more likely to be found in schools that have higher enrollment rates for girls, and which have more positive trajectories of achievement for girls. In such a case, a positive estimate of β_4 could be confounded by omitted variables correlated with both the probability of having a female teacher and having a steeper learning trajectory for girls. We address this concern by augmenting (1) with school fixed effects, and thereby estimating the impact of M_{itjk} using only variation *within* a school.

Nevertheless, a further concern could be that teachers are not assigned randomly to grades within schools, and a similar omitted variable concern would apply if female teachers are differentially assigned to grades in which girls also have steeper trajectories of learning growth (which may be the case if for instance, female teachers are more likely to be assigned to younger grades and if girls relatively outperform boys in earlier grades). Our preferred specifications

[5] In the case of grade 1 where there is no lagged score (since there was no test prior to joining school), we set the normalized lagged score to zero for all students.

[6] Specifically, $E_{itjk} = \alpha + \beta_2 T_{itjk} + \beta_3 F_{itjk} + \beta_4 M_{itjk} + \beta_5 S_{itjk} + \mu_{itjk}$, where E_{itjk} is now a measure of attendance.

therefore include school-grade fixed effects, which addresses this concern. The identifying variation in this case is coming solely from variation over time in the gender of the teacher in a given grade in a given school.[7]

A final concern could be that if grades have multiple sections, then the assignment of teachers to sections within grades could be based on omitted variables such as a greater probability of assigning female teachers to sections that have girls with a greater likelihood of improving test scores. However, this is not an important factor in our setting because schools typically have fewer teachers than grades, and the typical teaching arrangement is one of multi-grade teaching (where the same teacher simultaneously teaches multiple grades) and so there are only few cases where there are multiple sections per grade with different teachers assigned to different sections. We drop all cases (4.6% of observations) where there are multiple teachers per grade (though this ends up not making any difference to our estimates).

In addition to estimating the impact of gender matching in a student's own classroom on test score gains and attendance (using the specification above), our data and setting also allow us to estimate the impact of having teachers of the same gender in the school overall (outside the students' own classroom). The mechanisms for impact in this case (if any) are less likely to be from the direct pedagogical effects in the classroom, and more likely from channels such as a role model effect and perhaps a broader gender sensitization of the schooling environment (especially relative to a situation where *all* the teachers in the school are male). We test this by augmenting equation (1) with linear and quadratic terms in the fraction of *other* teachers in the school who are female and interactions of these terms with the student being female. As above, we estimate this equation with school-grade fixed effects, and the identifying variation is therefore coming from variation of the gender composition of teachers within a school over time. This variation is typically a result of teacher transfers that take place as part of a three to five year administrative cycle of rotation of teachers across schools and is typically determined administratively.[8]

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[7] Since the data are drawn from schools that were exposed to various experimentally-assigned programs, all estimates include dummy variables indicating the treatments that the schools were assigned to. But, this turns out to not matter in practice because our main estimating equations already include school (or school-grade) fixed effects, which makes the treatment status of the school irrelevant for identification purposes.

[8] While corruption and bribes for favorable postings are not uncommon (Beteille 2010), this does not pose a threat to our identification strategy because (a) we are using within as opposed to between school variation, and (b) the desirability of a particular post to a teacher is unlikely to be determined by the differential learning potential of students by gender in that school.

3.1. Testing the Identifying Assumptions

As discussed above, the main identification concern would be the possibility that female teachers are differentially assigned to schools/classes where girls have a potentially steeper learning trajectory. Table 4 - Panel A shows the correlation between various classroom characteristics and the probability of the classroom having a female teacher. The 2 correlations to highlight are the ones with the fraction of female students in classes with female teachers, and the mean test scores of the incoming cohorts, and we see that there is no significant correlation between having a female teacher and the fraction of girls in the classroom. In specifications without school fixed effects, female teachers on average have incoming cohorts of students with slightly lower math test scores (0.02 - 0.03σ) and slightly higher language scores of the same magnitude. However, once school fixed effects are included, these differences are negligible and insignificant (columns 3 and 4).

Female teachers *are* more likely to be assigned to younger grades, but once school-grade fixed effects are included, this is no longer an issue, and it continues to be case that having a female teacher in the class has no significant correlation with either the fraction of female students or the test scores of the incoming cohort (columns 5 and 6). We also verify that there is no significant difference between classrooms taught by male and female teachers on any of the household socio-economic variables listed in Table 1 (tables available on request), but we focus our attention on the test-scores of incoming cohorts as the most useful summary statistic of previous inputs into education to test balance on, because the sample size with the household survey is 30% smaller than that of just the test scores.

4. Results

Does Sharing the Female Gender Matter? Achievement:

Table 5a tests whether sharing of gender between a student and teacher increases academic achievement, and to what extent this differs by student gender. The first three columns show increasingly restrictive identification assumptions, with column (2) including school fixed effects and column (3) including school*grade fixed effects, our preferred specification. Column (5) includes teacher characteristics with school*grade fixed effects. Columns (3) and (5) suggests that whether or not we control for teacher observables, teachers are .035 standard deviations more effective in teaching to their own gender relative to a student of the opposite gender

compared to teachers of the other gender. In other words, female (male) teachers are .035 standard deviations more effective in teaching girls (boys) rather than boys (girls), relative to male (female) teachers. As seen in Table 5b and 5c, this effect is nearly identical in both subjects.

The statistically insignificant coefficient on female teacher in Table 5a, Column (3), indicates that boys do not fare much differently when taught by a male or a female teacher. The coefficient on female student is the marginal difference of a girl student with a male teacher relative to a boy student with a male teacher, indicating that male teachers are .01 standard deviations less effective when teaching girls (relative to boys). However, when we control for teacher observables (Column 5), we do see differences in the effectiveness of female teachers on boys relative to male teachers depending on the subject taught (Table 5b and 5c). Boys have slightly higher achievement (.0168 standard deviations) when taught by a male teacher compared to a female teacher in language, though we continue to see no statistically significant difference in math.

In determining the effectiveness of a policy of hiring female teachers, we are not only interested in the relative effectiveness of female teachers for girls (rather than boys) compared to male teachers, but also whether girls have higher achievement with female teachers than with male teachers. For example, it could be the case that female teachers are relatively more effective with girls, but that their overall effectiveness is significantly lower than male teachers, resulting in girls having higher achievement with male teachers despite the potential positive effect from sharing their teacher's gender. We formally test this by comparing the difference in test scores of girls taught by a female teacher (the sum of the coefficients of female, female teacher, and female student*female teacher) and test scores of girls' taught by a male teacher (the coefficient of female student), and find that girls are .04 standard deviations better off when taught by a female teacher relative to a male teacher. This effect is slightly higher in math (.04 standard deviations) than in language (.03 standard deviations).

We also formally test whether the gains incurred to girls by hiring a female teacher outweighs any potential negative effects of boys no longer being taught by a teacher of their same gender. In other words, we test the difference between test scores of a girl taught by a female teacher rather than a male teacher (the sum of the coefficients of female teacher and female student*female teacher) and a boy taught by a male teacher rather than a female teacher

(the negative of the coefficient on female teacher). We find that the overall increase in test scores of having female teacher is .04 standard deviations. The lack of any adverse effects of hiring female teachers is because of the overall lack of a negative effect of boys being taught by female teachers relative to male teachers. However, this effect differs when looking at subject specific effects. Because boys have higher test scores in language when taught by a male teacher compared to a female teacher, the gains for language (.03) are less when compared to math (.05).

Column (5) shows that we do see a reduction in the gains of hiring a female teacher when controlling for additional teacher covariates, especially in language, for both the gains to girls taught by female teachers relative to male teachers and the overall effect of gains to girls and boys.[9] This suggests that in addition to a pure "gender effect", there are observable characteristics that are correlated with being a female teacher that makes them more effective overall, increasing the welfare gains to employing more female teachers. The robustness of the coefficient on the shared gender interaction, however, suggests that there is a true effect of gender for girls when taught by female teachers relative to male teachers that is not due to an observable correlate with teacher gender.

To elucidate the tests in Table 5abc, Table 6abc shows the mirror difference-in-difference estimations using female teachers with girls students as the omitted category. As one can see, the coefficient on male teacher*male student is the same as the coefficient on female teacher*female student in Table 5, since both are the same estimate of the *relative* effectiveness of a teacher teaching students of their own gender. The coefficient on male teacher is the marginal decrease in test scores for girls taught by male teachers rather than female teachers (i.e., equivalent to test "Female Student*Female Teacher - Female Student*Male Teacher = 0" in Table 5).

These results suggest that learning for girls does increase when they are taught by female teachers relative to male teachers, even when controlling for teacher observables. From a policy perspective, female teachers seem to be correlated with observables that make them more effective teachers overall, suggesting that boys fare equally well with female teachers as male teachers and thus gains to girls outweigh any potential offsetting effects from boys.

Does Sharing the Female Gender Matter? Attendance:

[9] The robustness of column (4) compared to column (3) and (5), our basic school*grade fixed effects estimation using the limited sample of which we have teacher characteristics, provides confidence that the differences in results when controlling for teacher characteristics are not driven by changes in our sample.

Unlike achievement, Table 7 finds that sharing a teacher's gender does not have any statistically significant effect on attending school. If anything, female teachers have a small negative effect on attendance for boys. We perform the same tests as described in Table 5 and find no difference in attendance for a girl taught by a female teacher compared to when taught by a male teacher. The slight negative effect of female teacher's attendance on boys leads to a statistically significant negative overall effect of 1.3 percent fall in attendance from female teachers. However, once we control for observable teacher characteristics, Column (5) shows no difference in boys and girls overall attendance as a function of teacher gender, suggesting a lack of a pure "gender effect". These results are surprising since the rhetoric of hiring female teachers is often based the belief that a female teacher presence increases the safety and comfort of a school, and thus encourages girls' attendance of school. However, it could still be the case that a female teacher encourages girls' enrollment in school, even if not greater attendance. These results are robust to changes in sample size (Column 4).

Marginal Effect of Female Teachers on Female Students

Though female teachers may lead to overall achievement gains, it still may be the case that the marginal effect of an additional female staff member at a school decreases as the school gains more female teachers. If this is the case, then there may be an optimal number of female teachers to hire per school. To test this hypothesis, we include the fraction of female teachers at a school, the fraction of female teachers at a school interacted with a female student, and the squares of both variables. These variables are calculated as female fraction of teachers, not including the student's current teacher.

Table 8, Column (1), finds that additional female teachers increase test scores for both boys and girls, not including effects from one's own teacher's gender. However, it does so at a diminishing rate, and at high fractions of female teachers, the marginal effect even becomes slightly negative for both boys and girls. This pattern holds true for both boys and girls in both subjects. This suggests that introducing female teachers at schools where the fraction of female teachers is low is beneficial for both boy and girl students in terms of educational achievement, but that there may be such a concern of too many female teachers.

When controlling for the teacher composition outside of one's own teacher, we find that the coefficient on female teacher*female student continues to be robust, suggesting that each

teacher is still relatively more effective in teaching students of their own gender by approximately .03 standard deviations. However, this result now stems from girls doing even worse with male teachers relative to female teachers, offsetting the effect of boys doing relatively better with female teachers than male teachers. In other words, conditional upon teacher gender composition, male teachers are still more effective at teaching boys relative to girls (by -.0567 standard deviations), but overall boys are better off when taught by female teachers relative to male teachers (by .0362 standard deviations). However, we see that the increased female teacher effectiveness is only found in math and not language. In language, boys do not fare better or worse when taught by a female teacher relative to a male teacher, and male teachers are no longer as ineffective in teaching girls relative to boys (-.0840 standard deviations in math as compared to -.0333 standard deviations in language). Together, this suggests that even when controlling for teacher composition in the school, teachers are still relatively more effective in teaching their same gender by .03 standard deviations in both subjects, though the reasons behind this effectiveness differ by subject. This positive effect of being taught by a female teacher for boys and girls counters the negative marginal effect of female teachers when the fraction of female teachers are very high. These results are relatively robust to whether or not we include teacher covariates (Column 3).

5. Conclusion

In documenting the gender gaps of the public primary school system in Andhra Pradesh, India, we find girls have slightly lower achievement in higher grades than boys. We find that at the start of primary school, girls have a slight advantage in the local language (approximately .05 standard deviations) and are at par in math. However, in higher grades girls tend to lose the advantage in language (by 0.007σ/year) and fall behind in math (by 0.02σ/year). These trends are in addition to any sorting into private schools, and thus are likely to be a lower bound estimate of learning gaps in primary schools in general.

The findings in this paper render support for female teachers helping to close the educational gender gap by increasing girl students' educational outcomes in achievement. We find that relative to being taught by a male teacher, girl students perform .03 standard deviations higher when taught by a female teacher. We find that female teachers are relatively more effective in teaching girls (rather than boys) compared to male teachers by .035 standard

deviations. This result is driven by female teachers being more effective at teaching girls relative to boys, and male teachers being less effective at teaching girls relative to boys. These results hold true across subjects, with slightly larger magnitudes in math relative to language. We find no evidence of offsetting effects to boys in math, as boy students perform equally well with female and male teachers, but a slight increase in test scores of boys' taught by male teachers (compared to female teachers) in language. The magnitudes of the effects reduce slightly when controlling for observable teacher characteristics other than gender, suggesting that the characteristics correlated with female teachers make them slightly more effective overall, but that there is also a pure "gender effect" for girl students. We fail to find a similar effect of teacher gender on girls' or boys' attendance, contrary to the common belief that female teachers encourage girls to attend school.

We further find that an increased female teacher presence at school, even in addition to being taught by a female teacher, has a positive effect on students' achievement for both boys and girls. We find the marginal benefit, however, decreases with each additional female teacher, and even turns negative at very high fractions of female teacher compositions. Thus, at schools with low percentage of female teachers, a policy to hire greater female teachers will not only improve girls' learning, but also boys'. Even at higher fractions of female teachers, the positive effects of being taught by a female teacher may outweigh the negative marginal effects of increased female teachers for both boys and girls, suggesting that recruiting female teachers is still an effective mechanism for increasing achievement.

It is worthwhile to note that the extent to whether the benefit of sharing a teacher's gender supports the recruitment of female teachers still depends on the overall effectiveness of the female teacher pool. In our context, we find that girls benefit with female teachers and boys do not fare worse with female teachers when we do not control for other teacher characteristics. However, other contexts may have a different skill level of teachers correlated with female teachers that may outweigh the benefits from shared teacher gender, even if there is a pure "gender effect" of female teachers being relatively more effective in teaching girls (rather than boys) compared to male teachers. The findings in this paper support the increased recruitment of female teachers as a method to increase girls' educational achievement, as long as the pool of female teachers are similarly or more effective as male teachers on average.

Though we find that achievement is boosted by sharing a teacher's gender, the mechanisms through which shared gender influences achievement remains unanswered. Deciphering the underlying reason behind the significance of gender matching would possibly allow for other policies to capture these positive gains without having adverse effects on either gender.

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Table 1: Student Summary Statistics by Gender

	No. Obs.	Mean	Male	Female	Female - Male
Female	94599	50.90			
Attendance (Percent Present)	119276	57.74	56.34	59.15	0.028***
Scheduled Caste	94569	6.81	7.31	6.34	-0.967***
Scheduled Tribe	94569	19.91	20.21	19.62	-0.590**
Other Backwards Caste	94569	55.76	55.40	56.10	0.692**
Size of Family	67310	4.83	4.80	4.86	0.0648***
Tutor outside house	66156	13.07	13.08	13.06	-0.0121
Disabled	66678	1.50	1.70	1.32	-0.384***
Literate Father	66511	59.15	58.19	60.04	1.85***
Father Completed Class 5	66511	28.11	26.89	29.23	2.34***
Father Completed Class 10	66511	11.35	10.73	11.92	1.19***
Literate Mother	66827	43.90	42.87	44.86	1.99***
Mother Completed Class 5	66827	15.69	14.52	16.76	2.24***
Mother Completed Class 10	66827	3.87	3.68	4.04	0.364**
Owns Land	66502	38.93	38.86	38.98	0.124
Owns House	67057	94.66	94.63	94.69	0.0509
Thatched Hut	66851	18.98	19.67	18.35	-1.33***
Brick house with thatched roof	66851	49.95	49.77	50.12	0.347
Brick house with all-weather roof	66851	31.06	30.55	31.53	0.981***
Has Toilet	66974	28.93	28.38	29.43	1.06***
Has Electric Connection	66882	87.73	87.32	88.12	0.799***

Notes: All variables are binary indicators, except for size of family. All means are percentages, except for family size. All variables (except attendance) are for those students whom test score data exists. Basic demographic data (gender and caste) are obtained from school rosters, while other data is from household interviews.

* p<0.1, ** p<.05 , ***p<.01

Table 2: Teacher Summary Statistics

	No. Obs.	Total	Male	Female	Female-Male
Female	2679	45.76			
Scheduled Caste (SC)	2677	15.83	14.61	17.27	2.66*
Scheduled Tribe (ST)	2677	1.92	2.55	1.18	-1.37***
Other Backwards Caste (OBC)	2677	43.42	44.51	42.14	-2.36
Head Teacher	2679	28.81	37.77	18.21	-19.6***
Regular Teacher	2679	50.37	49.74	51.10	1.36
Contract Teacher	2679	18.79	11.57	27.34	15.8***
Highest Completed Education: 10th Grade	2679	99.33	99.06	99.64	0.576**
Highest Completed Education: 12th Grade	2679	93.06	96.24	89.29	-6.95***
Highest Completed Education: Bachelors	2679	76.81	82.08	70.57	-11.5***
Highest Completed Education: Masters	2679	22.60	27.02	17.36	-9.66***
Has Teacher Training	2660	83.29	90.84	74.26	-16.6***
Native to Village	2678	23.39	17.52	30.36	12.8***
Married	2675	81.02	84.51	76.90	-7.60***
Active in Union	2673	18.33	27.59	7.37	-20.2***
Salary (monthly)	2673	9563.08	10703.90	8208.48	-2495.4***
Age	2659	36.90	39.54	33.75	-5.792***
Teacher Experience	2285	12.95	14.47	11.08	-3.389***

Notes: All variables are binary indicators, except for teacher's teacher salary, age, and experience. All means are given as percentages, except for teacher salary, age, and experience.

* p<0.1, ** p<.05 , ***p<.01

Table 3 - Learning Gaps by Gender and Grade

Panel A: Gender Differentials in Test Scores by Grade

	Pooled Across Subjects		Math		Telugu	
	Dependent Variable: Normalized Test Score (Within Grade)					
	(1)	(2)	(3)	(4)	(5)	(6)
Female (Grade 1)	0.0279**	0.0206**	0.00238	-0.00376	0.0531***	0.0448***
	(0.0122)	(0.00925)	(0.0135)	(0.0101)	(0.0127)	(0.0100)
	66660	66660	33187	33187	33473	33473
Female (Grade 2)	0.00526	0.00571	-0.0271**	-0.0242***	0.0376***	0.0354***
	(0.0114)	(0.00828)	(0.0117)	(0.00880)	(0.0122)	(0.00889)
	70953	70953	35453	35453	35500	35500
Female (Grade 3)	-0.0217*	-0.0225***	-0.0569***	-0.0571***	0.0136	0.0121
	(0.0118)	(0.00813)	(0.0120)	(0.00863)	(0.0128)	(0.00894)
	74715	74715	37349	37349	37366	37366
Female (Grade 4)	-0.0442***	-0.0379***	-0.0956***	-0.0879***	0.00709	0.0122
	(0.0120)	(0.00771)	(0.0122)	(0.00815)	(0.0130)	(0.00864)
	79972	79972	39973	39973	39999	39999
Female (Grade 5)	-0.0262**	-0.0209***	-0.0749***	-0.0671***	0.0225*	0.0254***
	(0.0115)	(0.00738)	(0.0123)	(0.00771)	(0.0123)	(0.00846)
	85572	85572	42777	42777	42795	42795

Panel B: Trends in Gender Differentials in Test Scores from lower to higher grades

Female	0.0311**	0.0271***	0.0115	0.00812	0.0506***	0.0457***
	(0.0132)	(0.00993)	(0.0142)	(0.0106)	(0.0139)	(0.0107)
Female*Grade	-0.0144***	-0.0127***	-0.0207***	-0.0189***	-0.00805*	-0.00635**
	(0.00383)	(0.00281)	(0.00410)	(0.00298)	(0.00410)	(0.00308)
No. of Observations	377872	377872	188739	188739	189133	189133
School Fixed Effects	No	Yes	No	Yes	No	Yes

All regressions include previous year's test scores. Standard errors (in parantheses)are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 4: Correlates of Teacher Assignment by Gender

Panel A: Characteristics of Classrooms Assigned to Female Teachers

	(1)	(2)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Classroom Has a Female Teacher						
Proportion of Female Students	**0.00442**	**-0.00511**	**-0.0141**	**0.000836**	**-0.0147**	**0.00744**	**-0.0111**
	(0.0247)	(0.0261)	(0.0241)	(0.0217)	(0.0207)	(0.0211)	(0.0204)
Grade 1	0.0159	0.0238	0.0652***	0.0234*	0.0681***		
	(0.0148)	(0.0157)	(0.0147)	(0.0120)	(0.0117)		
Grade 2	0.0226	0.0272*	0.0495***	0.0277**	0.0495***		
	(0.0150)	(0.0159)	(0.0148)	(0.0122)	(0.0117)		
Grade 4	-0.0678***	-0.0728***	-0.0383***	-0.0683***	-0.0346***		
	(0.0149)	(0.0158)	(0.0147)	(0.0121)	(0.0116)		
Grade 5	-0.141***	-0.134***	-0.0573***	-0.134***	-0.0538***		
	(0.0148)	(0.0157)	(0.0149)	(0.0120)	(0.0118)		
Math Test Score of Incoming Cohort	**-0.0231***	**-0.0292****	**-0.0333*****	**0.00476**	**-0.00509**	**0.00650**	**0.00738**
	(0.0119)	(0.0126)	(0.0116)	(0.0100)	(0.00961)	(0.0101)	(0.00978)
Language Test Score of Incoming Cohort	**0.0283****	**0.0286****	**0.0317*****	**-0.00995**	**0.00386**	**-0.0109**	**-0.00524**
	(0.0124)	(0.0131)	(0.0121)	(0.0108)	(0.0103)	(0.0111)	(0.0107)
Number of Observations	10957	9744	9744	10957	9744	10957	9744

Panel B: Probability of a Female Student Being Assigned to A Female Teacher

	(1)	(2)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Dummy for Female Student						
Female Teacher	0.00406	0.00297	0.00262	0.00137	0.00152	0.00312	0.00376
	(0.00249)	(0.00265)	(0.00286)	(0.00304)	(0.00361)	(0.00376)	(0.00449)
Constant	0.498***	0.498***	0.489***	0.512***	0.507***	0.520***	0.544***
	(0.00395)	(0.00423)	(0.0358)	(0.00329)	(0.0381)	(0.00207)	(0.0447)
Number of Observations	166729	147712	147712	166729	147712	166729	147712
Teacher Characteristics	No	No	Yes	No	Yes	No	Yes
School Fixed Effects	No	No	No	Yes	Yes	No	No
School*Grade Fixed Effects	No	No	No	No	No	Yes	Yes
Restricted Sample	No	Yes	Teacher	No	Teacher	No	Teacher

"Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 ,***p<.01

Table 5a: Impact of Female Teachers on the Learning Gains of Female Students

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Female Student * Female Teacher	0.0385***	0.0364***	0.0357***	0.0358***	0.0353***
	(0.00995)	(0.00788)	(0.00753)	(0.00798)	(0.00798)
Female Student	-0.0123*	-0.0143***	-0.0130***	-0.0115**	-0.0110**
	(0.00676)	(0.00522)	(0.00498)	(0.00522)	(0.00522)
Female Teacher	-0.0146	-0.00273	0.00146	0.00420	-0.00393
	(0.0188)	(0.00629)	(0.00698)	(0.00760)	(0.00799)
Number of Observations	268295	268295	268295	237633	237633
Female Student*Female Teacher - Female Student*Male Teacher = 0	0.024	0.034***	0.037***	0.040***	0.031***
F-Statistic	1.698	31.839	31.291	30.568	16.695
Female Match Gain - Male Match Gain = 0	0.009	0.031***	0.039***	0.044***	0.027**
F-Statistic	0.067	10.857	11.572	12.466	4.137
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 5b: Impact of Female Teachers on the Learning Gains of Female Students in Math

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Female Student * Female Teacher	0.0341***	0.0338***	0.0340***	0.0332***	0.0324***
	(0.0111)	(0.00876)	(0.00843)	(0.00894)	(0.00894)
Female Student	-0.0379***	-0.0433***	-0.0413***	-0.0384***	-0.0377***
	(0.00727)	(0.00575)	(0.00553)	(0.00581)	(0.00580)
Female Teacher	-0.0129	0.00356	0.00919	0.0137	0.0100
	(0.0209)	(0.00701)	(0.00785)	(0.00857)	(0.00901)
Number of Observations	133780	133780	133780	118508	118508
Female Student*Female Teacher - Female Student*Male Teacher = 0	0.021	0.037***	0.043***	0.047***	0.042***
F-Statistic	1.055	31.307	33.225	33.067	24.143
Female Match Gain - Male Match Gain = 0	0.008	0.041***	0.052***	0.060***	0.053***
F-Statistic	0.043	15.133	16.685	18.338	11.891
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 5c: Impact of Female Teachers on the Learning Gains of Female Students in Language

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Female Student * Female Teacher	0.0430***	0.0393***	0.0374***	0.0389***	0.0387***
	(0.0104)	(0.00852)	(0.00819)	(0.00867)	(0.00866)
Female Student	0.00956	0.0102*	0.0111**	0.0107*	0.0111*
	(0.00724)	(0.00564)	(0.00539)	(0.00566)	(0.00566)
Female Teacher	-0.0169	-0.00831	-0.00489	-0.00357	-0.0168*
	(0.0182)	(0.00687)	(0.00763)	(0.00831)	(0.00874)
Number of Observations	134515	134515	134515	119125	119125
Female Student*Female Teacher - Female Student*Male Teacher = 0	0.026	0.031***	0.032***	0.035***	0.022***
F-Statistic	2.205	22.737	19.960	19.772	6.780
Female Match Gain - Male Match Gain = 0	0.009	0.023**	0.028**	0.032**	0.005
F-Statistic	0.071	4.844	4.910	5.325	0.122
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 6a : Impact of Male Teachers on the Learning Gains of Male Students

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Male Student * Male Teacher	0.0385***	0.0364***	0.0357***	0.0358***	0.0353***
	(0.00995)	(0.00788)	(0.00753)	(0.00798)	(0.00798)
Male Student	-0.0261***	-0.0221***	-0.0227***	-0.0242***	-0.0243***
	(0.00802)	(0.00606)	(0.00582)	(0.00622)	(0.00621)
Male Teacher	-0.0239	-0.0337***	-0.0372***	-0.0400***	-0.0314***
	(0.0183)	(0.00598)	(0.00664)	(0.00723)	(0.00767)
Number of Observations	268295	268295	268295	237633	237633
Male Student*Male Teacher - Male Student*Female Teacher = 0	0.015	0.003	-0.001	-0.004	0.004
F-Statistic	0.602	0.188	0.044	0.305	0.242
Male Match Gain - Female Match Gain = 0	-0.009	-0.031***	-0.039	-0.044***	-0.027**
F-Statistic	0.067	10.857	11.572	12.466	4.137
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 6b : Impact of Male Teachers on the Learning Gains of Male Students in Math

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Male Student * Male Teacher	0.0341***	0.0338***	0.0340***	0.0332***	0.0324***
	(0.0111)	(0.00876)	(0.00843)	(0.00894)	(0.00894)
Male Student	0.00385	0.00947	0.00728	0.00525	0.00533
	(0.00907)	(0.00668)	(0.00645)	(0.00691)	(0.00691)
Male Teacher	-0.0212	-0.0374***	-0.0432***	-0.0468***	-0.0425***
	(0.0206)	(0.00669)	(0.00750)	(0.00814)	(0.00864)
Number of Observations	133780	133780	133780	118508	118508
Male Student*Male Teacher - Male Student*Female Teacher = 0	0.013	-0.004	-0.009	-0.014	-0.010
F-Statistic	0.382	0.258	1.371	2.542	1.244
Male Match Gain - Female Match Gain = 0	-0.008	-0.041***	-0.052***	-0.060	-0.053***
F-Statistic	0.043	15.133	16.685	18.338	11.891
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 6c : Impact of Male Teachers on the Learning Gains of Male Students in Language

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable for all Panels: Normalized Test Scores (by Grades)				
Male Student * Male Teacher	0.0430***	0.0393***	0.0374***	0.0389***	0.0387***
	(0.0104)	(0.00852)	(0.00819)	(0.00867)	(0.00866)
Male Student	-0.0525***	-0.0496***	-0.0485***	-0.0496***	-0.0498***
	(0.00788)	(0.00647)	(0.00624)	(0.00664)	(0.00664)
Male Teacher	-0.0261	-0.0310***	-0.0325***	-0.0353***	-0.0219***
	(0.0175)	(0.00651)	(0.00727)	(0.00794)	(0.00842)
Number of Observations	134515	134515	134515	119125	119125
Male Student*Male Teacher - Male Student*Female Teacher = 0	0.017	0.008	0.005	0.004	0.017*
F-Statistic	0.861	1.464	0.411	0.184	3.675
Male Match Gain - Female Match Gain = 0	-0.009	-0.023**	-0.028**	-0.032**	-0.005
F-Statistic	0.071	4.844	4.910	5.325	0.122
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 7: Impact of Female Teachers on Attendance of Female Students

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Student Attendance				
Female Student* Female Teacher	**0.00308**	**0.00186**	**0.00245**	**0.00380**	**0.00437**
	(0.00465)	(0.00368)	(0.00368)	(0.00394)	(0.00393)
Female Student	0.0325***	0.0331***	0.0325***	0.0313***	0.0311***
	(0.00348)	(0.00263)	(0.00265)	(0.00279)	(0.00278)
Female Teacher	-0.00291	0.00519*	-0.00757**	-0.00350	-0.00268
	(0.00719)	(0.00278)	(0.00323)	(0.00358)	(0.00375)
Number of Observations	243249	243249	243249	215351	215351
Female Student*Female Teacher - Female Student*Male Teacher = 0	0.000	0.007***	-0.005	0.000	0.002
F-Statistic	0.001	6.625	2.560	0.007	0.207
Female Match Gain - Male Match Gain = 0	-0.003	0.012***	-0.013**	-0.003	-0.001
F-Statistic	0.041	8.872	5.793	0.294	0.025
Student Characteristics	No	No	No	No	No
Teacher Characteristics	No	No	No	No	Yes
School Fixed Effects	No	Yes	No	No	No
School*Grade Fixed Effects	No	No	Yes	Yes	Yes
Restricted Sample	No	No	No	Teacher	Teacher

"Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects.

* p<0.1, ** p<.05 , ***p<.01

Table 8: Impact of Fraction of Female Teachers in the School on Girls' Academic Achievement

	Pooled Across Subjects			Math			Telugu		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female Student*Fraction Female Teacher in School	0.229***	0.206***	0.207***	0.235***	0.206***	0.206***	0.225***	0.209***	0.211***
	(0.0448)	(0.0471)	(0.0471)	(0.0496)	(0.0524)	(0.0524)	(0.0477)	(0.0501)	(0.0501)
Female Student*(Fraction Female Teacher in School)^2	-0.212***	-0.181***	-0.182***	-0.227***	-0.190***	-0.190***	-0.202***	-0.178***	-0.180***
	(0.0451)	(0.0474)	(0.0474)	(0.0502)	(0.0529)	(0.0529)	(0.0478)	(0.0501)	(0.0502)
Fraction Female Teachers in School	0.476***	0.439***	0.438***	0.608***	0.594***	0.594***	0.328***	0.271***	0.270***
	(0.0788)	(0.0857)	(0.0863)	(0.0876)	(0.0956)	(0.0964)	(0.0866)	(0.0940)	(0.0945)
(Fraction Female Teacher in School)^2	-0.328***	-0.350***	-0.337***	-0.400***	-0.433***	-0.428***	-0.240***	-0.249***	-0.226***
	(0.0668)	(0.0725)	(0.0732)	(0.0754)	(0.0823)	(0.0831)	(0.0720)	(0.0779)	(0.0786)
Female Student * Female Teacher	0.0319***	0.0313***	0.0309***	0.0311***	0.0296***	0.0289***	0.0330***	0.0338***	0.0336***
	(0.00764)	(0.00808)	(0.00807)	(0.00858)	(0.00909)	(0.00908)	(0.00835)	(0.00883)	(0.00882)
Female Student	-0.0566***	-0.0529***	-0.0526***	-0.0840***	-0.0779***	-0.0772***	-0.0333***	-0.0327***	-0.0328***
	(0.0105)	(0.0111)	(0.0111)	(0.0116)	(0.0123)	(0.0123)	(0.0112)	(0.0118)	(0.0118)
Female Teacher	0.0362***	0.0288**	0.0228*	0.0546***	0.0509***	0.0481***	0.0189	0.00856	-0.000568
	(0.0112)	(0.0120)	(0.0122)	(0.0127)	(0.0136)	(0.0137)	(0.0123)	(0.0132)	(0.0133)
Number of Observations	268295	237633	237633	133780	118508	118508	134515	119125	119125
Student Characteristics	No	No	No	No	No	No	No	No	No
Teacher Characteristics	No	No	Yes	No	No	Yes	No	No	Yes
School Fixed Effects	No	No	No	No	No	No	No	No	No
School*Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Restricted Sample	No	Teacher	Teacher	No	Teacher	Teacher	No	Teacher	Teacher

"Fraction of Female Teacher in School" is the fraction of female teachers in the school, excluding the student's current teacher. "Student Socioeconomic Characteristics" are the variables listed in Table 1: Family size and indicators for students' caste, mother's education, father's education, disability, being tutored, household's land and house ownership, house quality, household toilet, and household electricity connection. "Teacher Characteristics" are the variables listed in Table 2: Salary, age, experience, and indicators for caste, teacher status, education, training, native to school location, marital status, and union status.

Standard errors (in parentheses) are clustered at the school level for OLS regressions not including school fixed effects, and are clustered at the student level for OLS regressions including school fixed effects; * p<0.1, ** p<.05 , ***p<.01

Cycling to School: Increasing Secondary School Enrollment for Girls in India

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Abstract: Gender gaps in primary school enrollment in development countries have been falling, but there continues to be a significant gender gap in secondary school enrolment. We study the impact of an innovative program in the Indian state of Bihar that provided girls who continued to secondary school with a bicycle that would improve access to school. Using data from multiple household surveys, we employ a triple difference approach (using boys and the neighboring state of Jharkhand as comparison groups) and find that the program increased girls' enrollment in secondary school by five percentage points and reduced the gender gap in secondary school enrollment by 20 percent. Parametric and non-parametric estimates of program impact as a function of distance to the nearest secondary school show that the impact of the program was significantly greater in villages where the nearest secondary school was further away, suggesting that a key mechanism for program impact was the reduction in the 'distance cost' of school attendance induced by the bicycle. We find modestly positive (but mostly insignificant) effects of the program on the probability of girls appearing in and passing the externally evaluated secondary school leaving examinations.

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CYCLING TO SCHOOL: INCREASING SECONDARY SCHOOL ENROLLMENT FOR GIRLS IN INDIA

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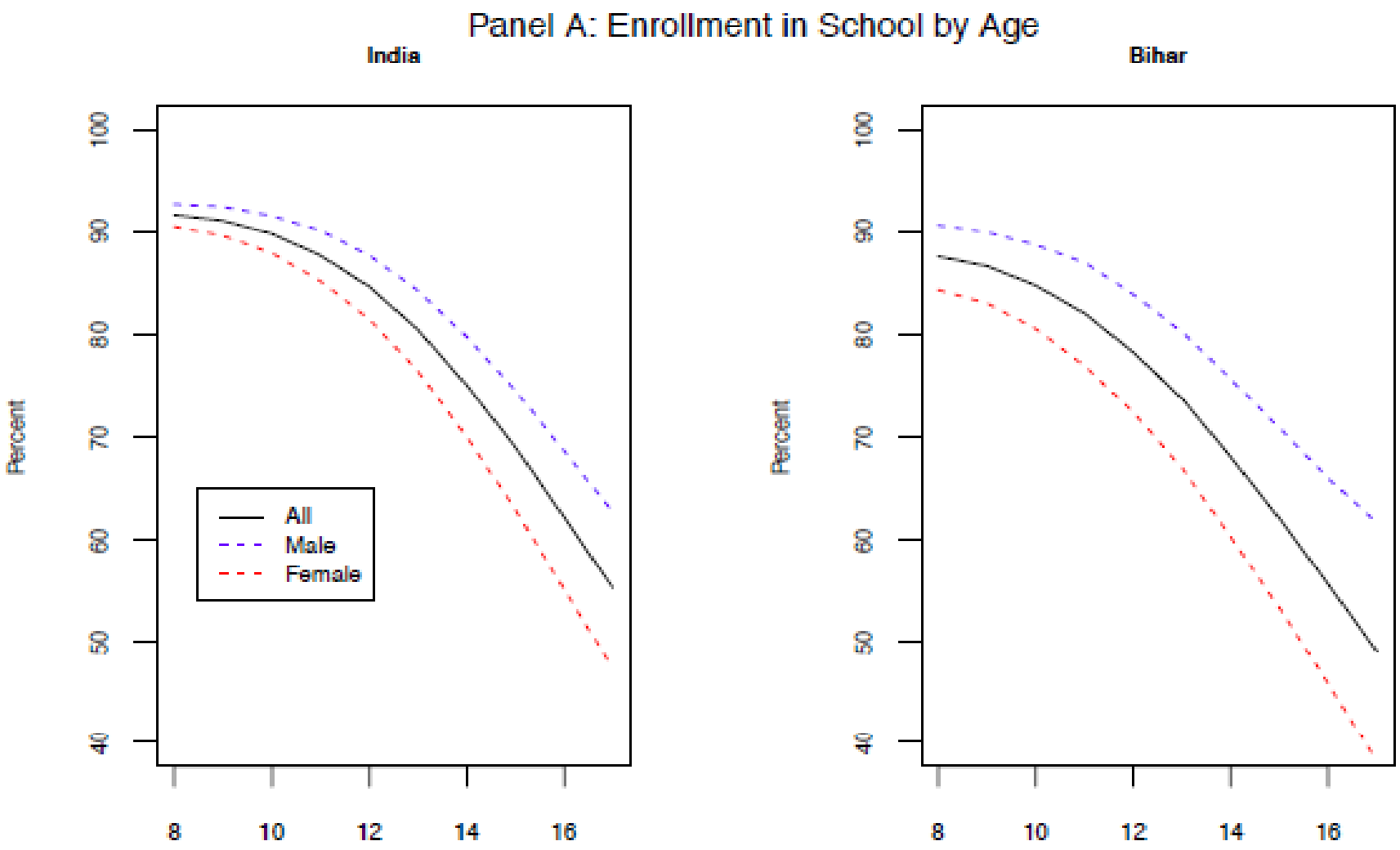
22 Jan 2013

PACDEV Submission

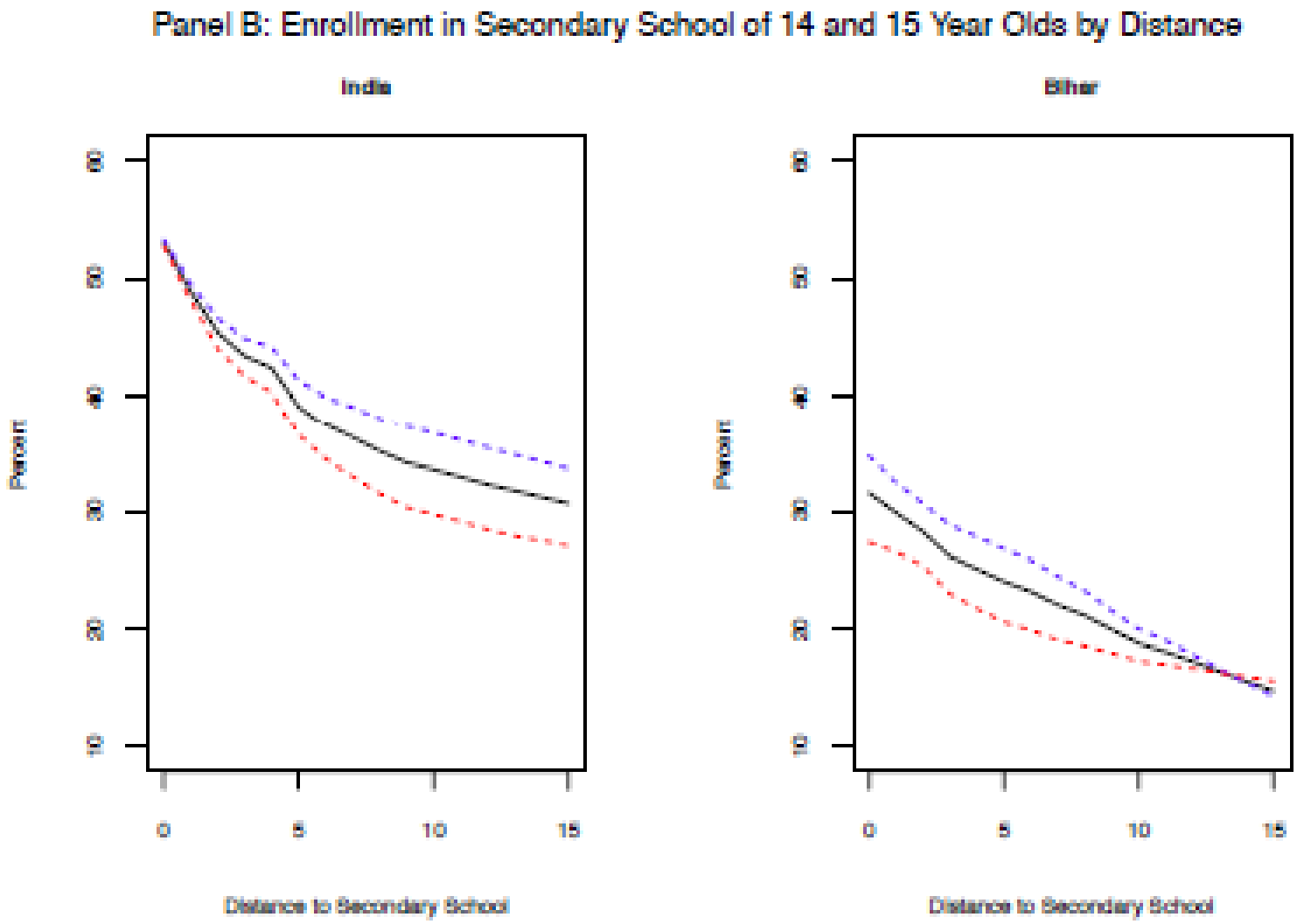
Background/Motivation

- Increasing female school attainment is one of the MDG's
- Improving female education directly contributes to the 'inclusive growth' agenda of the Government
  - Growth – by increasing human capital of the labor force
  - Inclusive – by allowing more people to participate in the growth process
- Large gender gaps in India (and especially in Bihar) in school attendance (grows with age)
- Primary schools now exist within 1km of most villages
- But distance is still an important barrier to secondary school attendance (again, more so for girls)

School Enrollment by Age & Gender



Enrollment of 14-15 year olds in Secondary School by Distance & Gender



Policy Intervention

- In 2006, the Govt. of Bihar initiated a program to provide bicycles to all girls studying in classes 9 and 10
  - Personal initiative of the Chief Minister
  - Program was called the "Mukhyamantri Balika Cycle Yojana (MBCY)"
- An allocation of Rs. 2000/student was made (now Rs. 2500)
- No direct provision of bicycles – cash was made available to eligible students through the schools, and receipts for purchase of cycles were collected
- This was effectively a CCT (or CKT) program and was India's first scaled up CT program for girl's secondary education
  - High-profile program, politically very visible (and also copied)
  - Concerns include fake enrolments, and leakage of funds
  - What was the impact of the program?

This Paper

- Aims to:
  - Evaluate impact on secondary school enrolment for girls
  - Examine the mechanism of impact (conditionality vs. cycle)
- Main challenge for the empirical analysis is that the program was implemented state-wide and so it is difficult to find a control group
  - Boys (double difference)
  - Jharkhand (triple difference)
- Even if you get an effect, there may be multiple mechanisms:
  - Conditionality; Bicycle; Third factors (other programs, returns)
- If the impact was because of the cycle itself, we should see differential impacts by distance to school
  - Quadruple difference (by distance)
  - Plot triple-difference by distance (non-parametric)

Data & Estimation Strategy

- We use the 2008 District-Level Health survey (DLHS)
  - Representative sample of ~1,000 HH/district (total sample of close to 50,000 HH across Bihar/Jharkhand)
  - Family roster with education histories
  - Village data includes distance to nearest secondary school
- Survey conducted ~1.5 years after MBCY launched
  - So we treat 14-15 year olds as 'treated' cohorts and 16-17 year olds as 'control' cohorts
  - Dependent Variable: Enrolled in or completed class 9
  - 14-15 vs.16-17 year old girls (first difference)
  - Compare with corresponding difference for boys (second difference)
  - Compare double difference across Bihar & Jharkhand (triple difference)
- But mechanism could be the 'conditionality' or the 'cycle' or other factors as well (other programs; changes in returns to education for girls in BH)
  - If the channel of impact is that the cycle reduces the 'distance cost' of attending school, then we should see a larger impact in villages where the nearest secondary school is further away (data lets us test this)

Results (Double Difference)

Difference in Differences Estimate for the Impact of Cycle Program on Girl's Enrollment (Comparing Changes in Enrollment for Girls and Boys in Bihar alone)

	(1)	(2)	(3)	(4)
Treat *Female dummy	**0.123*** **	**0.114*** **	**0.0908*** **	**0.0904*** **
	(0.0149)	**(0.0144)**	**(0.0135)**	**(0.0134)**
Treat	-0.192***	-0.184***	-0.167***	-0.166***
	(0.0108)	(0.0106)	(0.00992)	(0.00992)
Female dummy	-0.186***	-0.178***	-0.168***	-0.167***
	(0.0117)	(0.0112)	(0.0103)	(0.0103)
Constant	0.475***	0.823***	0.487***	0.502***
	(0.00980)	(0.0831)	(0.0622)	(0.0673)
Demographic Controls	NO	YES	YES	YES
Household Asset & Literacy Controls	NO	NO	YES	YES
Village-Level Controls	NO	NO	NO	YES
Observations	18,453	18,453	18,353	18,331
R-squared	0.038	0.106	0.225	0.227

Do Parallel Trends Hold (Double Diff)?

	(1) Grade 9 Log (Enrollment)	(2) Grade 10 Log (Enrollment)
Year_Female	0.0470***	0.0461***
	(0.00613)	(0.00544)
Female	-0.701***	-0.705***
	(0.0588)	(0.0591)
Year	0.0820***	0.0887***
	(0.00561)	(0.00534)
Constant	7.268***	7.133***
	(0.200)	(0.199)
Observations	30,597	30,585
R-squared	0.026	0.026

Robust standard errors
*** p<0.01, ** p<0.05, *

Not in the double difference!

Do Parallel Trends Hold (Triple Diff)?

VARIABLES	(1) Grade 9 Log (Enrollment)	(2) Grade 10 Log (Enrollment)
Female_Year_Bihar	-0.0156	-0.0155
	(0.0101)	(0.0101)
Year_Female	0.0626***	0.0616***
	(0.00802)	(0.00852)
Female_Bihar	0.0622	0.102
	(0.0974)	(0.0867)
Bihar_Year	0.0312***	0.0329***
	(0.00999)	(0.00878)
Female	-0.763***	-0.806***
	(0.0777)	(0.0637)
Year	0.0508***	0.0558***
	(0.00827)	(0.00698)
Bihar	0.525*	0.567**
	(0.265)	(0.270)
Constant	6.744***	6.566***
	(0.175)	(0.184)
Observations	36,884	36,866
R-squared	0.037	0.040

Robust standard errors
*** p<0.01, ** p<0.05, *

But, they do in the triple difference

Results (Triple Difference)

Triple Difference Estimate for the Impact of Cycle Program on Girl's Enrollment
(Comparing the Double Difference between Bihar and Jharkhand)

	(1)	(2)	(3)	(4)
Treat*Female dummy*Bihar dummy	**0.103*** **	**0.0912*** **	**0.0525** **	**0.0523** **
	(0.0302)	**(0.0294)**	**(0.0252)**	**(0.0253)**
Treat*Female dummy	0.0195	0.0235	0.0380*	0.0381*
	(0.0263)	(0.0256)	(0.0214)	(0.0215)
Treat*Bihar dummy	-0.0437**	-0.0418**	-0.0290*	-0.0281*
	(0.0179)	(0.0177)	(0.0160)	(0.0161)
Female dummy*Bihar dummy	-0.0942***	-0.0905***	-0.0686***	-0.0673***
	(0.0233)	(0.0226)	(0.0200)	(0.0201)
Treat	-0.148***	-0.143***	-0.138***	-0.138***
	(0.0143)	(0.0142)	(0.0127)	(0.0127)
Female dummy	-0.0915***	-0.0880***	-0.0986***	-0.0994***
	(0.0202)	(0.0196)	(0.0172)	(0.0172)
Bihar dummy	0.0115	-0.0437***	-0.0247*	-0.0378**
	(0.0163)	(0.0165)	(0.0146)	(0.0148)
Constant	0.464***	0.771***	0.503***	0.463***
	(0.0130)	(0.0240)	(0.0240)	(0.0393)
Demographic Controls	NO	YES	YES	YES
Household Asset & Literacy Controls	NO	NO	YES	YES
Village-Level Controls	NO	NO	NO	YES
Observations	30,295	30,295	30,147	30,112
R-squared	0.035	0.088	0.208	0.210

Sketch of Mechanism of Impact

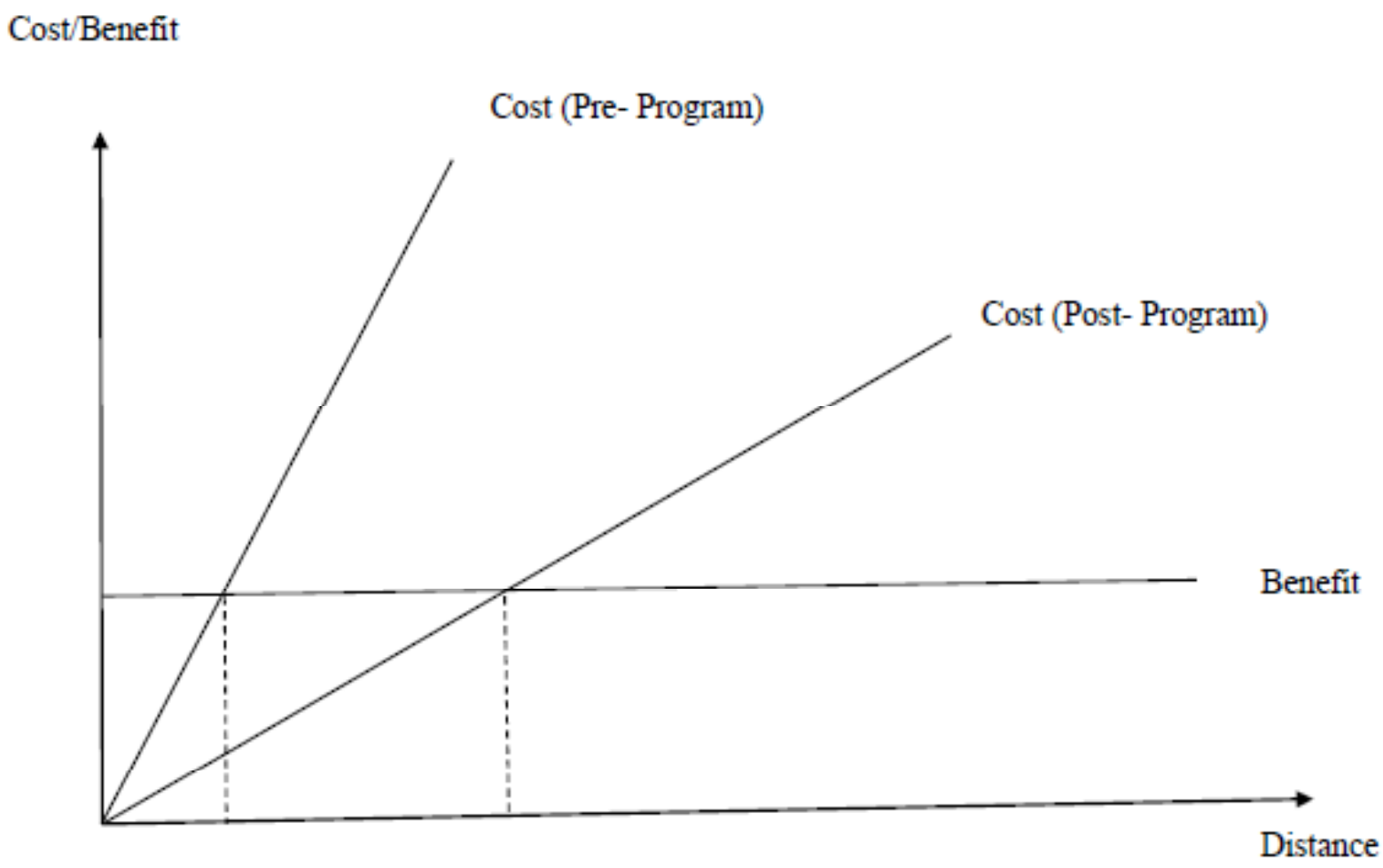
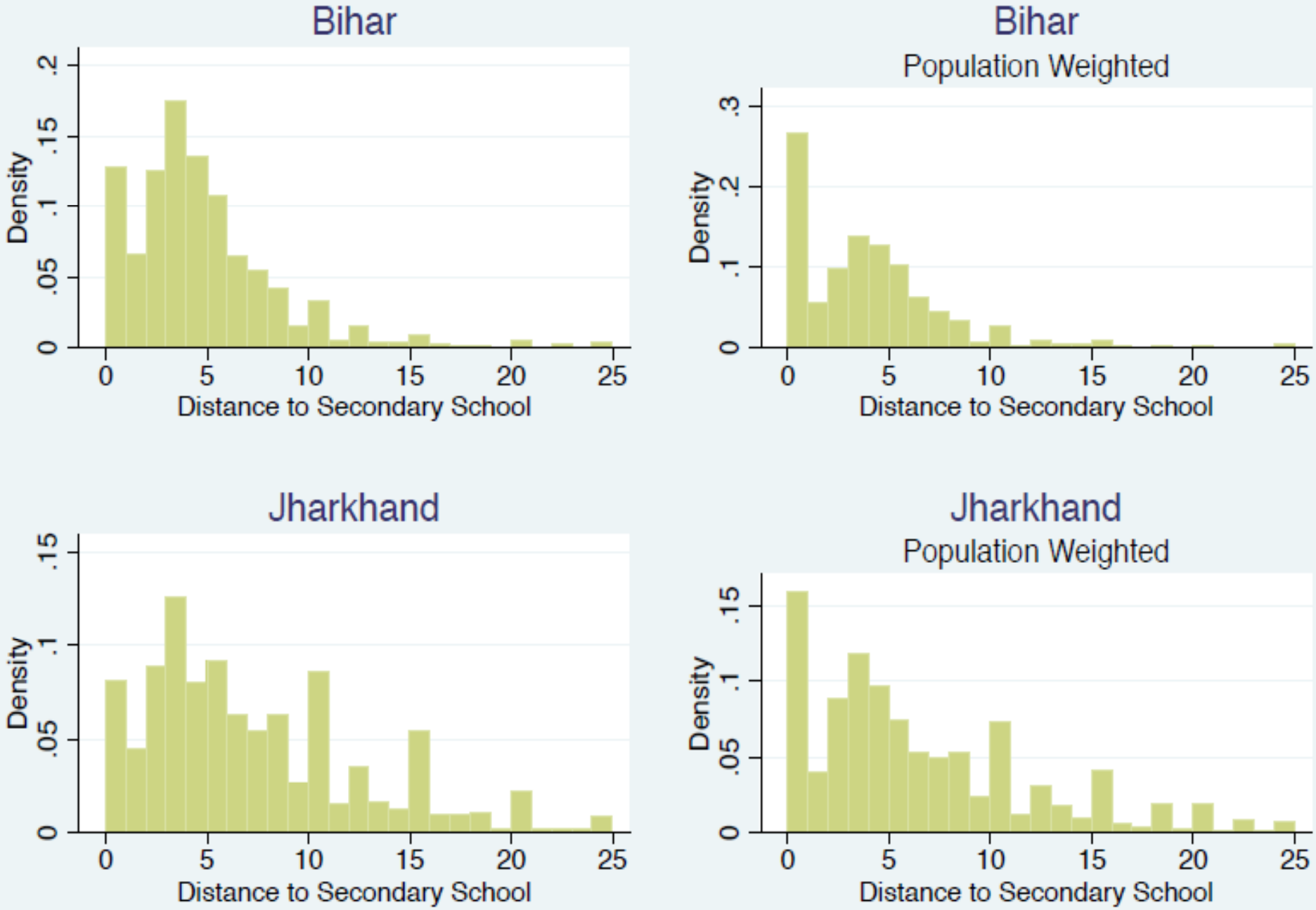


Figure 2: Distribution of Villages by Distance to Secondary School

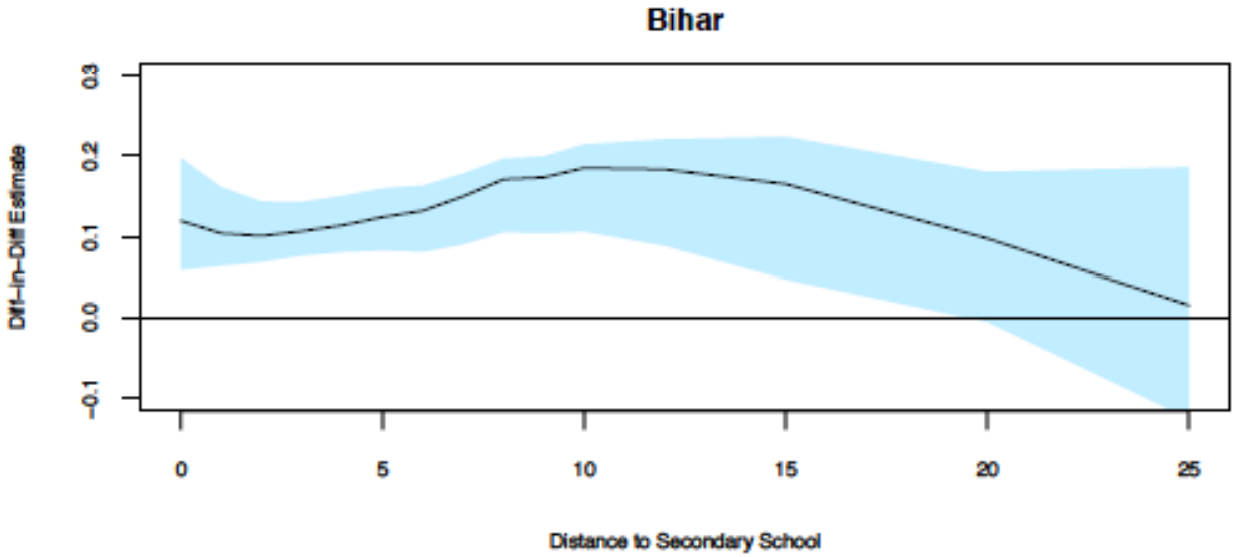


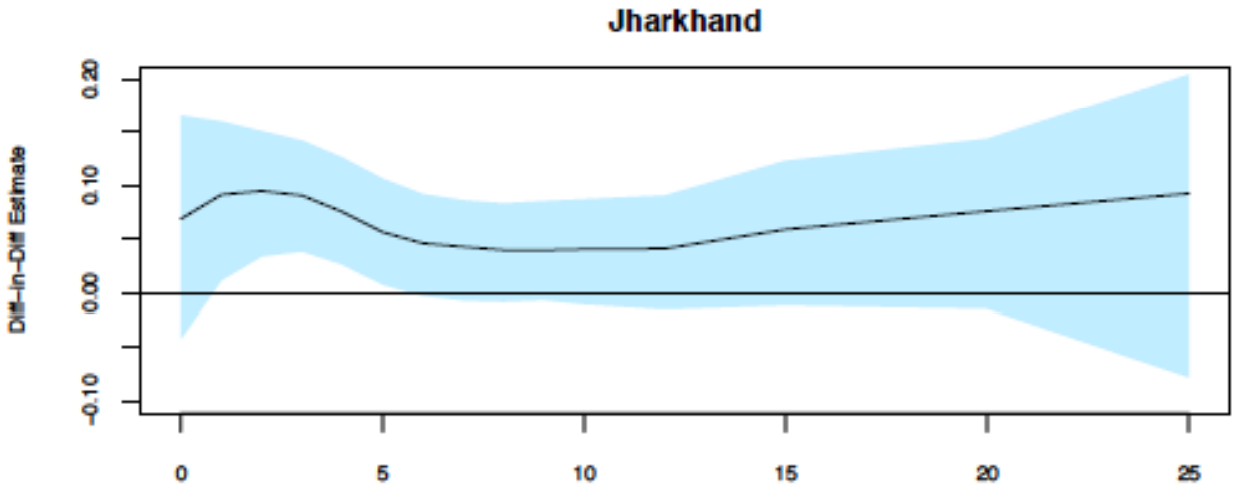
Quadruple Difference

Mechanism of Impact - Quadruple Difference (Triple Difference broken down into cases where distance to secondary school was greater than 3km versus less than 3km)

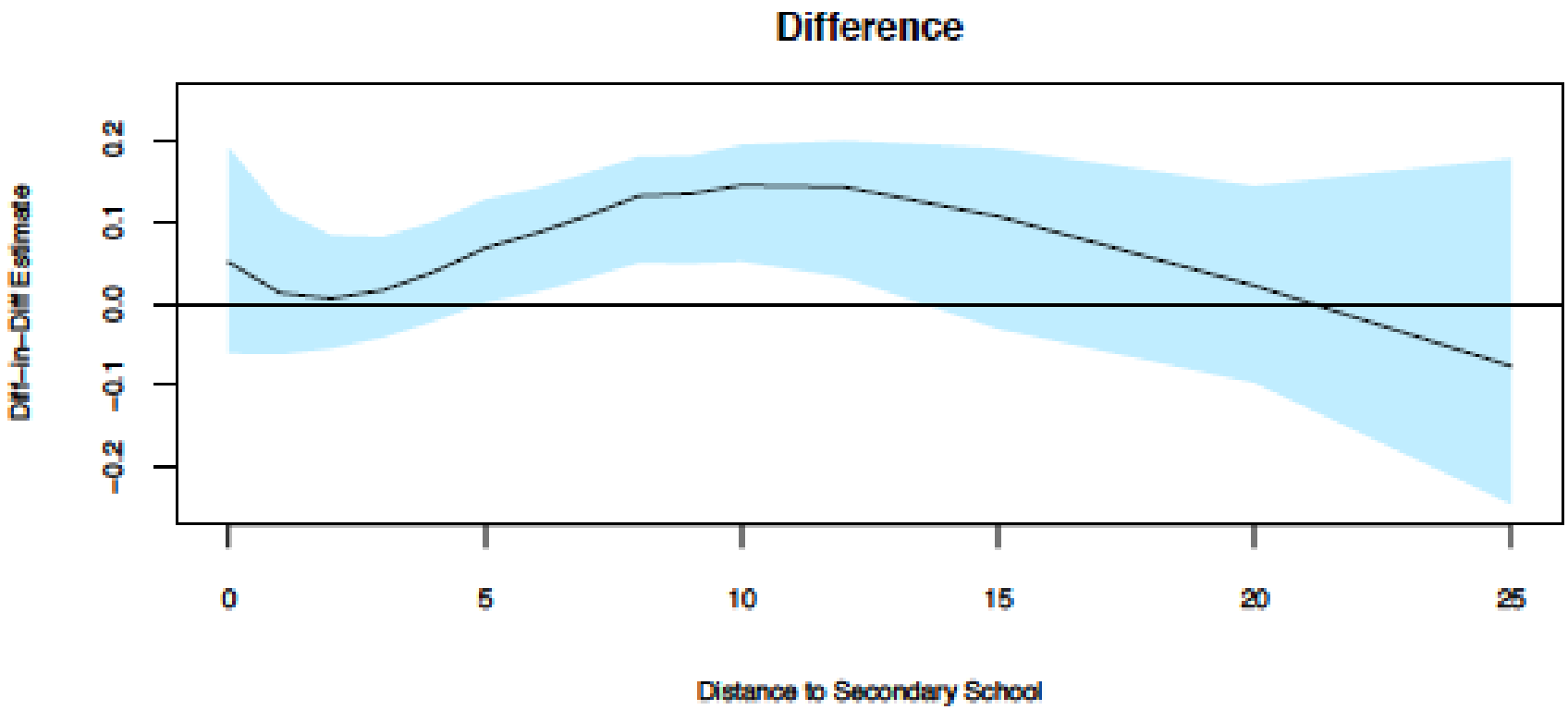
	(1)	(2)	(3)	(4)
Treat*Female dummy*Bihar dummy*SS is Far	**0.0940**	**0.0875**	**0.0898***	**0.0882***
	(0.0578)	**(0.0560)**	**(0.0503)**	**(0.0502)**
Treat*Female dummy*Long distance	-0.0788	-0.0803*	-0.0745*	-0.0733*
	(0.0496)	(0.0480)	(0.0427)	(0.0426)
Treat*Female dummy*Bihar	0.0426	0.0338	-0.00504	-0.00420
	(0.0410)	(0.0394)	(0.0376)	(0.0376)
Demographic Controls	NO	YES	YES	YES
Household Asset & Literacy Controls	NO	NO	YES	YES
Village-Level Controls	NO	NO	NO	YES
Observations	30295	30295	30147	30112
R-squared	0.039	0.091	0.209	0.210

Double Difference by Distance





Triple Difference by Distance



Cycle Ownership

- In looking at mechanisms, we may care about whether the 'treated' HH actually received the bicycle!

- Asset questions in DLHS include bicycle ownership
  - But it does not have 'number' of cycles (hence low-powered)
  - So the triple difference is positive but not significant

- But we compare bike ownership between HH with 14-15 year old girls in school and those with 14-15 year old girls who are not in school and see that the former HH are 20 percentage points more likely to own a bicycle

Learning Outcomes (Very Basic Skills)

Impact of Program on Enrollment and Learning Outcomes (Using Pratham ASER 2008 Data)

	(1)	(2)	(3)	(4)	(5)
	Enrollment	2 Digit Subtraction	Division	Read Std 1-level text	Read Std 2-level text
Treat*Female dummy*Bihar dummy	0.0600	0.0411	-0.00771	0.0478	-0.00634
	(0.0616)	(0.0413)	(0.0536)	(0.0349)	(0.0502)
Demographic Controls	YES	YES	YES	YES	YES
Household Asset & Literacy Controls	YES	YES	YES	YES	YES
Village-Level Controls	YES	YES	YES	YES	YES
Observations	8598	8598	8598	8598	8598
R-squared	0.100	0.025	0.102	0.019	0.084

Treatment group = Age 14 and 15

Control group = Age 16

- No measured impact, but the data is under-powered (both in terms of sample size and range of test questions)

Academic Outcomes (10th Standard) - DD

TABLE 8

Difference in Differences Estimates of Cycle Program on Performance in Grade 10 Exam

Dependent Variable	Log(Appeared)			Log(Passed)		
	School Level	Block Level	District Level	School Level	Block Level	District Level
	(1)	(2)	(3)	(4)	(5)	(6)
Female Dummy * Post	0.221***	0.252***	0.232*	0.167***	0.201***	0.212
	(0.0188)	(0.0193)	(0.133)	(0.0256)	(0.0266)	(0.145)
Post	0.273***	0.300***	0.290***	0.241***	0.244***	0.249***
	(0.0255)	(0.0254)	(0.0892)	(0.0281)	(0.0271)	(0.0942)
Female Dummy	-0.809***	-0.702***	-0.645***	-0.866***	-0.761***	-0.722***
	(0.0356)	(0.0407)	(0.0816)	(0.0384)	(0.0488)	(0.0889)
Constant	4.789***	6.078***	9.118***	4.420***	5.721***	8.776***
	(0.0343)	(0.113)	(0.0534)	(0.0445)	(0.111)	(0.0564)
Observations	32172	5815	456	31733	5794	456
R-squared	0.161	0.116	0.202	0.154	0.109	0.195

Notes: Clustered standard errors by village ID in parenthesis. We use Bihar Examination Record Data for this analysis. Asterisks denote significance levels: *: 10%; **: 5%; ***: 1%.

Academic Outcomes (10th Standard) - DDD

TABLE 9

Triple Difference Estimates of Cycle Program on Performance in Grade 10 Exam

Dependent Variable	Log(Appeared)			Log(Passed)		
	School Level	Block Level	District Level	School Level	Block Level	District Level
	(1)	(2)	(3)	(4)	(5)	(6)
Bihar Dummy*Female*Post	0.0524	0.123*	0.0580	-0.00533	0.107	0.0473
	(0.0325)	(0.0730)	(0.237)	(0.0374)	(0.0768)	(0.250)
Post	-0.104***	0.349***	0.349**	-0.162***	0.321***	0.258*
	(0.0332)	(0.0956)	(0.135)	(0.0397)	(0.0950)	(0.142)
Female Dummy	-0.621***	-0.626***	-0.484***	-0.690***	-0.690***	-0.529***
	(0.0657)	(0.0900)	(0.122)	(0.0643)	(0.0881)	(0.125)
Bihar Dummy	0.284***	0.207	0.518***	0.130	0.0745	0.402***
	(0.0938)	(0.155)	(0.0988)	(0.101)	(0.158)	(0.103)
Bihar*Post	0.377***	-0.0486	-0.0588	0.403***	-0.0769	-0.00892
	(0.0418)	(0.0989)	(0.162)	(0.0485)	(0.0988)	(0.171)
Female*Post	0.169***	0.129*	0.174	0.173***	0.0934	0.164
	(0.0265)	(0.0704)	(0.196)	(0.0273)	(0.0721)	(0.203)
Female*Bihar Dummy	-0.188**	-0.0759	-0.161	-0.176**	-0.0702	-0.192
	(0.0747)	(0.0987)	(0.147)	(0.0748)	(0.101)	(0.154)
Constant	4.506***	5.871***	8.599***	4.290***	5.646***	8.374***
	(0.0874)	(0.107)	(0.0831)	(0.0909)	(0.113)	(0.0858)
Observations	48360	7152	720	47619	7131	720
R-squared	0.141	0.113	0.225	0.130	0.106	0.191

Notes: Clustered standard errors by village ID in parenthesis. We use Bihar & Jharkhand Examination Record Data for this analysis. Asterisks denote significance levels: *: 10%; **: 5%; ***: 1%.

Conclusions and Policy Implications

- Estimates of the impact of the MBCY suggest that it increased girls enrollment in secondary schools by 5 percentage points
  - On a base of ~25%, this is a 20% increase in enrollment
  - The policy also reduced the gender gap in enrollment by ~25%
- The program had a greater impact for girls who lived further away from a secondary school, suggesting that a key mechanism for program impact was the reduction in the 'distance cost' of school attendance for girls due to the cycle
- Program was at least as cost effective as other comparable ones
- Implications for cash vs. kind transfers – kind may work well when:
  - There is a direct reduction in the marginal cost of schooling
  - The in-kind item is NOT infra-marginal to household spending
  - It helps the input 'stick' to the recipient as opposed to be subject to intra household bargaining/allocation
- Not much impact on learning outcomes (consistent with CT literature)

Like Father, Like Son? Intergenerational Education Mobility in India*

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Abstract

This paper employs a novel strategy to create a unique, nationally representative father-son matched data for India and documents the extent of intergenerational mobility in educational attainment. We provide an estimate of how India ranks among other nations, and study the evolution of intergenerational education mobility. For the birth cohorts from 1940-85, we find a declining cohort trend in the intergenerational elasticity (IGE) of educational attainment in India, at the aggregate level, for major castes, and states. Finally, we find a positive correlation between a state's ranking in per capita public education spending, and the IGE-based mobility measure.

JEL Codes: J6, I28

Keywords: Intergenerational Mobility, Educational Persistence, India

*The authors are responsible for the findings and opinions expressed, as well as all errors, in this paper. Contact the authors at mazam@okstate.edu or bhattvx@jmu.edu.

1. Introduction

In a recent opinion poll conducted in the U.S. a significant majority of the respondents indicated that equality of opportunity is more important than equality of outcomes.[1] Intergenerational persistence in economic status is an important mechanism in perpetuating inequality of opportunities in a society. For instance, such persistence may differ across groups of people in a society typically identified by race, gender, and region implying differential access to opportunities for different groups. Hence, the extent to which economic status is transmitted from one generation to the next has long been of interest to social scientists and policy makers.

India serves as an excellent case study for intergenerational mobility for two reasons. First, historically Indian society has been characterized by a high degree of social stratification governed by the caste system wherein lower castes were typically associated with poor economic outcomes. Although, the caste system has been weakened as a response to various policy measures taken by the government of India, social identity still remains an important dimension of social exclusion. Hence, gauging how such inertia in economic mobility has changed over time is of interest. Second, although India has experienced rapid economic growth in recent decades, this economic growth has been far from uniformly distributed on regional dimensions. Many large states have experienced below national average economic growth and also have significant differences in terms access to education opportunities (Chaudhuri and Ravallion, 2006; Emran and Shilpi, 2012; Asadullah and Yalonetzky, 2012).

Although, as argued above, understanding the extent of intergenerational mobility is especially important for India, this issue has received relatively less attention mainly because lack of suitable data for such kind of studies. Most of the existing studies rely on the co-residence condition to identify father-son pairs from cross-sectional data (Jalan and Murgai,

[1] In an opinion poll on Economic Mobility and the American Dream, Pew Charitable Trust March 2009, when asked whether it was "more important to reduce inequality in America or to ensure everyone has a fair chance of improving their economic standing", 71 percent favored ensuring everyone had a fair chance compared with 21 percent who thought it was more important to reduce inequality (Breen, 2010).

2008; Maitra and Sharma, 2009; Hnatkovskay et al., 2012; Emran and Shilpi, 2012) . This leads to a significant loss of observations and more importantly raises serious sample selection issue as coresident households may differ systematically from other households. For instance, the identification of parental information achieved through co-residence, will either lead to restricting the analysis to the young adults (Jalan and Murgai, 2008) or a cross -sectional estimate based on a sample that is not representative of the adult population (Hnatkovskay et al., 2012).[2,3] In this paper we address this issue by creating a unique father-son matched data, using the nationally representative India Human Development Survey, 2005 (IHDS), that is not limited to coresident households. We believe that our data is more appropriate for studying intergenerational mobility as it is representative of the entire adult male population in India.

In any intergenerational study, the measurement of economic status remains an important issue, and several studies proxy economic status by labor market characteristics such as earnings, occupation, and educational attainment. In this paper, we focus on intergenerational mobility in educational attainment. Specifically, we estimate the intergenerational elasticity (henceforth, IGE) of educational attainment as a measure of persistence (lack of mobility) across generations. Although education is not the only proxy for economic status, there are several advantages in using education instead of earnings to measure intergenerational mobility, especially in a developing country context where existence of long panel data is rare. First, on the measurement side, education is less prone to serious errors than earnings. Second, since most individuals complete their education by early or mid twenties, life cycle biases are unlikely to bias estimation when compared with earnings. Finally, there is a vast literature that shows that higher education is associated with higher earnings, better health, and other economic outcomes (see Black and Devereux, 2011), rendering a measure of intergenerational mobility based on education a reasonable proxy for mobility in overall

[2]Such limitations are expected if one uses data only for coresident parents to estimate intergenerational mobility because such a condition is more likely to be satisfied for young adults. As a result the estimates of intergenerational elasticities can be severely biased downwards (Franscesconi and Nicoletti, 2006).

[3]In Section 3.1 we discuss, in detail, the issue of co-residence in existing studies on India, the resulting decline in the sample size, and the sample selection issue that can arise due to the use of co-residence for matching children with parents.

economic status.

This paper attempts to address three important issues in the context of India. First, what is the extent of intergenerational mobility in educational attainment in India? Second, how this mobility has evolved over time at the aggregate level? Third, do we observe a social and a regional dimension in the evolution of intergenerational education mobility in India? To shed light on this issue, we investigate the cohort trend in IGE by major castes, and by major states.

The paper contributes to the existing literature in following ways. First, we are able to match about 97% of the males aged 20-65 in our sample with their father information. As a result, unlike other studies on India, the estimates presented in this paper do not suffer from sample selection bias caused by limiting the analysis to adults coresiding with their parents (see Section 3.1 for a detailed discussion of this issue). Second, following Hertz et al. (2007) methodology closely, we are able to rank India, in terms of intergenerational education mobility, among other nations. To the best of our knowledge, there exists no comparable estimate of intergenerational mobility that can be used to rank India among other countries. Third, we are able to track changes in mobility across birth cohorts going back to as early as 1940s. We provide mobility estimates for successive birth cohorts at the aggregate level, and for the social groups. Finally, the regional dimension of intergenerational education mobility in India remains largely unexplored. In this paper we attempt to fill this void in the literature and provide state-level estimates of intergenerational education mobility by birth cohorts.

There are several key findings. First, the average intergenerational correlation in educational attainment in India is 0.523 which is higher than the global average of 0.420 reported by Hertz et al. (2007). Second, between the birth cohorts of 1940 through 1985, there is a pronounced declining trend in the estimated IGE of educational attainment implying greater mobility for more recent cohorts in India. This cohort trend exists at the aggregate level, for major castes, and for major states. Third , at the state level, we observe significant variation in the estimated IGE, although this variation is smaller for more recent cohorts. We also

find that there is a strong positive correlation between educational mobility (based on IGE) across generations within a state and its ranking in terms of per capita public spending on education. Although not causal such an association between public education expenditure and intergenerational education mobility is suggestive of an important role played by public policy in affecting educational attainment in India. Such positive correlation is also consistent with similar findings for other countries (see Hertz et al., 2007). Finally, using education transition matrices, we find a significant increase in the probability of sons of less educated fathers achieving greater education than their fathers in more recent sons cohorts compared with earlier sons cohorts .

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature on the intergenerational mobility in educational attainment. Section 3 discusses the data, outlines our strategy to create a father-son matched data for India, and presents descriptive statistics for the sample used in the study. Section 4 outlines the conceptual framework underlying our empirical analysis. Section 5 presents the estimation results for our regression model. Section 6 provides estimates of mobility across the education distribution using transition matrices. Section 7 provides a discussion of our main findings and their implications for the education policy measures that have been implemented in post-independence India. Section 8 concludes.

2. Related Literature

The issue of intergenerational mobility in income, education, and occupation has been extensively explored in the literature. Black and Devereux (2011) present a recent survey of the evidence and methodological problems of the research available for the developed economies.[4] Hertz et al. (2007) study the trends in intergenerational transmission of education for a sample of 42 countries.[5] They document large regional differences in educational persistence, with Latin America displaying the highest intergenerational correlations, and

[4]See Solon (2002) for an earlier survey of the evidence on earning mobility across generations.
[5]Their sample does not include India

the Nordic countries the lowest. They estimate the global average correlation between parent and child's schooling to be around 0.420 for the past fifty years. Daude (2011) presents educational mobility estimates for 18 Latin American countries and found relatively low degree of intergenerational social mobility in Latin America.

The issue of intergenerational mobility in India has only recently started attracting attention.[6] Jalan and Murgai (2008) investigate the educational mobility among the age group 15-19 using 1992-93 and 1998-99 National Family Health Survey (NFHS) data. They found that education mobility for age group 15-19 has increased significantly between 1992-93 and 1999-00, and that education gaps between backward and forward castes are not that large once other attributes are controlled for. An important limitation of their analysis is that, in the NFHS data, respondents are not directly asked about the education of their parents. Hence, parental outcomes are only known for child-parent pairs that are still living in the same household. As a result they only focus on children aged 15-19 years who are more likely to be living with their parents.

Maitra and Sharma (2009) use the India Human Development Survey, 2005 (IHDS) to describe how educational attainments of adult male (20 and above) have changed across cohorts. They also explored the effect of parental education (both father and mother) on years of schooling of children, identifying children-parent pairs if they both reside in the same household. Thus, they only provide a point-in-time estimate of mobility based on a sample constructed through co-residence, and do not investigate the evolution of the intergenerational mobility in India.

Finally, Hnatkovskay et.al (2012) used five rounds of National Sample Survey (NSS), covering the period 1983-2005, to analyze intergenerational mobility in occupational choices, educational attainment and wages. They estimate intergenerational elasticities based on

[6]Munshi and Rosenzweig (2006) used a survey for 4900 households residing in Bombay and investigate the effect of caste-based labor market networks on occupational mobility. They found that for males there are strong effects of traditional networks on occupational choice. However, for females they found relatively greater mobility in occupational choices. Munshi and Rosenzweig (2009) used a panel data of rural households, 1982 Rural Economic Development Survey, that covered 259 villages in 16 states in India. They report low rates of spatial and marital mobility in rural India, and relate these to the existence of caste networks that provide mutual insurance to their members.

'synthetic' parent-child pairs, wherein they put all household heads into a group called 'parents' and the children/grandchildren into the group 'children'. Specifically, they focus on households with an adult head of household co-residing with at least one adult of lower generation (child and/or grandchild), both being in the age-group 16-65. They also removed individuals who were enrolled in school at the time of a particular NSS survey round from their analysis. They find that the period 1983-2005 has been characterized by a significant convergence of education, occupation distribution, wages and consumption levels of Scheduled Castes/Tribes toward non-Scheduled Castes/Tribes levels.

3. Data

We use data from the India Human Development Survey, 2005 (IHDS), a nationally representative survey of households jointly organized by the National Council of Applied Economic Research (NCAER) and the University of Maryland. The IHDS covers 41,554 households in 1503 villages and 971 urban neighborhoods located throughout India.[7] The survey was conducted between November 2004 and October 2005 and collected a wealth of information on education, caste membership, health, employment, marriage, fertility, and geographical location of the household.

There are two distinct advantages of using the IHDS data for an intergenerational education mobility study over the larger and more commonly used household surveys for India, such as the National Sample Survey (NSS) and National Family Health Survey (NFHS). First, the IHDS contains additional questions which are not asked in the NSS or NFHS. These questions allow us to identify father's education for almost the entire adult male population (in the age group 20-65), including father-son pairs who do not coreside, in our sample. As we discuss in the next section, this will mitigate any downward bias that may entail from sample selection issues associated with identifying parent-child pairs using the

[7]The survey covered all the states and union territories of India except Andaman and Nicobar, and Lakshadweep. These two account for less than .05 percent of India's population. The data is publicly available from the Data Sharing for Demographic Research program of the Inter-university Consortium for Political and Social Research (ICPSR).

co-residence condition. Second, the IHDS contain data on actual years of schooling rather than levels of schooling completed which is generally reported in the NSS data.[8] This avoids the discontinuities in schooling distribution as a result of the imputation of years of schooling from the categorical variable containing level of schooling completed.

3.1. Identification of Father's Educational Attainment

This section outlines the strategy we used to create a matched father-son data using the IHDS. Specifically, we highlight the additional information in IHDS data that is not available in the NSS or the NFHS that allows us to identify father's schooling for almost every adult male respondent in the 20-65 age group. Table 1 presents our sample selection process and the loss of observations at each stage.

The first variable we use is the *"ID of father"* in the household roster which helps linking individuals to their fathers directly if the father is living in the household.[9,10] Utilizing this information by default imposes the co-residence condition which severely reduces the sample size. From the last row of Table 1 we observe that using only this variable we were able to extract father's educational attainment for 34 percent of the male respondents in the 20-65 age group.

In contrast to the NSS and the NFHS, the IHDS data has another question regarding the education of household head's father (irrespective of the father living in the household or not).[11] Combining this variable with the *"ID of father"* variable, we are able to identify fathers schooling for about 97 percent of the adult male respondents (see second last row

[8] NFHS also report years of schooling.

[9] Question 2.8 on page 4 of the Household Questionnaire.

[10] In both the NSS and the NFHS, the analogous identification is achieved by utilizing the *"relationship to the household head"* question in the household roster (see Appendix A for a discussion of such identification in the NSS data).

[11] Question 1.20 on page 3 of the Household Questionnaire.

of Table 1).[12,13] In comparison, Hnatkovskay et al. (2012), who use several rounds of the NSS, were able to identify father's education for less than 15 percent of the male aged 16-65 interviewed in the NSS using their sample selection procedure.[14]

The above issue is of practical as well as theoretical importance as using only co-residence to identify parent's educational attainment may cause severe sample-selection problem. The issue of sample selection and the resulting non-randomness in survey data has been extensively documented in the literature. Franscesconi and Nicoletti (2006) showed that using co-residence to identify parent-child pair leads to a downward bias in intergenerational elasticity estimates in the range of 12 to 39 percent. In Section 5, we show that in our data imposing the co-residence condition leads to an estimate of the IGE that is 17 percent smaller than the estimate based on the full sample. Further, a sample of father-son pair achieved through co-residence may be misleading as it may not be a representative sample of the adult population of interest. For example, we find that in our sample, almost 86 percent of the respondents whose father is identified through co-residence condition are in the 20-35 age group. Hence, co-residence effectively over represents younger adults in a sample, which is expected as these individuals are more likely to be living with their parents.[15]

[12]We also identify fathers' years of education for some of the remaining adult males (who are not the household heads and whose fathers are not identified through co-residence) by exploiting relation to the head. A STATA do file used to construct son-father sample is available from the authors.

[13]Note that Maitra and Sharma (2009) also use the IHDS data in their analysis but use co-residence to identify parental educational attainment. As a result, their sample is restricted to only 27.7 and 6.4 percent of total adult male and female sample interviewed in the IHDS. For instance, in Table 4 of their paper, they report a sample size of 5789 and 11515 for males in urban and rural area, although the total adult male (20 and above) sample is 22071 and 40460 in urban and rural areas, respectively. Similarly, they have used only 1886 and 2078 adult female living in urban and rural areas, whereas the total adult female sample is 21790 and 40378 in urban and rural areas, respectively.

[14]In the supplement to their paper, Hnatkovskay et al (2012) report the sample sizes for each round of the NSS. See Table S2: Intergenerational Education Switches: Estimation Results. They report number of observations (son-father pair) of 24119, 28149, 25716, 25994, 27051 in 1983, 1987-88, 1993-94, 1999-00, and 2004-05; while the actual number of males age 16-65 surveyed in these cross-sections are 177,008; 196,412; 173,182; 183,732; and 188,585.

[15]In Appendix A we highlight this issue using the 2004-05 round of the NSS.

3.2. Descriptive Statistics

Given the objective of the study we focus on the adult male population which we define to be respondents in the 20-65 age group.[16] Since our survey is from 2005, this implies we have data on individuals born between 1940 and 1985. Hence, we can study the mobility in educational attainment across birth cohorts going as far back as 1940. We conduct our analysis at the all India level, by social groups, and by states. For the all India level and social group level analyses, we divide our sample into nine five year birth cohorts: 1940-45, 1946-50 $\cdots\cdots$ 1976-80, and 1981-85. At the state level, driven by sample size and space considerations, we concentrate on two 10 year cohorts: 1951-60 and 1976-85.[17,18]

The main variable of interest is the son's educational attainment which is measured as years of schooling. In the literature, parents' education is proxy by either father's education, maximum of parents' education, or average of both parents education. In the IHDS we do not have information on mother's education for the whole sample, and hence we proxy parents' educational attainment by father's years of schooling.[19] The sample statistics are presented in Table 2. In the top panel we report summary statistics at the all India level and by social groups whereas in the bottom panel we report these at the state level.

In column (1) of the top panel, we present the total sample size and the minimum sample size which is the size of the smallest five-year birth cohort we have for any given cohort. One issue in analyzing education data is the inclusion of individuals who have not completed their education in the sample. This right censoring in the data could reflect delayed completion and/or pursuit of higher education. The main consequence of including individuals who are

[16] We chose the lower limit as 20 as a majority of individuals in India finish their college (about 15 years of education) around this age. In our data only 10 (1) percent of age 20-24 (25-29) age group individuals are still in school and haven't completed the maximum of education. Following Behrman et al. (2001) we use an upper age limit of 65 years.

[17] We chose to present results for the 1951-60 cohort, as this is the first decade after independence.

[18] In our analysis, we adopt five/ten-year age-bands, and do not examine results under alternative aggregation schemes. As suggested by Hertz et al. (2007), such an aggregation scheme, though essentially arbitrary, should not bias the trend estimates unless it is chosen with particular set of results in mind.

[19] We also carried out our analysis using average education for both parents (44 percent of observations in our sample have information on mother's education). We find similar correlation coefficient but a larger estimated IGE, at the all India level. For brevity we do not report them in the paper and these results are available upon request from the authors.

still in school is that it can potentially bias the estimates of intergenerational persistence downward. To shed light on the incidence of right censoring in our data, in column (2) of the top panel, we report the shares of adults in our sample who are currently enrolled in school in two age groups. For those aged 20-24, these shares are on average 10 percent, whereas for the age group 25-29 the shares are less than 1.5 percent. Given the small shares of such individuals in our sample, and the fact that the true value of schooling is most likely to be just a year or two greater than what is observed for the right censored observations, it can be argued that the bias caused by their inclusion should be relatively small.

The last column in the top panel report the average levels of education for both generations for the first and the last five-year birth cohorts. We observe that sons on an average have higher level of education compared to their fathers. Further, between two cohorts, there has been an increase in educational attainment for both generations. This holds for the aggregate as well as across major castes. At the major castes level, Higher Hindu castes are more educated than other groups, and this difference holds for both generations and across cohorts.

In the bottom panel of Table 2, column (1) contains the the sample sizes for each state in our data. In column (2) we report the average educational attainment for the two generations for the two ten year birth cohorts, 1951-60 and 1976-85.[20] In all states, sons are more educated than fathers and there has been an increase in the educational attainment of both generations. However, there is significant variation across states. For instance, Southern states such as Kerala and Tamil Nadu have much higher average educational attainment for both generations when compared to the relatively poorer states of Bihar and Orissa. Between the two cohorts, at least in terms of average educational attainment, there seems to be some convergence across states.

[20]Due to sample size considerations, we conduct our state level analysis for ten-year birth cohorts rather than five. Also, we exclude Jammu and Kashmir, Delhi, Assam, and the smaller states in the Northeast because the sample sizes in those states for the concerned cohorts fall below 300 father-son pairs.

4. Conceptual Framework

In this section, we outline the conceptual framework underlying the empirical analysis conducted in our study. Theories of parental investment in children identify several channels through which family economic circumstances may influence their children's educational attainment (Becker and Tomes, 1979, 1986). In these models, decisions regarding child birth and the education of children are determined by the interplay of parental preferences and constraints faced by the family. Such a framework identifies many possible mechanisms that would lead to a direct effect of parental education on child education. First, higher educated parents generally have higher incomes which may positively affect educational attainment of their children by relaxing the family budget constraint. Second, education may increase productivity of the parent in child-enhancing activities which in turn may translate itself into higher educational attainment for the child. In this paper, we are not attempting to uncover the underlying mechanism through which parents' education affects their children's educational attainment. The objective is to simply measure the association between parent and child education and how this association has evolved over time. It can be argued that the estimated regression coefficient ($\widehat{\beta}_c$) overstates the true effect, due to the bias caused by omitting confounding socioeconomic factors that may influence education in both generations positively (Hertz et al., 2007).

One objective of this paper is to provide an estimate of the ranking of India, in terms of intergenerational education mobility, amongst other nations. We will compare our estimates for India with the estimates for other nations reported in Hertz et al. (2007). Hence, our empirical methodology closely follows theirs to render our results directly comparable to those reported in Hertz et al. (2007). At the all India level, we estimate the following regression model:

$$y_c^1 = \alpha + \beta_c y_c^0 + \epsilon_c^1 \tag{1}$$

where c denotes birth cohort, and superscript $i \in [0, 1]$ denotes generation i. y_c^i denotes

years of schooling of generation i belonging to cohort c. We estimate equation (1) above for each of the 5-year birth cohort between 1940-1985. The estimated coefficient of y_c^0, $\widehat{\beta}_c$, is the estimated intergenerational elasticity (IGE) of educational attainment for the cohort c. A higher value of the IGE indicates greater intergenerational persistence (or lower mobility) in educational attainment. Alternatively, $(1-\widehat{\beta}_c)$ is a measure of intergenerational mobility. Comparing $\widehat{\beta}_c$ across birth cohorts in our sample will give us a measure of how intergenerational persistence in education has changed over time.

In the literature, a second measure of persistence, is the intergenerational correlation coefficient, ρ_c, which is given by the following expression:

$$\rho_c = \beta_c \frac{\sigma_c^0}{\sigma_c^1}$$

where σ_c^i is the standard deviation of educational attainment of generation $i \in [0,1]$ for cohort c.

Hence, the correlation coefficient factors out the cross-sectional dispersion of educational attainment in the two generations, and in that sense is a *standardized* measure of persistence. In contrast, the regression coefficient is affected by the relative variance of education across generations. As a result changes in the relative standard deviations will cause both measures to evolve differently over time. For this reason, it is a common practice in the literature to report both measures of persistence. In our empirical results we follow this convention and report both the estimated IGE and the correlation coefficient across different cohorts in our sample.

The choice of which measure to use will depend on the question of interest. If we are only interested in intergenerational mobility across generations, we should use estimated IGE. In contrast, if we are interested in intergenerational mobility, conditional on the overall dispersion of educational attainment for each generation, then we should focus on $\widehat{\rho_c}$ as a measure of persistence. In this paper, we focus on the estimated IGE when discussing the evolution of intergenerational mobility in educational attainment in India.

5. Empirical Results

In this section we present our estimation results. We first present our findings at the all India level for the pooled sample. This is followed by a cohort-level analysis of intergenerational mobility in educational attainment, at the aggregate level, for major castes, and for major states in India.

5.1. Intergenerational educational persistence in India

Table 3 presents the estimation results for our pooled sample. There are several findings of interest. First, from column (1) we observe that the estimated intergenerational education elasticity is 0.634. Hence, in our data father's education has an economically and statistically significant effect on the child's education. As discussed earlier one advantage of our father-son matched data is that it is not contingent on father coresiding with the child. Hence, our estimate is not affected by the sample selection bias that may arise from imposing such a condition. To illustrate the consequence of imposing the co-residence condition, we estimated the IGE using the sample of adult males coresiding with their father. The estimated regression coefficient is 0.525 which is roughly 17 percent lower than the estimate based on our full sample. We also conducted a chi-square test for the equality of the estimated regression coefficient from the full sample and that based on the co-residence sample. The test statistic is 224.99 with a p-value of 0.000. Hence, we fail to accept the null hypothesis of the equality of the two estimates at any conventional level of significance. From this exercise one may infer that the use of co-residence is likely to provide an underestimate of the intergenerational education elasticity.

An important determinant of educational attainment in the India is the caste membership. Many studies have documented a relatively lower average level of education among scheduled castes and tribes (SC/ST) and other backward castes (OBC) (see Jalan and Murgai (2008), Maitra and Sharma (2009), Kingdon (2007)). Further, state of residence is also likely to affect the access of education opportunities. For instance, Asadullah and Yalonetzky (2012) study the state level variation in the degree of inequality of educational opportunities

and found that although India has made sizable progress in bringing children from minority social groups to school, significant variation remain in educational achievements at the state level. Hence, in column (2) we add controls for caste membership and in column (3) we add controls for both caste membership and state of residence. Based on our most general specification of column (3) we find that the estimated IGE falls by roughly 9.5 percent (from 0.634 to 0.567). The relatively small effect of caste membership and state of residence on intergenerational persistence is consistent with the findings in the literature (Emran and Shilpi (2012), Hantskovska et al. (2012)).[21]

5.2. A cohort analysis of intergenerational education mobility in India

In this section we investigate the evolution of intergenerational mobility in educational attainment in India. The objective of this exercise is two fold. First, we want to document the cohort trend in intergenerational educational mobility for India. Second, we want to document how different cohorts within a caste group, and within a state, have fared in terms of intergenerational education mobility.[22] In our knowledge, this is the first study to present such a cohort analysis for India and it will supplement our results from the previous section.

[21] We also estimated the effect of caste and state of residence on the estimated IGE, by cohort. As expected, we found that the importance of caste and state of residence in explaining observed persistence educational attainment was much higher for the older cohorts when compared with the more recent birth cohorts. On average, for the birth cohorts from 1940-65, the estimated IGE is roughly 16.7 percent lower when caste membership and state of residence were accounted for in the regression specification. The corresponding number for the birth cohorts from 1966-85 is 10.6 percent. For brevity we do not report these regressions by cohort and they are available upon request from authors.

[22] Note that we are only interested in analyzing the cohort trend in intergenerational education mobility within each group, where we identify a group by caste membership, and by state of residence. This analysis is based on intergenerational education elasticities estimated separately from a subsample of observations belonging to a particular group. Such an analysis is only useful in describing the extent of intergenerational mobility in educational attainment within a group. However, these intergenerational education elasticities are not very informative for comparisons across groups. The reason is that the estimated elasticity for any group only provides an estimate of the rate to regression to the mean of that particular group and not for the overall education distribution. Hence, the results presented in this paper cannot be directly applied to answer questions such as which caste group or state is most mobile in India. See Hertz (2005, 2008), Mazumder (2011) for a detailed discussion of group-specific measure of intergenerational persistence .

5.2.1. Cohort analysis at the all India level

At the all India level we estimate the regression equation (1) for nine five-year birth cohorts from 1940 through 1985. Table 4 presents the results of this exercise. As we observe from Table 4, father's education has an economically and statistically significant effect on the child's education for each birth cohort. We also observe a pronounced decline across cohorts with the estimated IGE falling from 0.739 for 1940-45 cohort to 0.508 for the most recent cohort, 1980-85. This provides evidence for increased mobility in educational attainment over time in India based on the estimated IGE. However, there is no such trend visible in the standardized measure of intergenerational coefficient, $\widehat{\rho_c}$. This finding is similar to the findings of Hertz et al. (2007). They used data for 43 countries and show that although there is a declining trend in intergenerational persistence based on $\widehat{\beta_c}$, there is no trend in $\widehat{\rho_c}$. They argued that although the standard deviation of child education has remained roughly constant, the dispersion in parental education in their sample was significantly higher for younger cohorts. This will lead to a lower regression coefficient for younger cohorts implying an increase in mobility. However, the correlation coefficient may not reflect such an increase over time.

Following Hertz et al. (2007) we compute the trend in average schooling and in the standard deviations of educational attainment of both generations in our sample. From Figure 1 we observe that there is an increase in the average level of schooling for both generations. However, across cohorts, the standard deviation of son's schooling has decreased whereas that of the father's schooling has increased. Further, for most cohorts, except the most recent one, the variance of son's schooling was greater than that of the father's schooling. This implies the ratio of the standard deviation of fathers education to that of their sons' will be less than one because of which $\widehat{\rho_c}$ is less than $\widehat{\beta_c}$ for all cohort bands between 1940-80. For the 1981-85 cohort, the ratio becomes greater than one implying a correlation coefficient that is greater than the estimated regression coefficient. These patterns are similar to those reported by Hertz et al. (2007) for other countries. As noted by Hertz et al., these trends in the standard deviations of education of the two generations only explains why the

slope of the time trend in estimated regression coefficient is less than that of the estimated correlation coefficient. However, they do not explain the sign of the trends underlying these two measures of mobility/persistence. A negative trend in $\widehat{\beta_c}$ implies increases in average educational attainment are driven primarily by increases among children of less educated parents. In contrast, the trend in $\widehat{\rho_c}$ are much more difficult to explain. For instance, we may see a positive trend in $\widehat{\rho_c}$ along with a negative trend in $\widehat{\beta_c}$, if data becomes more clustered around the regression line (Hertz et al. (2007)).

To compare the level of persistence and rank India in terms of the intergenerational transmission of educational attainment among other countries we follow the approach of Hertz et al. (2007).[23] We compute a simple average of estimated correlation coefficients across cohorts in our data. We find this average to be 0.523 for India which is above the global average of 0.420 reported by Hertz et al. (2007). Figure 2 presents the ranking of India in terms of intergenerational correlation in educational outcomes. We find that India is placed better than other developing countries such as Brazil, Chile, and Indonesia. But it is ranked below than the USA, UK, Malaysia, and Egypt.

5.2.2. Cohort analysis by caste

Given the historical significance of the caste system in determining economic outcomes in India, we now turn to uncovering the patterns of intergenerational education mobility across cohorts that may be hidden in the estimated trend at the aggregate level. For this purpose we consider four social groups, namely, Scheduled Caste and Scheduled Tribe (SC/ST), Other Backward Castes (OBC), Muslims, and Higher Hindu Castes (HHC).[24]

The regression model we estimate is:

$$y^1_{cg} = \beta_0 + \beta_{cg} y^0_{cg} + \epsilon^1_{cg} \tag{2}$$

[23]Following similar methodology, Fessler et al. (2012) provide a ranking for Austria.

[24]SC/ST are historically disadvantaged groups in India, and have enjoyed affirmative policies in education and employment since the independence. OBCs were given reservation in employment in the 1993. Muslims are largest minority religious group in India, and according to GOI (2006), their performance on many economic and educations indicators are comparable to SC/ST.

where c denotes birth cohort, g denotes caste, and superscript $i \in [0, 1]$ denotes generation i. y^i_{cg} denotes years of schooling of generation i belonging to cohort c and social group g. We estimate the above equation for each of the four aforementioned social groups and for the nine five-year birth cohort bands from 1940-1985.

In Table 5, we present the regression coefficients and estimated correlation by membership to a particular caste for each of the five-year birth cohort band. The results are more or less similar to our findings for the all India level. Within each major caste, we find a negative cohort trend in the estimated IGE implying a regression to the group mean over time. Hence, there is increased intergenerational education mobility across generations in each of the major castes in India since 1940s. Similar to our findings at the all India level, no such trend is discernible in intergenerational correlation coefficients for the HHC, SC/ST, and Muslims. However, for the OBC, we find a positive trend in the estimated correlation coefficient. As pointed out by Hertz et al. (2007) this could happen if observations for a group become clustered around the regression line over time. In Figure 3 we provide evidence for this phenomenon for the OBC in India. We can observe that the data points for this group lie closer to the regression line for the 1981-85 cohort when compared to the earlier cohort. This sheds light on why we observe a declining trend in IGE coupled with a rising trend in estimated correlation coefficients for the OBC in India.

5.2.3. Education mobility in Indian States

Most of the studies addressing intergenerational mobility in economic outcomes in India have emphasized the social dimension and addressed how the caste system in India has affected such mobility. However, another important dimension to this issue is the state of residence. The rapid economic growth in recent times has been far from uniformly distributed across state boundaries in India. Chaudhuri and Ravallion (2006) document that, between 1978 and 2004, among the 16 major states, Bihar (including the newly created state of Jharkhand) had the lowest growth rate of 2.2 percent, whereas Karnataka had the highest, 7.2 percent. Such large state-wise variation in growth rates implies increasing regional dispari-

ties in India. Asadullah and Yalonetzky (2012) study the state level variation in the degree of inequality of educational opportunities and found that although India has made sizable progress in bringing children from minority social groups to school, there are significant variation in educational achievements at the state level. They document that Southern states experienced lower inequality in educational opportunity when compared to Northern states. Furthermore, till the mid 1970s, the education policy was under the purview of state governments, which in principle could generate significant variation in education policies across states. In order to achieve the national objective of Universal Elementary Education, in 1976, the 42nd amendment to the Indian constitution placed education on the concurrent list.[25] The main implication of this amendment is that the Center government can directly implement any education policy decision in the states. One possible consequence of this change is increased uniformity in education policies across state boundaries, which in turn should reduce variation in educational opportunities across states. Hence, it can be argued that different cohorts may get differential access to educational opportunities across generations depending on their state of residence. In essence, the evolution of IGE of educational attainment at the state level is an empirical question that we seek to answer in this section.

For the state wise analysis, we exclude all the smaller states in the Northeast, Delhi, Jammu and Kashmir, and Assam due to smaller sample size.[26] We then estimate the following regression equation :

$$y^1_{cs} = \beta_0 + \beta_{cs} y^0_{cs} + \epsilon^1_{cs} \tag{3}$$

where c denotes birth cohort, s denotes state, and superscript $i \in [0, 1]$ denotes generation i. y^i_{cs} denotes years of schooling of generation i belonging to cohort c living in state s. We estimate the above equation for each state for two birth cohorts, 1951-60 and 1976-85. This gives us the intergenerational education elasticity for each state for the two birth cohorts.

[25]Indian Constitution defines the power distribution between the federal (center) government and the States of India. Both the Center and the States have power to legislate in the areas mentioned under the concurrent list.

[26]We only selected those states which has at least a sample size of 300 son-father pairs for each of the 10 year cohort we studied, i.e. 1951-60 and 1976-85 birth cohorts.

Table 6 presents the results of this exercise. We find that for most states, there is a decline in the estimated regression coefficient of father's education, implying increased mobility across generations for the more recent cohort of 1976-85. In Figure 4 we plot the estimated IGE for the major states in India. On X-axis we have the estimated IGE for each state for the 1951-60 birth cohort, whereas on the Y-axis we have the corresponding state level estimates for the 1976-85 cohort.

The solid line in the figure is a 45 degree line. Any point on this line implies no change in the regression coefficient between the two cohorts and hence reflects no change in mobility. A point above the 45 degree line implies increased IGE estimate between the two birth cohorts whereas a point below indicates a decrease in the IGE. Hence, the vertical difference between the 45 degree line and symbols for states identifies an improvement in mobility across generations over time for that state. Most states, with the exception of Tamil Nadu, fall below the 45 degree line implying increased mobility in educational attainment in these states. However, there is wide variation in the performance of different states in terms of improvements in intergenerational mobility between the cohorts. For instance West Bengal has witnessed very little improvement whereas Madhya Pradesh, Karanataka, and Orissa have experienced significant improvement in mobility between the two cohorts. One plausible explanation for this variation is the state-level differences in education policy. In Section 7 we provide suggestive evidence for this hypothesis by documenting the correlation between per capita state education expenditure and a measure of intergenerational mobility based on the estimated state level IGE.

To discern the regional variation in intergenerational elasticities, note that in Figure 4 the horizontal differences between points reflect regional variation for the 1951-60 cohort whereas vertical differences reflect such variation for the 1976-85 cohort. Since these elasticities are estimated using subsamples for each state, they ignore the between-state differences in average education levels, and only captures the transmission of educational status across generations within each state. Hence, estimated state level IGE do not accurately capture the regional variation in intergenerational persistence per se (see Hertz , 2008; Mazumder,

2011). However, we do observe interesting regional patterns in estimated intergenerational education elasticities in Figure 5. For instance, there is substantial variation across states in the estimated IGE for both cohorts. Further, this regional variation is much smaller for the more recent cohort implying some convergence among states in terms of intergenerational education elasticity. Interestingly this coincides with the timing of the addition of education to the concurrent list that assigned greater role to the center government in affecting education policy at the state level. A full causal analysis of how such a change in policy impacted intergenerational education mobility is beyond the scope of the current study. Our finding is purely descriptive in nature and points toward one possible explanation underlying the regional patterns presented here.

6. Education Transition Matrix

In this section, we investigate the extent of education mobility conditional on the location of the father along the education distribution. For this purpose we compute transition matrices, which show how father-son pairs are moving across the distribution of educational attainment. We carry out this analysis at the all India level as well as by major castes for the two birth cohorts, 1951-55 and 1981-85. For each of these cohorts we compute p_{ij} where where i denotes the education category of the father and j denotes the education category of the son. Thus, p_{ij} is the probability of a father with education category i having a son with education category j. Larger values for the diagonal terms, p_{ii} , reflect lower mobility. Larger values for off diagonal items, p_{ij}, in contrast reflect higher mobility.

Table 7 summarizes the results of this exercise with Panel A reporting transition matrix for the cohort 1951-55 , and Panel B document these for the 1981-85 cohort. Each row of the table shows the education of the father while columns indicate the education category of the son. Thus, the row labeled "Below Primary" suggests that in 1951-55, 50 percent of the adult male children of below primary parents themselves attained below primary education, 18.54 percent finished primary education, 11.89 percent had middle school education, 12.31 percent had secondary education, and 7.14 had post secondary education. Column "size"

reports the average share of parents in each education category. Hence, the last cell of the row labeled "Below Primary" suggests that, for the birth cohort 1951-55, roughly 77 percent of the parents had less than primary education.

Table 7 reveals some interesting patterns as regards intergenerational education mobility in India. First, the intergenerational persistence in educational attainment has fallen across birth cohorts, both at the bottom and at the top end of the educational distribution. For instance, for fathers with below primary education, the percentage of sons being in the same education category has fallen from 50.12 for the 1951-55 cohort to 33.18 percent for the 1981-85 cohort. Second, a large part of this upward intergenerational education mobility was due to sons of fathers with less than primary education beginning to acquire middle school or higher education levels. For instance, in 1951-55, 31.4 percent of the sons of fathers with less than primary education achieved education level greater than or equal to middle school. In 1981-85, this number increased to 45.1 percent. Finally, there seem to be a decline in persistence at the top end of the distribution, which suggests a regression in sons' educational attainment. For the 1951-55 cohort, 80.2 percent of the sons of fathers with post secondary education remained in that category. For the 1981-85 cohort, this percentage had decreased to 72.7 percent. Finally, we also observe a decline in the share of parents belonging to less than primary education category, and increase in share of parents belonging to secondary and post secondary education category.

Next, we investigate whether this pattern differs across social groups. For this purpose, we look at four social groups, namely, Higher Hindu Castes (HHC), Scheduled Caste/Tribes (SC/ST), Other Backward Castes (OBC), and Muslims. In order to avoid the problem of thin cell size, we conduct this analysis for three possible education categories for both generations: less than and equal to primary, middle school, and greater than and equal to secondary. We compute transition matrices for each group for two birth cohorts, 1951-55 and 1981-85 and present the results in Tables 8.A and 8.B.

There are several findings of interest. First, from Table 8.A we find that for both HHC and SC/ST there is a decline in the persistence in at the lower end of the education distribution.

For the 1951-55 cohort of the HHC, 45.5 percent of the sons whose fathers had less than equal to primary education remained in that category. For the 1981-85 cohort, this percentage had declined to 33.7 percent. For SC/ST, the corresponding numbers were 79.2 percent and 53.8 percent. Second, a large part of this mobility was due to sons of fathers with less than and equal to primary education acquiring middle school or higher education levels. For both groups this number increased between two cohorts, from 45.5 percent to 66.3 percent for HHC and from 29.8 percent to 46.2 percent for SC/ST. Finally, at the top end of the education distribution, we observe a significant decline in persistence for SC/ST which suggests a regression in sons' educational attainment. For SC/ST, 84.6 percent of the sons of fathers with greater than equal to secondary education remained in that category for the 1951-55 cohort. For the 1981-85 cohort, this percentage had decreased to 67.8 percent. However, the share of parents with secondary or higher education was only 2.7 percent in 1950-51 sons' cohort for SC/ST, which increased to 9.7 percent in 1981-85 sons cohort. Similar to our findings at the all India level, for HHC, the share of parents in the less than primary education category declined from 74.6 to 46.6 percent whereas for SC/ST, it fell from 94.6 to 81.3 percent.

From Table 8.B we observe slightly different patterns for OBC and Muslims. Similar to our findings for Higher Caste Hindus, and Scheduled Castes/Tribes, both of these groups experienced a rise in mobility at the lower end of the educational distribution. However, at the top end of this distribution, here both groups experience an increase in persistence compared with decline in persistence observed for SC/ST. For OBC, 82.9 percent of the sons of fathers with greater than equal to secondary education remained in that category for the 1951-55 cohort. For the 1981-85 cohort, this percentage had increased to 84.9 percent. The corresponding numbers were 70.3 percent and 71.6 percent for Muslims. Finally, for OBC, the share of parents in the less than primary education category declined from 93.5 to 65.8

percent whereas for Muslims, it fell from 88.7 to 71.8 percent.[27]

Overall, we find that both at the all India level as well as by major castes, there is strong evidence for upward mobility in education at the lower end of the educational distribution. At the top end of the distribution, we find increased persistence for Other Backward Castes and Muslims and lower persistence for Scheduled Castes/Tribes. These results uncover interesting patterns in mobility across social groups along the education distribution that were not discernible from our regression analysis, and hence complements our findings in Sections 5.1 and 5.2.

7. Discussion

The results presented in this paper provide a description of how different cohorts have faired in terms of educational attainment, conditional on their fathers' education. Based on the estimated intergenerational elasticity, the transmission of educational attainment from father to son has decreased significantly across birth cohorts in last 45 years. This trend holds true across social groups and geographic boundaries. However, based on the estimated correlation between father-son educational attainment, no such trend is visible. As discussed earlier, the discrepancy between the two measures is due to the evolution of the dispersion in educational attainment of the two generations. Choosing between the two depends on the perception one has about the appropriate measure of differences in economic outcomes. In this section we attempt to correlate the declining cohort trend in estimated IGE (or a rise in intergenerational mobility) with various education policy measure undertaken by the Indian

[27]In a recent paper, Hnatkovskay et al. (2012) used the NSS data and presented transition matrix for education mobility for year 1983 and 2004-05 based on cross-section data. For both rounds they document an unusually high level of regression of education attainments of children with almost 50 (63 for SC/ST) percent of the children of highly educated parents getting less education than their parents (see Table 5, Hnatkovskay et al., 2012). Since our analysis is done by cohorts, the results presented here are not directly comparable to those presented in Hnatkovskay et al. However, we believe that one plausible explanation for their findings is their sample selection procedure that rests on co-residence sample and also an age cut off of 16-65 for both son and father. In Appendix A, we illustrate how imposing co-residence leads to an over representation of younger adults in the NSS sample and may severely affect mobility estimates based on the coresident sample. In addition to the coresident, they also drop the enrolled students from their sample. As, the proportion of enrolled persons is quite high at lower ages (e.g., in age 16-20), they lose a significant proportion of persons who would been counted in the higher cells.

government.

The issue of how changes in policy is correlated with changes in educational attainment of individuals has been extensively addressed in the literature (Black and Deveraux, 2011). Hertz et al. (2007) provide a detailed survey of studies that document correlation between changes in policy environment and intergenerational educational mobility for various countries. One important stylized fact reported in this literature is that greater government expenditure on primary schooling is negatively associated with educational persistence. Given that we find declining cohort trend in intergenerational education elasticity for India, one plausible explanation for this finding can stem from the changes over time in the educational policy environment in India. From 1950 onwards the Government of India (GOI) has undertaken several policy measures to promote Universal Elementary Education (UEE) in an attempt to eliminate all forms of discrimination based on caste, community and gender. In recent decades, India has made significant progress in increasing enrollment and school completion (Kingdon, 2007). The policy efforts are reflected in the Five year plans as well as specific policy measures undertaken to promote education. Table B in the appendix B provide a brief chronology of the education policy in India. In light of these policy measures, it can be hypothesized that our finding of rising mobility in educational attainment across cohorts to some degree reflects the success of these policies in equalizing educational opportunities over time and across regional boundaries.

One of the important findings we report in this paper relates to the regional variation in the estimated IGE across birth cohorts. We present some evidence for correlation between this regional variation and state-level education policy. Under the Indian constitution, education was the responsibility of the state until 1976. In 1976, education was added to the concurrent list and since then the Center government has played an increasing role in expanding education and achieving greater uniformity in education policy across regions. This has often been supplemented by efforts from state governments who have undertaken

considerable educational investments in recent decades.[28] Asadullah and Yalonetzky (2012) emphasize the importance of state-level differences in policies and institutions in generating inequality in educational opportunity.

One possibility for observed regional variation in the IGE could be differing state education expenditure.[29] Although not causal, an association between state education spending and the estimated patterns in IGE will be of policy interest. In order to investigate this connection, we follow Asadullah and Yalonetzky (2012) and use Besley, Burgess, and Esteve-Volart (2007) ranking of Indian states in terms of state education expenditure per capita for the period 1958-2000. In Figure 5, we plot this measure of policy performance against estimated mobility measure for each state $(1 - \widehat{\beta_{cs}})$ for the birth cohort 1951-60 and 1976-85, respectively. We observe that states that are ranked higher in terms of per capita education spending on an average have higher intergenerational mobility (lower educational persistence) in educational attainment across generations. The direction of this correlation is consistent with the findings reported in Hertz et al. (2007). Further, we find that this association is stronger for the birth cohort of 1976-85, a cohort that would have been in school during most of 1980s and 1990s. This is expected given the lags involved in policy implementation and effects. Our policy measure is based on average state expenditure for the period 1958-2000. Given this timing, one would expect to find stronger association for later cohorts than for the earlier cohort of 1951-1960, as a significant fraction of the older cohort may have completed their schooling before being impacted by state level spending that was initiated between 1958-2000. The evidence presented here, although not causal, seem to suggest strong positive association between the estimated IGE and public spending on education, at the state level. Hence, it can be argued that part of the cross-state variation in intergenerational mobility could have been generated by the regional variation in public spending in education.

[28]Some examples of state sponsored education schemes include Education Guarantee Scheme in Madhya Pradesh, Basic Education Program in Uttar Pradesh, Lok Jumbish and Shiksha Karmi programs in Rajasthan, and Balyam Program of Andhra Pradesh (Asadullah and Yalonetzky, 2012).

[29]Note that we are not arguing that education spending by state will suffice to equalize opportunities. As Asadullah and Yalonetzky (2012) points out, educational policies implemented in states can play a crucial role in determining a state's success in equalizing educational opportunities.

8. Conclusion

Using a nationally representative survey of households, the IHDS, we create a unique father-son matched data for India that does not require the co-residence condition and hence is not subject to the sample selection issues that typically plague most studies for India. We use this data to document the extent of intergenerational mobility in educational attainment in India We find that the average intergenerational correlation for the India is 0.523, which is higher than the average global correlation of 0.420 reported by Hertz et al. (2007). Further, a pronounced declining cohort trend in the estimated IGE is visible at the aggregate level as well as for major castes, and for major states in India, implying greater educational mobility across generation in more recent birth cohorts. No such trend is visible for intergenerational correlation coefficient, a finding that is consistent with the results reported for other countries in Hertz (2007). Using transition matrices, we also find that there has been an improvement in mobility for all major castes, especially at the lower end of the education distribution. This provides suggestive evidence that the universal primary education program adopted by the Indian government since 1970s has impacted the availability of education opportunities for all. Finally, although not causal, we provide suggestive evidence for a strong association between state level spending on education and the estimated state level intergenerational mobility in educational attainment.

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Table 1: Sample Selection

	Number of Observations	Treatment
Males aged 20-65 in IHDS-2005	58,194	
Years of schooling missing	*306*	*Dropped*
Male aged 20-65 with schooling information	57,888	
Individual is household head's father, no information about head father's father in data	*591*	*Dropped*
Males aged 20-65 who can be potentially be matched with father information in data	57,297	
(Percentage of Male aged 20-65 with school information)	(99.0%)	
Number of individuals that could not be matched with father	532	*Dropped*
Number of Individuals matched with father in data	56,765	
Father identified but missing years of schooling	724	*Dropped*
Final Sample: Son-father pairs with education information	55480	
(Percentage of Male aged 20-65 who can be potentially matched)	(96.8%)	
Son-Father pairs with education information using Co-residence	19,490	
(Percentage of Male aged 20-65 who can be potentially matched)	(34.0%)	

Table 2: Descriptive Statistics

Socio-group	(1) Sample Size		(2) Share enrolled*		(3) Average Years of education			
					Father		Son	
	Total	Min	Age 20-24	Age 25-29	1940-45	1981-85	1940-45	1981-85
All	**55450**	**3419**	**10.3**	**1**	**2**	**4.9**	**4.3**	**8.3**
Higher Hindu castes (FC)	13,160	1,836	14.9	1.5	3.8	7.3	7.3	10.3
Other Backward Castes (OBC)	18,946	2,583	9.3	0.6	1.5	5	4	8.6
Scheduled Castes/ Tribes (SC/ST)	10753	1,333	8.2	1.1	0.8	3.1	2.2	7
Muslim	6,409	794	10.6	0.7	2	4.3	3.8	6.9

State	(1) Sample Size		(2) Average Years of education			
			Son		Father	
	1951-60	1976-85	1951-60	1976-85	1951-60	1976-85
Andhra Pradesh	472	878	4.2	7.6	1.4	3.1
Bihar	602	1,040	5	7.1	2	4.1
Gujarat	507	794	6.2	7.9	2.5	5
Haryana	395	871	6	8.6	2	4.3
Himachal Pradesh	337	586	7.1	9.8	1.7	5
Karnataka	979	1,731	5.4	8.1	2.1	4.2
Kerala	443	578	8.2	10.5	4.1	6.1
Madhya Pradesh	957	1,894	5.1	7.2	1.8	4
Maharashtra	827	1,501	6.8	9.8	2.6	5.5
Orissa	488	790	5.2	7.7	1.8	3.6
Punjab	430	803	6.7	9	2.5	5.2
Rajasthan	597	1,157	5.1	7.1	1.4	3.7
Tamil Nadu	549	736	6.5	9.3	2.1	5
Uttar Pradesh	900	1,722	5.7	7.6	2	4.5
West Bengal	581	874	6.4	6.8	3.8	4.8

i) The total sample size refers adult male persons aged 20-65 in 2004-05, born between 1940 and 1985.
ii) Minimum sample size refers to the size of the smallest five-year birth cohort we have for any given cohort.
iii) Father refers to fathers of the persons belonging to different cohorts.
iv) * Enrolled and have less than the highest achievable (15 years) education years.
v) Time interval refers to son's birth cohort. For example, 1951-55 represents cohort of sons born during this period.
6) Jammu and Kashmir, Delhi, Assam, and North East excluded the sample size was below 300.

Table 3: Intergenerational Education Elasticity, All India Level

Dependent Variable: Son's Years of Schooling	(1)	(2)	(3)
Father's Years of Schooling	0.634***	0.577***	0.567***
	(0.006)	(0.006)	(0.006)
Controls for caste	No	Yes	Yes
Controls for state of residence	No	No	Yes
Observations	55,450	55,450	55,450
R-squared	0.297	0.325	0.338

Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Cohort Trend in Intergenerational Mobility in Education, All India

Dependent Variable: Son's years of schooling	Son's Birth Cohort								
	1940-45	1946-50	1951-55	1956-60	1961-65	1966-70	1971-75	1976-80	1981-85
Father's Years of schooling ($\widehat{\beta}$)	0.739***	0.699***	0.690***	0.698***	0.686***	0.650***	0.583***	0.533***	0.508***
	(0.024)	(0.027)	(0.024)	(0.020)	(0.016)	(0.015)	(0.014)	(0.015)	(0.013)
Correlation ($\widehat{\rho}$)	0.53	0.512	0.507	0.532	0.529	0.518	0.529	0.519	0.535
R-squared	0.281	0.262	0.257	0.283	0.28	0.268	0.28	0.269	0.287
Observations	4005	3419	4453	5566	6018	7008	7286	8341	9354

*** p > 0.01; ** p> 0.05; * p>0.10.
Robust standard errors are in parentheses.

Table 5: Cohort trend in Intergenerational Mobility in Education, by Caste

Dependent variable: Son's years of schooling

	Son's Birth Cohort								
	1940-45	1946-50	1951-55	1956-60	1961-65	1966-70	1971-75	1976-80	1981-85
	Higher Hindu Castes								
Father's years of schooling ($\widehat{\beta}$)	0.582***	0.596***	0.495***	0.560***	0.510***	0.510***	0.455***	0.436***	0.406***
	(0.033)	(0.034)	(0.038)	(0.028)	(0.025)	(0.023)	(0.025)	(0.035)	(0.021)
Correlation ($\widehat{\rho}$)	0.524	0.552	0.484	0.534	0.521	0.526	0.518	0.525	0.52
Observations	967	869	1,140	1,370	1,474	1,634	1,783	1,905	2,018
R-squared	0.275	0.305	0.235	0.285	0.271	0.276	0.268	0.275	0.271
	Other Backward Castes								
Father's years of schooling ($\widehat{\beta}$)	0.608***	0.547***	0.643***	0.589***	0.645***	0.621***	0.559***	0.477***	0.487***
	(0.065)	(0.070)	(0.053)	(0.044)	(0.033)	(0.030)	(0.026)	(0.025)	(0.028)
Correlation ($\widehat{\rho}$)	0.387	0.367	0.412	0.432	0.466	0.476	0.487	0.455	0.516
Observations	1,411	1,172	1,519	1,920	2,027	2,363	2,530	2,890	3,114
R-squared	0.15	0.135	0.17	0.187	0.217	0.226	0.237	0.207	0.267
	Scheduled Castes/Tribes								
Father's years of schooling ($\widehat{\beta}$)	0.680***	0.702***	0.760***	0.705***	0.685***	0.649***	0.595***	0.525***	0.467***
	(0.081)	(0.060)	(0.038)	(0.045)	(0.043)	(0.041)	(0.030)	(0.027)	(0.027)
Correlation ($\widehat{\rho}$)	0.398	0.403	0.457	0.427	0.449	0.387	0.44	0.438	0.424
Observations	1,014	915	1,166	1,458	1,667	1,950	1,922	2,298	2,622
R-squared	0.158	0.162	0.209	0.182	0.201	0.15	0.194	0.192	0.179
	Muslims								
Father's years of schooling ($\widehat{\beta}$)	0.718***	0.626***	0.682***	0.742***	0.622***	0.588***	0.589***	0.615***	0.571***
	(0.065)	(0.088)	(0.060)	(0.047)	(0.051)	(0.046)	(0.042)	(0.034)	(0.026)
Correlation ($\widehat{\rho}$)	0.516	0.459	0.525	0.567	0.466	0.469	0.504	0.556	0.555
Observations	442	352	462	580	628	814	802	1,013	1,316
R-squared	0.266	0.211	0.275	0.322	0.217	0.22	0.254	0.309	0.308

*** p > 0.01; ** p> 0.05; * p>0.10.
Robust standard errors are in parentheses.

Table 6: Cohort Trend in Intergenerational Mobility, State Level

	Son's Birth Cohort: 1951-60		Son's Birth Cohort: 1976-85	
State	*beta*-Coefficient	Correlation	*beta*-Coefficient	Correlation
Andhra Pradesh	0.710	0.466	0.553	0.476
	(0.062)		(0.035)	
Bihar	0.709	0.524	0.573	0.575
	(0.047)		(0.025)	
Gujarat	0.717	0.518	0.478	0.512
	(0.053)		(0.028)	
Haryana	0.651	0.529	0.425	0.472
	(0.053)		(0.027)	
Himachal Pradesh	0.539	0.401	0.330	0.440
	(0.067)		(0.028)	
Karnataka	0.810	0.556	0.497	0.483
	(0.039)		(0.022)	
Kerala	0.447	0.449	0.378	0.467
	(0.042)		(0.03)	
Madhya Pradesh	0.856	0.568	0.511	0.509
	(0.040)		(0.020)	
Maharashtra	0.620	0.491	0.367	0.440
	(0.038)		(0.019)	
Orissa	0.802	0.498	0.496	0.457
	(0.063)		(0.034)	
Punjab	0.579	0.438	0.443	0.542
	(0.057)		(0.024)	
Rajasthan	0.775	0.474	0.515	0.501
	(0.059)		(0.026)	
Tamil Nadu	0.421	0.338	0.471	0.516
	(0.05)		(0.029)	
Uttar Pradesh	0.751	0.526	0.529	0.533
	(0.041)		(0.020)	
West Bengal	0.696	0.613	0.673	0.670
	(0.037)		(0.025)	

i) Jammu and Kashmir, Delhi, Assam, and North East excluded because sample size was below 300.
ii) Robust standard errors are in parentheses.

Table 7: Intergenerational Transitional Probabilities, All India

Panel A- Son's Birth Cohort: 1951-55

	Son's Education:					
	< Primary	*Primary*	*Middle School*	*Secondary*	*Post Secondary*	*size*
Father's Education:						
< Primary	0.501	0.185	0.119	0.123	0.071	0.773
Primary	0.099	0.234	0.207	0.215	0.245	0.112
Middle	0.046	0.052	0.293	0.308	0.301	0.044
Secondary	0.029	0.035	0.114	0.376	0.446	0.041
Post Secondary	0.017	0.030	0.070	0.081	0.802	0.030

Panel B- Son's Birth Cohort: 1981-85

	Son's Education:					
	< Primary	*Primary*	*Middle School*	*Secondary*	*Post Secondary*	*size*
Father's Education:						
< Primary	0.332	0.217	0.224	0.117	0.110	0.495
Primary	0.105	0.198	0.293	0.173	0.231	0.173
Middle	0.053	0.105	0.321	0.192	0.330	0.116
Secondary	0.024	0.048	0.167	0.238	0.523	0.125
Post Secondary	0.008	0.022	0.078	0.165	0.727	0.092

i) Each cell ij represents the average probability (for a given cohort) of father with education level i having a son with education attainment level j.
ii) Column titled *"size"* reports the fraction of parents in each education category.

Table 8. A: Intergenerational Transitional Probabilities, Social Groups

Panel A- Son's Birth Cohort: 1951-55

	Higher Hindu Castes					Scheduled Castes/Tribes			
	Son's Education:					Son's Education:			
Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*	Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*
$\leq$*Primary*	0.455	0.159	0.386	0.746	$\leq$*Primary*	0.792	0.095	0.113	0.946
Middle School	0.094	0.285	0.621	0.087	*Middle School*	0.097	0.359	0.544	0.027
$\geq$*Secondary*	0.041	0.093	0.867	0.168	$\geq$*Secondary*	0.071	0.083	0.846	0.027

Panel B- Son's Birth Cohort: 1981-85

	Higher Hindu Castes					Scheduled Castes/Tribes			
	Son's Education:					Son's Education:			
Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*	Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*
$\leq$*Primary*	0.337	0.240	0.423	0.466	$\leq$*Primary*	0.538	0.232	0.230	0.813
Middle School	0.119	0.288	0.593	0.141	*Middle School*	0.205	0.304	0.491	0.089
$\geq$*Secondary*	0.034	0.102	0.864	0.393	$\geq$*Secondary*	0.088	0.234	0.678	0.097

i) Each cell ij represents the average probability (for a given cohort) of father with education level i having a son with education attainment level j.
ii) Column titled *"size"* reports the fraction of parents in each education category.

Table 8. B: Intergenerational Transitional Probabilities, Social Groups

Panel A- Son's Birth Cohort: 1951-55

	Other Backward Castes					Muslim			
	Son's Education:					Son's Education:			
Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*	Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*
$\leq$*Primary*	0.597	0.148	0.255	0.935	$\leq$*Primary*	0.808	0.082	0.110	0.887
Middle School	0.119	0.231	0.650	0.028	*Middle School*	0.114	0.309	0.577	0.044
$\geq$*Secondary*	0.100	0.071	0.829	0.038	$\geq$*Secondary*	0.066	0.231	0.703	0.069

Panel B- Son's Birth Cohort: 1981-85

	Other Backward Castes					Muslim			
	Son's Education:					Son's Education:			
Father's Education:	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*	Father's Education	$\leq$*Primary*	*Middle School*	$\geq$*Secondary*	*size*
$\leq$*Primary*	0.450	0.264	0.286	0.658	$\leq$*Primary*	0.602	0.215	0.182	0.718
Middle School	0.123	0.369	0.509	0.124	*Middle School*	0.254	0.293	0.453	0.107
$\geq$*Secondary*	0.047	0.104	0.849	0.219	$\geq$*Secondary*	0.104	0.181	0.716	0.175

i) Each cell ij represents the average probability (for a given cohort) of father with education level i having a son with education attainment level j.
ii) Column titled *"size"* reports the fraction of parents in each education category.

Figure 1: Average and Standard Deviation of years of schooling, ALL India

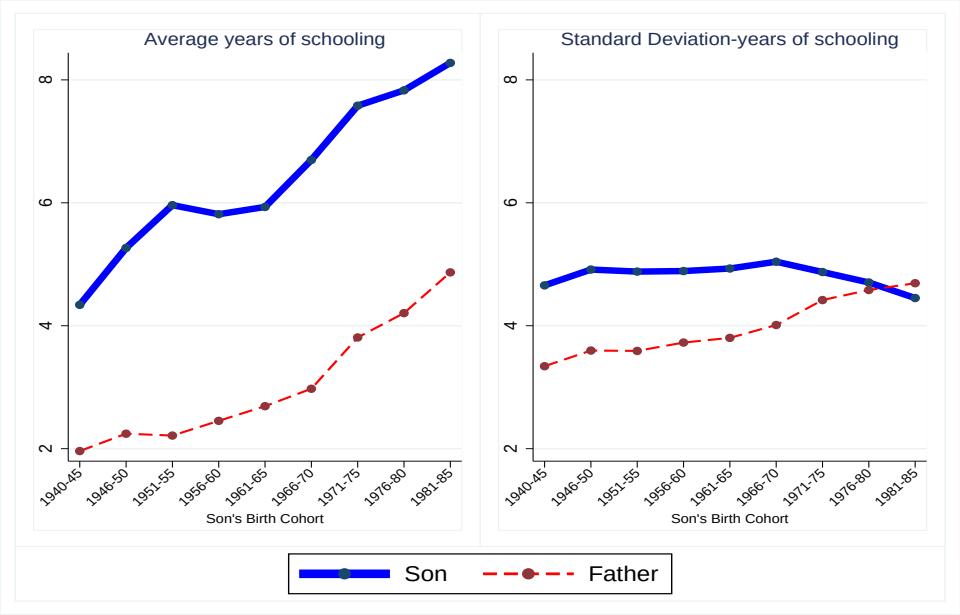
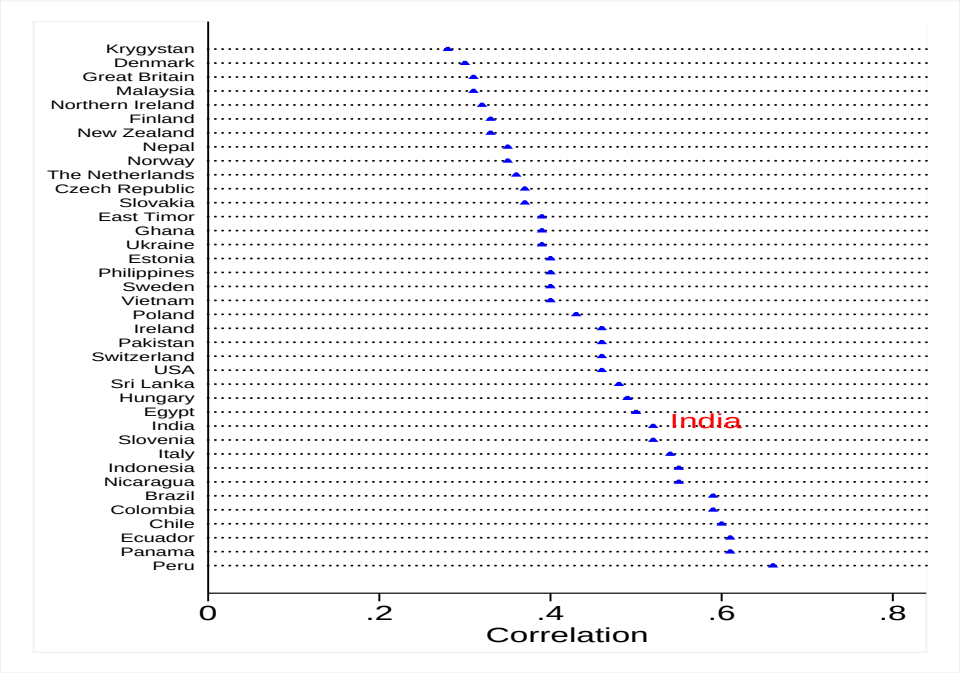


Figure 2: Ranking India in terms of Intergenerational Mobility



Note: Estimate for India are from Authors' calculation. Estimates for other nations are from Hertz et al. (2008), Table 2.

Figure 3: Clustering of observations around the Regression line for the OBC

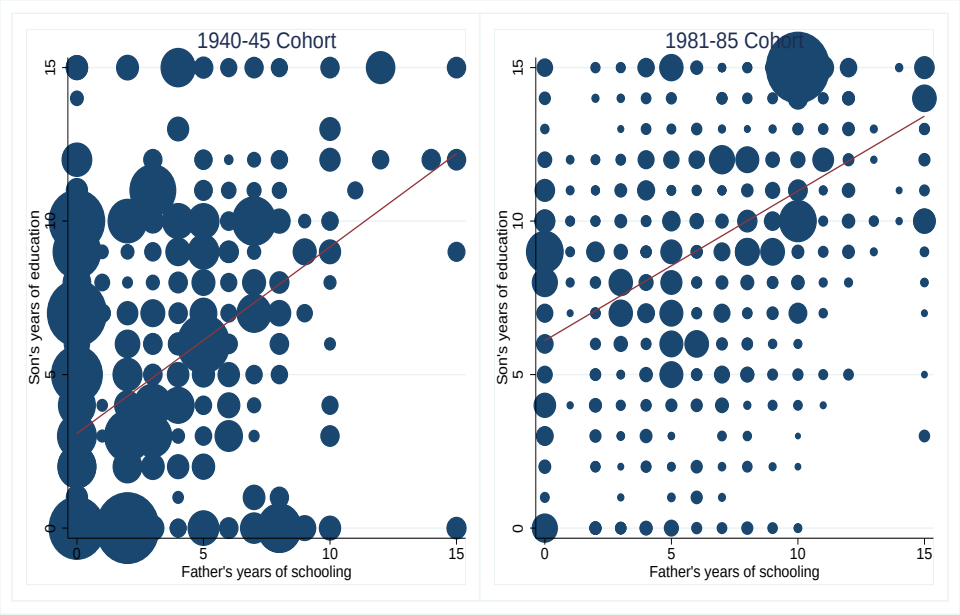
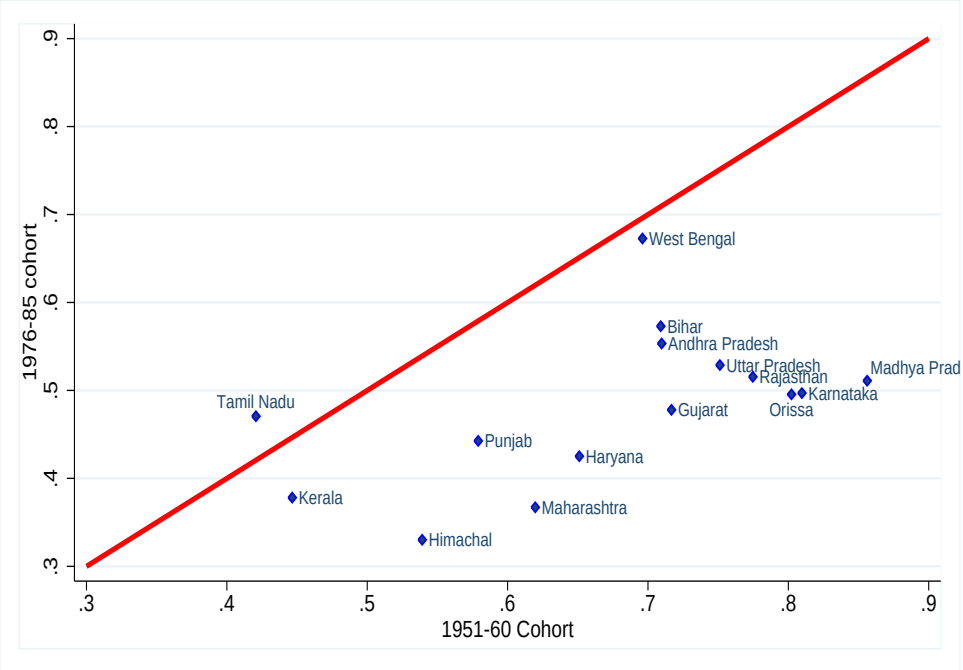


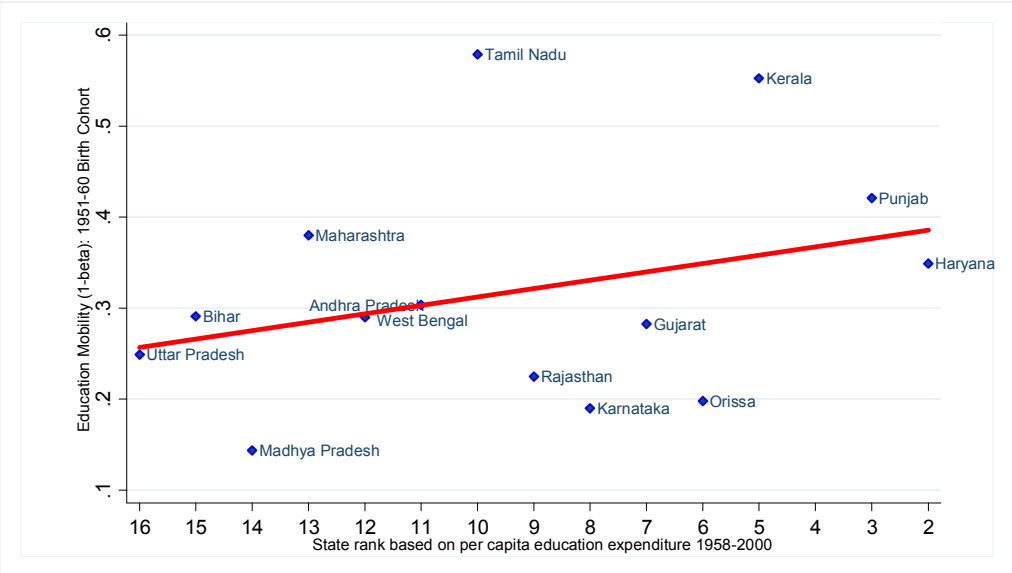
Figure 4: Intergenerational Education Mobility, State Level



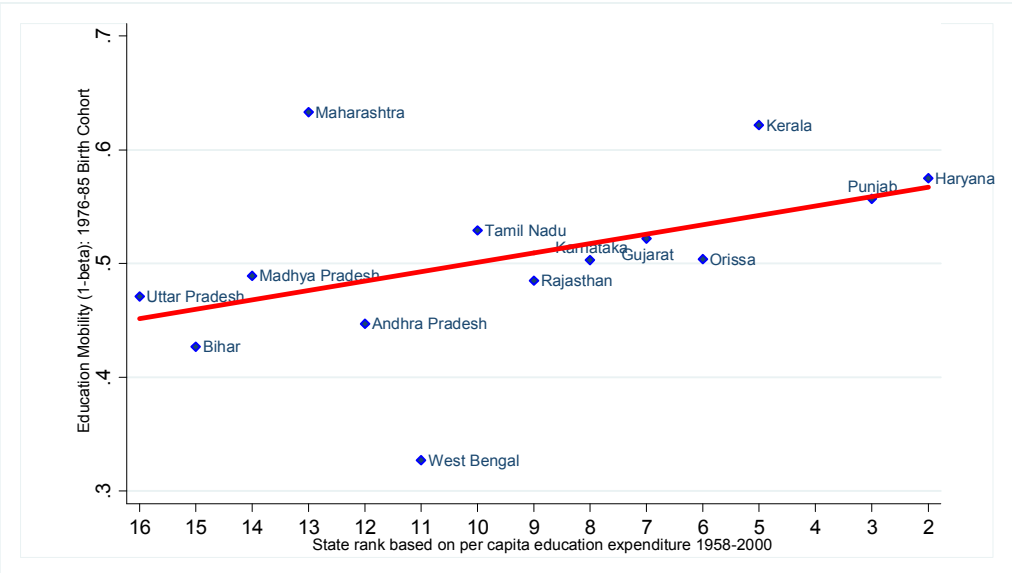
Note: Jammu and Kashmir, Delhi, Assam, and Northeast excluded because of smaller sample sizes. See text for details.

Figure 5: Intergenerational Mobility and Public Educational Spending, State Level

5a) Birth Cohort: 1951-60



5b) Birth Cohort: 1976-85



Note: Jammu and Kashmir was ranked 1 in terms of per capita education spending. However, our analysis excludes this state due to smaller sample size.

Appendix A: Co-residence condition and Sample Selection in the NSS

In this section, we illustrate the sample selection issues that may arise due to the identification of father-son pairs based on co-residence. Using the 61st round of the NSS (2004-05), we first show that the sample of adult males that can be matched with their father's information using the co-residence condition disproportionately represents younger individuals. Then, we also show that even one concentrates on relatively younger cohorts (i.e. restricting the analysis to only younger cohorts, such as 20-30 age group), the persons for whom father's information is identified may not be a random subsample of the concerned age group.

Table A.1: Distribution of population aged 20-65 based on the relationship to head, NSS 2004-05

Relation to the Head (Code)	Relation to the Head	Sample Size	
		Male	Female
1	Self	101,053	12,284
2	Spouse of head	338	96,721
3	Married child	25,954	2,720
4	Spouse of married child	881	25,823
5	Unmarried child	24,927	10,845
6	Grandchild	1,111	662
7	Father/ mother/ father-in-law/ mother-in-law	1,296	7,556
8	Brother/ sister/ brother-in-law/ sister-in-law/ other relatives	7,314	5,860
9	Servants/ employees/ other non-relatives	564	203
Total		**163,438**	**162,674**

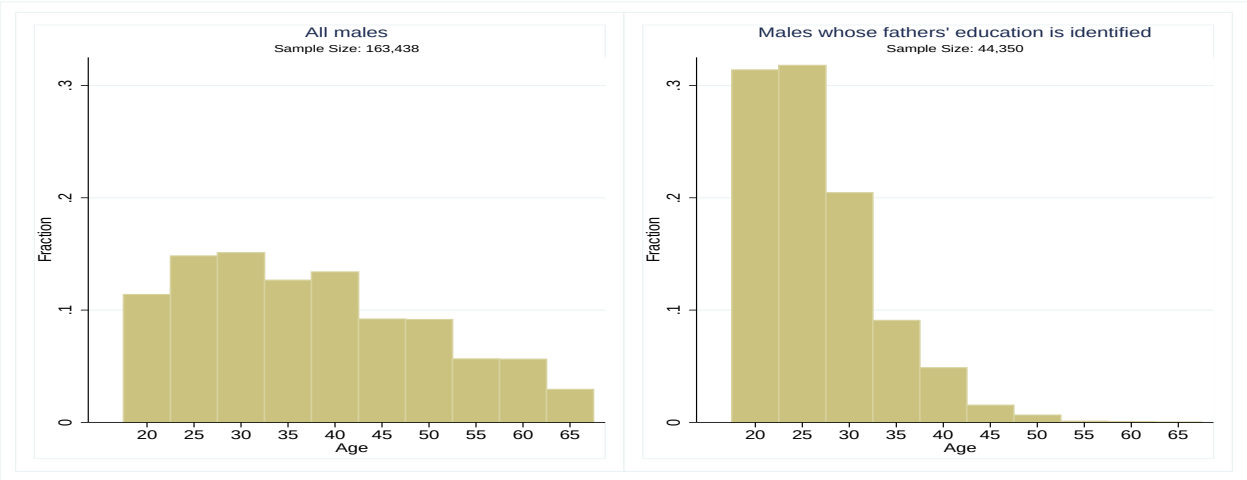
Source: NSS 61st Round Employment and Unemployment Survey, 2004-05

In the NSS data set (similarly, in the NFHS), parents identification is achieved through imposition of co-resident condition and exploiting the "*relationship to head*" information. Table A.1 provide the information on the various types of relationship captured in this variable and the corresponding sample sizes in the 2004-05 round of the NSS.[30] As is evident from the sample sizes reported in Table A.1, using co-residence to identify father's information would lead to severe loss of observations. This is because almost 62 percent of adult

[30]In the NFHS (2005-06), "*relation to head*" has following categories: 1-self, 2-wife or husband, 3-son/daughter, 4-son/daughter-in-law, 5-grandchildren, 6-parents, 7-parents-in-law, 8-brother/sister, 9-brother/sister-in-law, 10-niece/nephew, 11-other relatives, 12-adopted/foster/step child, 13-domestics servants, 14-other non relatives.

male sample consist of household's head whose father information is not available. One can potentially identify fathers' for only those male persons in age 20-65 who has reported relationship to head as married/unmarried child (50,881 individuals or 31 percent of the entire adult male population). Hence males in age 20-65 who reported as child of head can be matched to head if head is male or with spouse (if alive and co-resident) of head if head is female. Out of 50,991 persons who reported as child of head, 44,228 live in male headed households, while 6,653 live in female headed households. However, 6508 female headed households do not have spouse of head living in household. Hence, through co-resident, we could identify father's education only for 44,373 males in age 20-65, which is merely 27 percent of the total males in age 20-65.

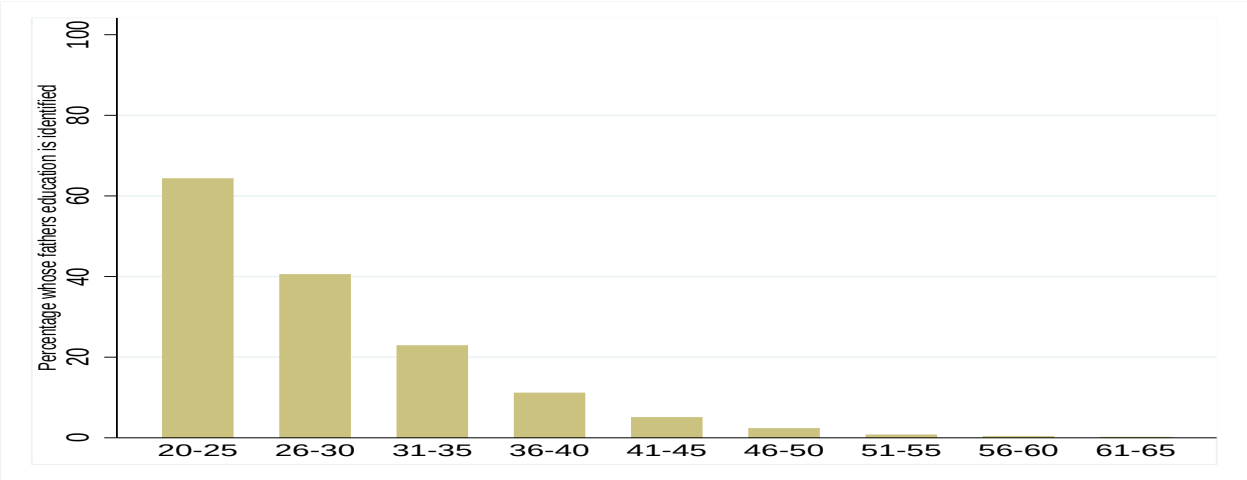
Figure A.1: Age distribution of males in the age group 20-65, NSS 2004-05



Note: Survey weights are used to get the age distribution.

Figure A.1 presents the age distribution of male in the age group 20-65 for the entire sample and for the co-resident sample (matched with their father using the co-residence condition). As we observe from this figure, there are significant difference in the age distribution of the two samples. Specifically, a large majority of the co-resident sample is concentrated in the 20-30 age group (roughly 80 percent). Hence, using co-residence we have an oversample of younger adults which is expected as these individuals are more likely to be residing with their parents.

Figure A.2: Proportion in each age group (male) whose father education is identified in the NSS, 2004-05



Note: Survey weights are used to calculate the proportions.

In addition to having a non-representative sample of the adult male population, the father's education information identified in each age group may not be randomly distributed across observations. In Figure A.2, we plot the proportion in each age group (male) whose father education is identified using the co-resident sample from the 2004-05 NSS round. Again, we find that in the co-resident sample, although the percentage of individuals whose father's education can be identified are much higher for the younger age groups, it remains a non random sub sample of that particular age group. As a result, not only the estimates (cross-section estimates) of intergenerational mobility based on the father-son pair identified through co-residence would be biased, but also the bias will not be eliminated even if one concentrate on only younger age groups.

Appendix B: Evolution of Education Policy in India

Table B: Education Policy in India 1951-2005

Period	Policy Framework	Policy Measures and Programmes
1951-68	Constitution of India	Expansion of the formal schooling system. State governments shoulder the responsibility for primary education.
1968-86	National Policy on Education, 1968	1976: Education shifted to the Concurrent list thereby giving the GOI and state governments equal responsibility for promoting and managing education. 1980s: Non-Formal Education introduced to supplement formal schooling, thereby increasing Central investment in primary schooling.
1986-92	National Policy on Education, Jomtien Conference for Education for All, followed by EFA projects most of them with foreign aid	Andhra Pradesh Primary Education Project, early 1980 1986 (British ODA) Environmental Education, 1986 (Domestic Resources) Rajasthan Shiksha Karmi Project, 1987 (Sida) Total Literacy Campaign, 1988 (Domestic resources) Mahila Samakhya in Karnataka, UP and Gujarat, 1989 (Dutch Government) Bihar Education Project, 1991 (UNICEF) Rajasthan Lok Jumbish, 1992 (Sida) UP Basic Education Project, 1992 (World Bank)
1992-2002	Revised National Policy on Education Mid-day meal, 1995, Supreme Court Order on Mid-day meal, 2001	District Primary Education Programme (DPEP), 1993 National Programme of Nutritional Support to Primary Education (Mid Day Meal), 1997, Sarva Shiksha Abhiyan, 2001
2002 onwards	Free and compulsory education bill, 2004 Revised Mid-day meal Programme in 2004	Free and Compulsory Education made fundamental right of children in the age group 6-14 Universal Mid-day meal across primary schools in the country

Source: Ensuring Universal Access To Health and Education In India, November 2007.