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Working Paper

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An International Study of Childhood Poverty

How Girls Fall Behind On Cognitive Performance

Quantile Decomposition Evidence from Andhra Pradesh, India

Divya Nair

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The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (in Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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How Girls Fall Behind On Cognitive Performance: Quantile Decomposition Evidence from Andhra Pradesh, India

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Abstract

Cognitive competence is a fragile construct and a range of factors influence whether individuals perform above or below their ability. Gaps in cognitive performance early in life are a predictor of future differences in health, wages and productivity. Using Young Lives data from the state of Andhra Pradesh, India (2002-2009), this paper studies two cohorts of children at two time points (at 5 and 8 years, and 12 and 15 years of age) and examines gender inequality in performance in language and math tests. It looks at the contribution of a rich set of explanatory variables to the gender gap from middle childhood through adolescence. Applying newly developed quantile estimation techniques in conjunction with traditional Blinder-Oaxaca decompositions, this paper examines the gender gap in test scores. I also examine the difference in change in scores over time for boys and girls.

The evidence suggests that: (a) Gender differences at the mean mask substantial heterogeneity across quantiles. (b) Girls fall behind particularly in math by the age of 15. Even at 5 years, girls have no cognitive advantage in language or math – despite contrary evidence from other contexts. (c) The largest gains experienced over the two rounds is by 15 year old boys in the 95th percentile of math performance (0.68 standard deviations), and the largest losses are by 15 year old girls at the median of math scores (-0.61 standard deviations). (d) A widening of the boy-advantage takes place over time and across quantiles for the younger cohort in language, and for the older cohort in math. (e) Unexplained effects contribute most to girls falling behind in math scores at 15 years of age – providing possible evidence of gender discrimination.(f) Child-level factors contribute the most to changes (explained and unexplained) in scores. This highlights the influence of characteristics such as self-efficacy on the relatively poor test performance of (the brightest) girls in the current context.

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1. Background on gender gaps

Gender differences in language and math performance have been a topic of some research and contention. While some studies question the very existence of a performance gap, others debate its origin and in particular whether these gaps may be attributed to biological, social, or testing biases. In India, gender gaps persist across a wide range of health and labor outcomes, and girls continue to under-perform at school, as reflected in higher drop-out rates than boys (International Institute for Population Sciences 2009; ASER 2011). Differences in cognition or learning levels have important implications for the future of young men and women – gender differences in education contribute significantly to productivity and wages gaps between men and women around the world (World Development Report 2012).

The faculty of language is often considered advantageous for women, on the basis that "females are more verbal than males" (Koles et al. 2010). But are the roots of this difference biologically based and dependent on the functional organization of the brain as suggested in some research (Koles et al. 2010; Shaywaitz et al. 1995)? Other studies of language acquisition find that differences by gender either do not exist or tend to disappear early (Wallentin 2009). While an analysis of Scholastic Aptitude Tests in the United States[1] finds a 0.30 standard deviation difference in math, no gap is found in language (cited in Fryer and Levitt 2010). Differences by gender might be negligible to begin with as children enter school, but they can become accentuated over time (Fryer and Levitt 2010; Hyde and Mertz 2009) – and this is more often in math. Yet in the United States, there is also evidence that this gap is closing (or has closed) and girls have reached parity with boys in math (Hyde and Mertz 2009). A meta-analysis of math performance across countries finds that while more males scored above the 95th to 99th percentiles, this gap is context-specific and "largely an artifact of changeable sociocultural factors, not immutable, innate biological differences" (Hyde and Mertz

[1] Children who take this test are not representative of the general US population

2009). Another meta-analysis of cross-country data showed that differences in math achievement by gender are on average very small in magnitude and often insignificant (Else-Quest et al 2010).

Yet, around the world even as participation rates have increased in schools and the labor force, women continue to be in very different educational and occupational streams as they follow certain gender norms (World Development Report 2012).Moreover, boys score higher on self-efficacy and self-concept than girls, and attitudes towards math and achievement in tests are positively associated at the individual level (Else-Quest et al 2010). Numerous explanations have been put forth for the gender gaps. Many studies have linked performance gaps on cognitive tests – both at the mean and at the tails of the distribution – with cultural and social factors related with gender inequality (Baker and Jones 1993; Else-Quest et al. 2010). Generally, future labor market opportunities are seen to shape expectations – of the concerned children, their parents, peers, teachers, role models and leaders in society –about how much importance girls should place on performance in these tests, and this in turn is seen to affect their actual scores (Baker and Jones 1993). For example, in the US one reason girls performed poorly on math tests was because they took less advanced classes than boys in high school, and subsequently this is happening less, and more girls are performing at par with boys (Hyde and Mertz 2009).

In sum, social forces and situational variables are acknowledged as strongly influencing test scores via self-fulfilling prophecies (Aronson and Steele 2005). Specific mechanisms via which gender stratification is perpetuated have been examined by psychologists and behavioral economists. Here researchers point to the fragility of competence, that it is easily undermined by how others may view an individual and that "it is transacted within a web of social relations" (Aronson and Steele 2005, p. 437). Stereotypes about a female's social identity (these identities may be based on race, caste, ethnicity etcetera) or inferiority in certain subjects, and comparatively higher male confidence during adolescence are seen to influence test scores (Else-Quest et al 2010).

There is also a great deal of heterogeneity across and within countries in the gender gap (Baker and Jones 1993; Bharadwaj et al. 2012). India ranks 105 of 135 on the Global Gender Gap Report that examines gender gaps in economic participation and opportunity, health and survival, education and political empowerment (Hausman et al. 2012). While it performs above average on political empowerment it lags behind on the other three outcomes, which is likely to undermine India's future growth and development.

Thus, in this paper I ask the following questions: is there is a gender gap in cognitive performance in a predominantly rural context in India, and how do these patterns evolve over time? Using decomposition techniques, what are the determinants of this gap?

2. Analytical Framework

Cognitive performance is modeled as a function of inputs at various levels – ranging from innate child characteristics, to parental, household, school and social inputs. Moreover taking a lifecourse perspective, these inputs are cumulative and can include past along with current inputs (Todd and Wolpin 2003).

The empirical analysis begins with an examination of bivariate associations to confirm that there are gender difference in test scores and these inputs. Next, multivariate conditional quantile regressions are implemented using cross-sectional data. These regressions help to characterize the entire distribution of cognitive performance. While ordinary linear regressions aim at estimating conditional mean functions, quantile regressions minimize asymmetrically weighted absolute residuals and estimate conditional median functions and other conditional quantile functions (Buhia, 2004). After stratifying the sample into percentiles, the variance–covariance matrix of the estimators is obtained via bootstrapping. Conditional quantile regressions have been applied in various scenarios and allow an estimation of the marginal effect at the quantiles for the conditional distribution of the outcome, given explanatory variables.

Recently Fipro et al. (2009) have introduced unconditional quantile regressions that provide an estimation of marginal effects at quantiles of the marginal distribution of the outcome. This entails running regressions of the recentered influence function of the unconditional variable on the explanatory variables. These combine both a within-group and between-group effects as compared with conditional quantile regressions that are restricted to a within-group (or quantile) interpretation (Fipro et al. 2009; Fortin et al. 2011).

Oaxaca decomposition, explained further below, is implemented to apportion the difference in cognitive scores into an explained and unexplained part – this is performed on both cross-sectional and panel data. First, I decompose the overall difference in gender scores and then examine the change in gender scores over time. This allows an examination of the divergence that takes place between genders over time. Unconditional quantile regressions have been newly introduced into the decomposition literature and allow decompositions to move beyond the mean. Thus, after obtaining values for the recentered influence function for each group at particular quantiles (for instance, at the 5th, 50th and 95th quantiles) using these newly introduced second generation techniques, Oaxaca decomposition is implemented at each quantile to examine either the gender differences at that quantile or the change in scores over time for each gender at the quantile of interest.

The Oaxaca Decomposition method

This method was historically conceptualized to examine gender disparities in wages. It has subsequently been implemented in the education literature to examine gaps in test scores by country (McEwan and Marshall 2004) and schools (Krieg and Storer 2006). It is thus apt for examining differences in cognitive scores. The method cannot generally be interpreted as providing a causal link though the unexplained part of the decomposition may be interpreted as a sort of treatment effect (Fortin et al. 2011).

As per standard representation of these models (Fortin et al. 2011), the difference in mean cognitive scores for the groups Boys and Girls (represented as ‘b’ and ‘g’) is shown as follows where the outcome variable (Y) is linearly related to covariates (X), and the error term is assumed to be conditionally independent

$$Y_{si} = \beta_{so} + X\beta + \mu_{si}, \text{ where sex (s) is = Boy, Girl} \qquad \text{--------(1)}$$

The difference between boys and girls in the average cognitive score is $\hat{\Delta}_0^{\mu} = \bar{Y}_b - \bar{Y}_g$ is re-written as follows whereby the gap in cognitive outcomes is decomposed into two parts, the sum of the composition effect $(\hat{\Delta}_x^{\mu})$ related to the differences in covariates associated with each gender, and the coefficient effect, which in this case, is the effect of being a girl $(\hat{\Delta}_s^{\mu})$ (Fortin et al. 2011).

$$\hat{\Delta}_0^{\mu} = \underbrace{\sum_{k=1}^{K} (\bar{X}_{bk} - \bar{X}_{gk})\hat{\beta}_{gk}}_{\text{Explained part } (\hat{\Delta}_x^{\mu})} + \underbrace{(\hat{\beta}_{b0} - \hat{\beta}_{g0}) + \sum_{k=1}^{K} \bar{X}_{bk} (\hat{\beta}_{bk} - \hat{\beta}_{gk})}_{\text{Unexplained part } (\hat{\Delta}_s^{\mu})} \qquad \text{--------(2)}$$

Thus, each of the $\bar{\beta}_{so}$ and $\bar{\beta}_{sk}$ represents the intercept and slopes for boys and girls respectively. As per common usage in this literature, the first component of equation (2) is often understood to represent the ‘explained’ portion (or endowment/composition effects) , and the second is the ‘unexplained’ portion (or the ‘gender effect’) of the decomposition (also called coefficient effects). Thus, the endowment/composition effect refers to the expected change in girls’ mean cognition if girls had boys’ endowments, it answers the question: “what would the average cognitive score of girls be if they had the same characteristics as boys?" Similarly, the coefficient effects refer to the effect on girls' cognitive scores if they had boys' coefficients (Jann 2008).

In a detailed decomposition the unexplained and explained parts are further divided as per the contribution that is attributable to each covariate[2]. In categorical variables that do not have a natural zero the reference point has to be selected arbitrarily and this causes interpretation issues in OB methods. A decomposition procedure is then path dependent if the order in which variables are added affects the results of the decomposition. A number of solutions have been proposed to address this problem. In this paper I group variable as per Jann (2008). Another solution is based on transforming dummy vectors as deviations from the grand mean (Yun 2005). Yet Fortin et al (2011) warn that solving this problem of invariance comes at the expense of interpretability and can make results sample specific. As far as possible, where the reference category makes sense, I do not resort to normalizations.

Another parameter of interest for this model is the reference category, varied models use different reference categories. Neumark (1988) proposed using coefficients from a pooled regression as the reference coefficients. It has been suggested that in these models some of the unexplained portion can be transferred to the explained part, and that the estimated coefficients may be biased (Jann 2008; Fortin et al. 2011). In response, an additional indicator for group membership is now included in most pooled analyses (Jann 2008).

Finally, second generation decomposition methods entail 'going beyond the mean', and this is an ongoing area of investigation (Fortin et al. 2011). Once again, some of these techniques were introduced to study gender differences (in wages) by quantiles (Machado and Mata 2005). Machado and Mata (2005) use a counterfactual technique, but this is known to be computationally intensive

[2] In the case of wages, the unexplained part may represent a measure of gender discrimination that also includes gender differences in the unobserved variables.

(Albrecht 2003). The latest method is the previously described recentered influence function (RIF) introduced by Fipro et al (2009). It has also been successfully applied by and Heywood and Parent (2012), and Fortin et.al. (2013). The technique involves using the RIF on the left hand side, once the RIF is estimated, a standard OB decomposition is performed (Fortin et al. 2011).

3. Data

3.1. Context of study and sample

Data are used from three waves of the Young Lives longitudinal study. Young Lives is an international, longitudinal study of childhood poverty that is following 12,000 children in 4 countries for 15 years, from 2002 to 2017. Within India, the undertaking is funded by the Department for International Development (United Kingdom) and based on a partnership between the University of Oxford, Save the Children United Kingdom, The Open University and prominent national research and policy institutes. This study has followed two cohorts of children in the state of Andhra Pradesh, India. The younger cohort (n =2000) has been followed at ages 1, 5 and 8 years, and the older cohort (n=1000) was followed at 8, 12 and 15 years of age (both were studied in 2002, 2006 and 2009). Cognitive performance was assessed over time for both cohorts. However, in the first round no measure of cognition is available at 1 year of age for the younger cohort; similarly, for the older cohort only the Ravens test performance is available. Subsequently, in rounds 2 and 3 all children took the Peabody Picture Vocabulary Test and math assessment tests. To ensure comparability across cognitive outcomes only cognitive performance assessed in rounds 2 and 3 are examined in this paper while relevant measures collected during round 1 are included as covariates in the analysis[3].

The state of Andhra Pradesh is India's fifth largest and has a population of 84.7 million. It is predominantly (67%) rural (Census 2011). The Young Lives study collected information from about

[3] These rounds are referred to as wave 0, wave 1 and wave 2 respectively.

100 villages in six of 23 districts in the state, using a sentinel site (cluster) method, ensuring uniform distribution of districts across major regional groupings within the state. In terms of education, gender disparities are significant in Andhra: while the male literacy rate is 75.6% the female literacy rate is 59.8% (Census 2011). On average, within the 6-16 year age group, 66% of girls are enrolled in school compared with 77% of boys; moreover in rural parts, among the 15-17 age category, only 23% of girls are enrolled compared with 46% of boys (NFHS 2006 per Young Lives).

3.2. Variables of interest

Measures of cognitive achievement

Performance on both language and math tests are the two dependent variables that are assessed at 5, 8, 12 and 15 years. Given the lack of context-specific test norms, each score is standardized per round to have a mean zero and standard deviation of one. Thus, comparisons over time (across rounds) provide an estimate of the change in relative rankings for each child or gender.

The Peabody Picture Vocabulary Test (PPVT): Vocabulary is required to understand classroom directions and it lays the foundation for future comprehension and academic success in all subjects (Beck et. al 2002). This measure has been widely used in previous studies (Paxson and Schady 2007; Blau 1999) and is also used in federal programs such as Head Start, Even Start in United States. Developed in 1959 and updated several times since then, the PPVT is a measure of receptive vocabulary for persons above 2.5 years. The PPVT-III-A, developed in 1997, was administered for this study. The test contains 17 sets of 12 items. It is individually and orally administered, untimed, norm-referenced, based on the test-taker choosing the right picture from a set of options in response to an oral question. Items are arranged in order of difficulty, with the examiner choosing a start point based on the child's age, and moving forward till the child reaches a ceiling within their critical range. In a set of 12 items, the basal set is established as the set with one or no error, and the ceiling set is established as the set with eight or more errors. Raw scores are calculated by subtracting the total number of incorrect responses from ceiling set (Cueto et al., 2009). The test was conducted in the local languages. The validity and reliability of the tests in Andhra Pradesh has been assessed for the Young Lives sample. Pilots were conducted for all tests in a similar population in Andhra Pradesh (Cueto et al., 2009).

The Mathematics Achievement Test: This test was developed by the International Evaluation Association in 2003. Administered among 12 and 15 year old children, it constitutes 10 multiple-choice or short-answer items related to number sense (it was assumed that testing on geometry, algebra etc. may not be fair to children who may not be in school). Cronbach's Alpha was recorded at 0.6 (acceptable) for this sample for both tests. Given the low reliability, math scores are examined in conjunction with language scores.

Independent variables

A range of relevant explanatory variables are included that are known in the literature to affect cognitive outcomes. Inputs at the child, parent, household, school and social levels are included. For the younger cohort measures of early childhood input (a measure of level of antenatal care and a dichotomous measure of maternal depression) [4] are also added to examine the influence of early endowments on later outcomes (Grantham-McGregor et al. 2007). Child level characteristics include an anthropometric measure (height-for-age), age in months and a question assessing child self-efficacy that asks children if they made plans about their future work (responses are on a scale of 1-5, ranging from 'strongly disagree' to 'strongly agree').

[4] Antenatal care was constructed per Young Lives where a child with no antenatal visits was assigned a value of 0; those who had antenatal visits got 1 point 1 if the first visit was at 4 months pregnancy or before; another point was added if they had 5 or more visits in total; and 1 point was added if they were given tetanus injections. While maternal depression is a dichotomous measure, we have missing data for 110 children – these are included in the analysis and coded as missing.

Parent characteristics include a dummy for whether the mother is literate. Parent aspirations are known to be important determinants of cognitive and schooling outcomes (World Development Report 2012). Parents were asked ideally what occupation they would like their child to do when s/he is older. This ambition was then coded according to the Indian Occupation classification to rank them by 'prestige'. Thereafter, the variable was dichotomized such that parents who wanted their child to become either of the top two ranks (professional or manager) were coded as 1, and others were coded as zero. For the younger cohort, parents were asked ideally what grade they would like their child to complete, and this measure was used to assess parent ambition (since questions about occupations were not asked of parents of 5 year olds).

Within household characteristics, measures are included for a continuous wealth index, household size, a dummy for being of Hindu religion and living in a rural community. Variables at the school level include whether it is a private school and what grade the child is enrolled in. These are important variables in the context of Andhra Pradesh where parents tend to believe that private schools provide better education, and where grade repetition is very high. Social characteristics are captured via a dummy for caste – in the given context caste is an important feature of a family's identity and this is often associated with access to a wide range of caste-based educational, informational and financial resources.

4. Results

4.1. Sample description

Table 1 provides summary statistics for variables across the two cohorts over time and by gender; bivariate tests examining mean differences by gender are also conducted. In the first panel, outcomes are displayed for each cohort. For both cohorts, there is no significant difference at the mean in language scores in wave 1 (at 5 and 12 years), but there is a significant difference by wave 2 favoring boys (at the 1% level) when the children are 8 and 15 years respectively. This is despite evidence that girls have a cognitive advantage in early childhood (Bharadwaj et al. 2012). Similarly, there is a difference in mean math scores at age 15 years favoring boys (significant at the 5% level).

A number of other significant differences in characteristics across gender are worth noting. Boys have poorer nutritional status than girls (as measured via their height-for-age) in the younger cohort, in the older cohort this pattern is flipped with girls being further from expected World Health Organization norms for their age. Parental ambition, measured as the grade parents want their child to ideally complete is higher for boys in the younger cohort. When in the older cohort these ambitions are assessed per the prestige of the occupation parents would like their child to achieve; here parents are more ambitious for their daughters – indicating perhaps aspirations that favor girls achieving 'respectable' jobs if they work. Across both cohorts, boys tend to be enrolled in private school at higher rates than girls. While there is no difference in school enrollment among the younger cohort, 15 year old boys tend to be in higher grades than girls(significant at the 10% level) – indicating that girls at this age are both dropping out of school and falling behind.

4.2. Quantile regressions results – examining the distribution

Table 2 displays results from simultaneous conditional quantile regressions for the 5th, 50th and 95th percentiles for each cohort. Wald tests are conducted to assess significant differences across quantiles per Weesie (1999). An examination of the coefficients on a varied set of determinants of cognitive performance reveals a great deal of heterogeneity by quantile, cohort and cognitive outcome. In particular, the regressions display a widening of the gender gap among higher performing students for both language and math for the younger cohort, and for math for the older cohort. These coefficients on girls are negative and significant for language for the younger cohort and for math for the older cohort – this is indication that high performing girls start to fall behind over time in math.

The strength (and significance) of determinants at the child, household, parent levels varies by quantile. Child-level characteristics such as height-for-age and child efficacy have a stronger association among the older cohort for language scores, and among the younger cohort for math scores – indicating that timing of these determinants varies for each outcome. Among parental characteristics, maternal literacy is a significant determinant of language scores for the younger cohort, and is strongly associated with math scores for both cohorts – and the strength of this association increases for higher performing children (though the difference across quantiles is not statistically significant). Household wealth is a stronger determinant of outcomes (both language and math) for the younger cohort, and the returns from wealth are monotonic for language with differences across quantiles significant at the 10% level, and for math this association is stronger at the median compared to at the at 5th percentile. However, wealth is not a significant determinant of cognitive performance for the older cohort. Schooling attributes have a stronger association with math scores than language scores for both cohorts. The grade a child is enrolled in significantly affects their performance, with higher grades associated with higher scores. In addition, children in higher quantiles gain more from being enrolled in higher grades for both language and math. On the converse, going to a private school is associated with lower returns for children at higher ends of the distribution – this is particularly so for math (significant at the 5% level). Thus, weak students perhaps gain more from private schools – 8 year old children in the 5th percentile in private schools are 0.50 standard deviations ahead of similar children in public schools, and their gains are significantly higher than the median child who gains 0.29 standard deviations.

Finally, the caste of a child is a stronger determinant of math scores than language, and early childhood attributes are not found to be significant contributors to cognitive performance in any of these quantiles.

4.3. Quantile decomposition of the boy-advantage in scores (cross-sectional analysis)

In Table 3, I examine the boy-advantage in cross-sectional models, while controlling for all covariates that are shown in Table 2. Results are from the pooled Oaxaca decompositions for language and math using methods developed by Jann (2008)[5]. While I employ OLS regressions for decomposition at the mean, I also examine the distribution of scores across unconditional quantiles using RIF methodology developed by Fipro et al. (2009). The table provides mean decompositions for all ages and quantile results from the latest waves (at 8 and 15 years). Figure 1 provides an overview of this boy-advantage across all ages and quantiles (including 5 and 12 years).

The decompositions at the mean (columns 1, 2, 6 and 7) show that while the gender gap ("difference in scores") at the mean for the younger cohort remains unchanged for both language and math, there is a widening of the boy-advantage for the older cohort in both language and math. At 15 years of age, the difference in scores is 0.38 and 0.36 standard deviations in language and math respectively, while it was 0.10 and 0.09 at 12 years.

Looking beyond the mean, it becomes clear that doing so is helpful since differences that do not appear large or significant at the mean, are often present at higher quantiles. Similar to Table 2, the overall gender difference is almost always present at the median and it is generally largest at the 95th percentile across cohorts and outcomes. The exception is math performance for the younger cohort, where there is no significant difference across the distribution. Yet for this cohort there is a language

[5] Other decomposition techniques were also implemented to ensure that results were robust. In pooled models the coefficient from a combined model of boys and girls is used as the reference coefficient.

gap, where boys outperform girls at the median and this increases at the 95th percentiles. The boy-advantage is wider for the older cohort, where the widest gap is in math at the 95th percentile (0.65 standard deviations), and for language at the median (0.47 standard deviations).

The gender gap (as shown in figure 2) is decomposed into the unexplained 'coefficient effects' and the explained 'composition effects'. The unexplained part – that is often interpreted as gender discrimination in the literature – is a larger contributor to the gender gap than the explained part for the younger cohort. For the younger cohort, the contribution of these unexplained effects is monotonic across quantiles for language, with the largest component at the 95th percentile (0.40 and significant at the 1% level). In math, the two components balance each other out (as there is no gender difference for math in the younger cohort), with the unexplained component larger at the 5th percentile and the explained component larger at the 95th percentile. For the older cohort, the picture is more mixed, with the explained portion contributing most to differences in language abilities and the unexplained part contributing significantly to math differences (0.37 and 0.58 standard deviations at the 50th and 95th percentiles).

4.4. Quantile decomposition of the change in boy-advantage (boy and girl panels pooled)

In Table 4, (also see figure 3) I decompose by gender the *differential change* in cognitive scores that boys and girls experience over the two waves. This is done for each cohort and outcome, while controlling for all covariates that are shown in Table 2. If causal relations are to be surmised it is more appropriate when examining these panel estimates that also account for past inputs. These models showcase the diverging of boys' performance from girls' performance, with older boys making the most gains across time.

If one focused on mean performance, boys' improve their scores compared to girls across cohorts in in language and in the older cohort for math. When considering the entire distribution, as seen earlier, boys experience generally larger and significant improvements or smaller declines in language performance both over time and across cohorts. In math their gains are small and non-significant among the younger cohort, while gains in math are large and significant for the older cohort. The largest differences in change by gender are at 15 years, where there is a 0.49 standard deviation greater increase (significant at the 1% level) in math scores for boys compared to girls at the 95th percentile, and a 0.29 standard deviation greater increase (significant at the 1% level) at the median.

In these models that control for inputs for a given child over two successive waves, it emerges that the difference in change is generally explained by difference in characteristics (explained change) between boys and girls than by difference in coefficient effects (unexplained change). The exception is performance on math tests – which are the largest changes – in the older cohort where the unexplained component comprises more than three-fourths of the difference in changes experienced.

4.5. Quantile decomposition of the change in scores over time (panels stratified by gender)

Finally, having examined patterns in the gender gap, in Tables 5A and B I explore the change in scores for each gender separately to understand why these patterns may have emerged. Here I use detailed decompositions to understand what contributes to the change each gender experiences – we thus look at the change in scores between 5 and 8 years for the younger cohort, and 12 and 15 years for the older cohort for girls and boys separately. Grouped variables are assessed, as recommended in the literature (Fortin et al. 2011) – the groupings are shown in Table 1 and 2.

Panel A provides an overview of the aggregate decompositions. It confirms and explains some of the previous gender gaps noted. In language, both girls' and boys' scores decrease over time among the younger cohort, with girls' scores falling by a greater amount (and significantly) at the median and 95th percentiles. The largest drop is among girls at the 95th percentile, where scores fall by 0.49 standard deviations (significant at the 5% level). Boys who were already doing well fall by 0.11 but this is not significant. Among the older cohort, most children improve their scores except for the median girl, whose scores fall by 0.26 (significant at the 1% level). Moreover, while boys in the 5th and 95th percentiles improve their scores significantly, girls' increase in language scores is not significant. For math, patterns for girls and boys look very similar over time. Both boys and girls in the 95th percentiles experience an increase in scores while most others decline in their performance. However, the magnitude of change among the older cohort favors boys: At 15 years, boys in the 95th percentile perform significantly better with a gain of 0.68 (significant at the 1% level) while girls' increase is 0.05 and non-significant. Similarly, while the median boy's score falls by 0.29, the median girl's score falls by 0.61 (both significant at the 1% level).

As shown in Figure 4a, on aggregate, patterns of explained and unexplained change over time are somewhat similar by gender, and often an improvement in characteristics (explained change) is balanced by a fall in coefficient effects (unexplained change); the ratio of explained to unexplained change is generally somewhat close to one. This is more so for language than math, and more so for the younger cohort than the older cohort. For the younger cohort, unexplained changes over the two waves contribute to a decline in aggregate scores over time and the explained component contributes to an improvement in scores over time. For the older cohort the pattern is similar except for the changes in language scores for boys and girls in the 5th percentile. For these boys at the bottom of distribution, positive unexplained change overshadow negative explained changes to improve their scores by 0.21 standard deviations over time (significant at the 10% level for boys, the effect is not significant for girls). The other exception where unexplained changes positively contribute to the aggregate change is for boys at the 95th percentile – these boys experience positive explained and unexplained changes that help them gain 0.68 standard deviations over time (significant at the 1% level).

Explanatory variables that contribute to changes in scores

Next, the detailed decompositions in Panel B (and Figure 4b) provide some explanation for the changes. Within explained changes (composition effects) child characteristics stand out. Variables included under child characteristics are anthropometric status, age and child self-efficacy. Improvements in these characteristics are particularly large for both genders in the 95th percentile. This is so for language for both cohorts and in math for the younger cohort. In fact only older boys in the 95th percentile of math do not experience a significant improvement in child characteristics. The other characteristic of note that contributes to explained changes is schooling. Though the contribution is much smaller than child characteristics, schooling characteristics are a significant contributor to changes in scores across the distribution (and cohorts) for language performance. Schooling characteristics also contribute positively to improvements in math scores for the older cohort, the exception is math scores for the younger cohort.

Within the unexplained change (or coefficient effects), the contributors are more mixed. Changes in child coefficients are generally negatively associated with language and positive for math. In the younger cohort these child coefficients are largest for boys in the 95th percentile for both outcomes, yet their signs are in opposite directions. Thus, if young boys in the 95th percentile had similar child coefficients in wave 2 as in wave 1, they would perform better in math, but worse in language. Among the older cohort, child coefficient effects are larger compared to other unexplained effects but they are non-significant. Similarly, school coefficient effects are often negatively associated with changes in language and positively associated with math scores. This pattern may indicate the response of shifts towards private schooling over time that are seen in Table2, private schools are often associated with high scores in math but low scores in language.

Household coefficients are generally non-significant contributors to the unexplained changes in language while for math they are larger and significant at the higher ends in the younger cohort and for boys in the 95th percentile in the older cohort. Given that these boys make the largest gains across all children in the study it is pertinent to note that unexplained household coefficient effects are the largest contributor to their improvement. Thus these boys gain especially from the effects of wealth, household size or being Hindu. In the same vein, being of lower caste contributes especially negatively to older girls' language and math performance at the higher end of the distribution and also to younger boys' math performance at the top of the distribution. Early childhood effects are null across all models. Similarly, the contribution of parent coefficient effects is limited – it is significant only for the change in median boys' language scores.

5. Discussion and conclusions

In this paper I employ a variety of innovative decomposition techniques to describe the systematic differences by gender in cognitive performance in Andhra Pradesh. Results are heterogeneous but robust across a variety of models. I examine two cohorts of children, which allows some insights into the timing of determinants.

Girls are known to have a cognitive advantage in early childhood (Bharadwaj et al. 2012), yet I do not find this in these data. For example, girls at 5 years are not significantly better performers on language or math tests. I also find that gender differences at the mean mask substantial heterogeneity across quantiles.

Girls do not display an advantage in language or math in wave 1 (at 5 and 12 years). Moreover, in language a boy-advantage emerges early – as discerned among the younger cohort (by age eight). This gap widens at higher ends of the distribution. In the older cohort (at 15 years), girls at the highest end somewhat reduce the boy-advantage but significantly lag behind at the mean and median. Moreover for math, even if the boy-advantage was not present initially (at 5, 8 or 12 years), it is strong by age 15. In math the gender gap is strongest at the 95th percentile. This is perhaps in consonance with evidence of stream divergence and higher aspirations among boys. Top male performers in secondary school have been found to be more likely to choose male-dominated fields than other males and thus perform better. But test scores have been found to make no difference to the choices top female performers make (World Development Report 2012).

Given international evidence that girls have early advantages in language and that these gaps disappear over time, the patterns evidenced here are peculiar, with an initial disadvantage that on average persists or increases. Internationally, there is evidence from contexts of girl-disadvantage that the gap in math widens over time – this is clear in the current context. Together, both trends confirm the strength of the local Andhra context that is known to be patriarchal and biased against girls.

Few previous studies have examined both language and math skill acquisition. I find that the production function for language and math look quite different with varied predictors that are important for each. Yet child characteristics are important for both language and math models. School characteristics are much smaller, but important contributors. Schools appear to be more important for math achievement and the gender gap among older children. Differences in school composition and coefficient effects appear to be via the differential drop-out of older girls and boys in secondary schools, the grades each is enrolled in, and that boys are more likely to be enrolled in private schools. Child coefficient effects tend to be negative across language decomposition models and positive for math decomposition models.

The results indicate a negative trend in scores. This is in line with recent evidence from India. ASER data indicates that learning levels have a negative trend among primary school children. Muralidharan and Zieleniak (2012) use item response theory to link scores over time and find that "less than 20% of students who do not correctly answer a grade N-level question at the end of grade N, are able to answer it correctly at the end of grade N+1" (cited in Bhardwaj 2012).

This study is not without limitations, results are inconsistent if unobserved characteristics explain the difference between boys' and girls' scores. As long as we assume that there is no systematic ability difference between boys and girls once we control for schooling and parenting the results are consistent (Fortin et al 2011). Moreover, I do not have data on quality of parenting, teaching, or the school environment – these are important variables that are known to affect how girls and boys perform on tests. Yet, a rich set of covariates is available and child and parent aspirational measures are included, which is an advantage over a number of other studies. The decomposition method cannot generally be interpreted as providing a causal link in this study. Fortin et al (2011) put forth two reasons that are pertinent in the study of gender differences: first, gender is not a choice variable (and thus not a 'treatment'), and second, the observable variables are not really pre-treatment variables (and more likely the consequence of a particular gender). In addition, while the decomposition literature assumes the unexplained part as discrimination, it has been argued that it could be an omitted variable problem instead. This is possible, as seen also by the large contribution of the constants (shown in figure 4). Yet given the longitudinal nature of the current study and the gendered patterns that emerge it is quite clear that gender gaps exist in cognitive performance in this context and that they worsen over time.

Finally, while school enrollment is relatively well studied, examinations of cognition or learning levels are unusual. Moreover, school-based studies (as compared to the current household survey and cohort study) tend to miss children that have dropped out of school – these often tend to be girls. Given that gaps in cognitive performance tend to persist and widen over the lifecourse, and that they are predictors of disparities in adult health, wages and other outcomes (see Cunha et al. 2006; Grantham Mc-Gregor et al. 2007; Hart and Risley 1995; Heckman 2008; Paxson and Schady 2007; Carneiro et al. 2005) this paper adds to a body of evidence that girls in India are disadvantaged in varied and often subtle ways. India has made significant progress in increasing school enrollment. But this paper adds to the pressing evidence that learning *outcomes* need to be prioritized, and the entire of distribution performance should be examined in future work. By doing so, low achievement and widespread disparities in gender will become clearer and this could enable policy to focus on leveling the field.

6. References

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7. Appendix

Table 1. Sample characteristics

		Sample characteristics, by Gender and Cohort																			
		Younger cohort										**Older cohort**									
		At 5 years					**At 8 years**					**At 12 years**					**At 15 years**				
		Boy		**Girl**			**Boy**		**Girl**			**Boy**		**Girl**			**Boy**		**Girl**		
		Mean	SD	**Mean**	SD		**Mean**	SD	**Mean**	SD		**Mean**	SD	**Mean**	SD		**Mean**	SD	**Mean**	SD	
	Language Z Score	**0.02**	1.01	**-0.02**	0.99		**0.10**	1.06	**-0.11**	0.92	***	**0.05**	1.00	**-0.05**	1.00		**0.20**	0.98	**-0.19**	0.98	***
Outcomes	Math Z Score	**0.01**	1.00	**-0.01**	1.00		**0.00**	0.99	**0.00**	1.01		**0.04**	0.99	**-0.04**	1.01		**0.19**	1.05	**-0.18**	0.91	***
	Age (month)	**64.79**	3.85	**64.80**	3.85		**96.04**	3.92	**95.99**	3.93		**148.38**	4.32	**148.60**	4.13		**179.70**	4.30	**179.81**	4.19	
	Height-for-age	**-1.71**	1.07	**-1.57**	1.15	***	**-1.49**	1.03	**-1.36**	1.33	**	**-1.51**	1.49	**-1.77**	1.79	**	**-1.62**	1.11	**-1.70**	0.99	
Child	Makes plans for future						**3.61**	1.15	**3.58**	1.11		**3.44**	0.90	**3.49**	0.92		**3.90**	0.93	**3.93**	1.00	
	Mother is literate	**0.47**	0.50	**0.50**	0.50		**0.47**	0.50	**0.50**	0.50		**0.31**	0.46	**0.31**	0.46		**0.31**	0.46	**0.31**	0.46	
	Happiness ladder	**3.16**	1.35	**3.15**	1.41		**3.88**	1.51	**3.83**	1.53											
	Grade aspirations	**3.91**	1.53	**3.48**	1.49	***	**3.94**	1.34	**3.40**	1.46	***										
Parent	Parent ambition											**0.41**	0.49	**0.55**	0.50	***	**0.29**	0.45	**0.52**	0.50	***
	Wealth quintile	**2.98**	1.42	**2.97**	1.41		**2.99**	1.42	**2.98**	1.40		**3.01**	1.42	**2.97**	1.41		**3.01**	1.40	**2.95**	1.44	
	Household size	**5.50**	2.16	**5.53**	2.30		**6.71**	2.89	**6.94**	3.15	*	**5.23**	2.04	**5.16**	1.61		**6.11**	2.74	**6.15**	2.54	
	Hindu	**0.91**	0.28	**0.94**	0.24	**	**0.91**	0.28	**0.94**	0.24	**	**0.87**	0.33	**0.88**	0.33		**0.87**	0.33	**0.88**	0.33	
Household	Rural	**0.74**	0.44	**0.75**	0.43		**0.74**	0.44	**0.75**	0.43		**0.73**	0.45	**0.75**	0.43		**0.72**	0.45	**0.73**	0.45	
	Private school	**0.38**	0.48	**0.32**	0.47	**	**0.49**	0.50	**0.37**	0.48	***	**0.29**	0.45	**0.19**	0.39		**0.32**	0.47	**0.23**	0.42	***
School	Current grade/enrolled	**0.93**	0.25	**0.93**	0.25		**0.99**	0.09	**0.99**	0.11		**5.94**	2.48	**5.81**	2.72		**7.51**	4.33	**6.98**	4.74	*
	Scheduled caste	**0.17**	0.38	**0.19**	0.39		**0.17**	0.38	**0.20**	0.40		**0.22**	0.41	**0.20**	0.40	***	**0.22**	0.41	**0.20**	0.40	
	Tribal	**0.14**	0.35	**0.12**	0.32		**0.14**	0.35	**0.12**	0.32		**0.09**	0.29	**0.12**	0.33		**0.09**	0.29	**0.12**	0.33	
Caste	Backward	**0.45**	0.50	**0.51**	0.50	**	**0.46**	0.50	**0.51**	0.50	**	**0.48**	0.50	**0.45**	0.50		**0.48**	0.50	**0.45**	0.50	
Early	Antenatal care	**4.45**	15.49	**4.85**	16.50		**4.45**	15.49	**4.85**	16.50											
childhood	Maternal depression	**5.36**	21.73	**6.45**	23.93	**	**5.36**	21.73	**6.45**	23.93	**										
Control for PPVT	Base PPVT	**1.96**	9.31	**1.66**	11.11		**14.85**	22.04	**11.95**	19.08	***	**44.49**	41.56	**37.19**	37.48	***	**67.88**	38.76	**49.60**	39.68	***

1 Differences by gender within cohorts * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level. T-tests and chi2 tests implemented for continuous and categorical variables respectively

2. Some variables differ by cohort depending on availablity of information - these are shown as blanks. While current grade used for older cohort, enrolled in school used for younger cohort.

Table 2A. Simultaneous quantile regression – Language

					Simultaneous quantile regressions						
	Dependent variable:					LANGUAGE					
	Cohort:	**Younger cohort**					**Older cohort**				
	Age:	8 years					15 year				
		(1)	(2)	(3)	Wald tests		(4)	(5)	(6)	Wald tests	
	Percentile:	**5th**	**50th**	**95th**	5th and 50th	50th and 95th	**5th**	**50th**	**95th**	5th and 50th	50th and 95th
	Girl	-0.05*	-0.07**	-0.31***		**	-0.13	-0.00	-0.01		
		(0.03)	(0.03)	(0.12)			(0.08)	(0.05)	(0.07)		
Child	Age (months)	0.01	0.00	-0.00			-0.00	-0.00	-0.01		
		(0.00)	(0.00)	(0.01)			(0.01)	(0.01)	(0.01)		
	Height-for-age	0.02	0.03*	0.06			0.04	0.08***	0.07**		
		(0.01)	(0.01)	(0.04)			(0.04)	(0.02)	(0.03)		
	Makes plans for future	0.00	0.01	-0.01			0.02	0.06**	0.03		
		(0.01)	(0.01)	(0.05)			(0.05)	(0.02)	(0.04)		
Parent	Mother is literate	0.08**	0.09***	0.11			0.11	0.04	-0.01		
		(0.03)	(0.03)	(0.14)			(0.14)	(0.05)	(0.08)		
	Parent ambition (professional =1)	-0.00	-0.02	0.06			0.03	-0.06	-0.01		
		(0.03)	(0.03)	(0.14)			(0.08)	(0.05)	(0.06)		
	Happiness ladder	0.01	-0.01**	-0.02							
		(0.01)	(0.01)	(0.04)							
Household	Wealth quintile	-0.00	0.03**	0.14**	*	*	0.05	0.05**	0.04		
		(0.02)	(0.01)	(0.06)			(0.04)	(0.03)	(0.03)		
	Household size	0.00	-0.00	0.01			0.04**	0.00	-0.01		
		(0.00)	(0.00)	(0.02)			(0.02)	(0.01)	(0.01)		
	Hindu	0.00	0.03	0.12			0.20	-0.02	0.03		
		(0.05)	(0.07)	(0.29)			(0.15)	(0.07)	(0.12)		
	Rural	0.01	0.01	0.16			0.15	0.06	-0.02		
		(0.04)	(0.05)	(0.13)			(0.15)	(0.06)	(0.07)		
School	Private school	0.06	0.11***	0.17			-0.07	0.03	0.04		
		(0.05)	(0.03)	(0.14)			(0.13)	(0.06)	(0.07)		
	Current grade	0.02	0.04***	0.19***		***	0.02*	0.05***	0.03***	**	**
		(0.01)	(0.01)	(0.05)			(0.01)	(0.01)	(0.01)		
Caste	Scheduled caste	0.10*	0.06	-0.35		*	-0.09	-0.09	-0.11		
		(0.06)	(0.05)	(0.26)			(0.18)	(0.08)	(0.09)		
	Tribal	0.07	0.10*	-0.11			-0.04	-0.03	0.01		
		(0.06)	(0.05)	(0.27)			(0.18)	(0.09)	(0.10)		
	Backward	0.01	0.06	-0.20			-0.13	0.01	-0.01		
		(0.04)	(0.05)	(0.21)			(0.16)	(0.06)	(0.07)		
Early childhood	Antenatal care	-0.00	0.00	0.00							
		(0.00)	(0.00)	(0.00)							
	Maternal depression	0.00	-0.00	-0.00							
		(0.00)	(0.00)	(0.00)							
	Constant	-1.74***	-1.23***	-0.13			-2.14	-0.96	0.83		
		(0.39)	(0.39)	(1.28)			(1.95)	(0.96)	(1.00)		
	Observations	1,900	1,900	1,900			942	942	942		

1. Standard errors are in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at

2. Base PPVT is included (not shown)

3. Conditional quantile regressions are estimated per Koenker and Hallock (2001)

4. Bootstrap standard errors calculated with 100 replications

5. Tests across quantiles conducted per Weesie (1999)

Table 2B. Simultaneous quantile regression – Math

Simultaneous quantile regressions

		MATH									
	Cohort:	**Younger cohort**					**Older cohort**				
	Age:	8 years					15 year				
		(1)	(2)	(3)	Wald tests		(4)	(5)	(6)	Wald tests	
	Percentile:	**5th**	**50th**	**95th**	5th and 50th	50th and 95th	**5th**	**50th**	**95th**	5th and 50th	50th and 95th
	Girl	-0.06	-0.06	-0.18			0.00	-0.15*	-0.23**	*	
		(0.07)	(0.04)	(0.11)			(0.06)	(0.08)	(0.10)		
Child	Age (months)	0.02**	0.01***	0.03**			-0.00	0.00	0.01		
		(0.01)	(0.00)	(0.01)			(0.01)	(0.01)	(0.01)		
	Height-for-age	0.08**	0.06***	0.02			0.03	0.02	0.07		
		(0.04)	(0.02)	(0.04)			(0.03)	(0.03)	(0.05)		
	Makes plans for future	0.08***	0.09***	0.07*			0.03	0.06	0.05		
		(0.03)	(0.02)	(0.04)			(0.03)	(0.04)	(0.05)		
Parent	Mother is literate	0.24***	0.26***	0.30***			-0.05	0.19**	0.36***	**	
		(0.06)	(0.05)	(0.11)			(0.09)	(0.09)	(0.12)		
	Parent ambition (professional =1)	0.09	0.15***	0.20*			-0.07	0.00	-0.11		
		(0.07)	(0.05)	(0.11)			(0.07)	(0.08)	(0.09)		
	Happiness ladder	0.00	0.01	-0.04							
		(0.02)	(0.01)	(0.04)							
Household	Wealth quintile	0.04	0.10***	0.07*	*		0.01	0.04	0.08		
		(0.03)	(0.02)	(0.04)			(0.02)	(0.03)	(0.05)		
	Household size	0.00	0.00	0.02			-0.00	-0.02*	-0.03		
		(0.01)	(0.01)	(0.02)			(0.01)	(0.01)	(0.03)		
	Hindu	0.45***	0.33***	0.22			0.19	0.22*	0.41*		
		(0.13)	(0.09)	(0.22)			(0.12)	(0.12)	(0.21)		
	Rural	0.29***	0.36***	0.46***			0.12	0.14	-0.12		*
		(0.10)	(0.07)	(0.16)			(0.10)	(0.10)	(0.13)		
School	Private school	0.50***	0.29***	0.32**	**		0.34***	0.44***	0.07		**
		(0.09)	(0.07)	(0.14)			(0.11)	(0.09)	(0.12)		
	Current grade	0.21***	0.28***	0.35***	**		0.03***	0.06***	0.06***	***	
		(0.03)	(0.02)	(0.05)			(0.01)	(0.01)	(0.01)		
Caste	Scheduled caste	-0.14	-0.21***	-0.31**			-0.15	-0.34***	-0.09		
		(0.14)	(0.07)	(0.14)			(0.10)	(0.13)	(0.20)		
	Tribal	-0.15	-0.33***	-0.38**			0.01	-0.12	-0.14		
		(0.12)	(0.09)	(0.15)			(0.11)	(0.14)	(0.17)		
	Backward	-0.12	-0.12**	-0.03			-0.16*	-0.12	-0.09		
		(0.11)	(0.06)	(0.10)			(0.09)	(0.11)	(0.15)		
Early childhood	Antenatal care	-0.00	-0.00	-0.00							
		(0.00)	(0.00)	(0.00)							
	Maternal depression	-0.00	0.00	-0.00							
		(0.00)	(0.00)	(0.00)							
	Constant	-4.75***	-3.65***	-3.37**			-1.39	-1.79	-1.28		
		(0.76)	(0.51)	(1.36)			(1.19)	(1.49)	(1.82)		
	Observations	1,903	1,903	1,903			973	973	973		

1. Standard errors are in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level
2. Bootstrap standard errors calculated with 100 replications
3. Conditional quantile regressions are estimated per Koenker and Hallock (2001)
4. Tests across quantiles conducted per Weesie (1999)

Table 3. Decomposition of the boy-advantage by age and quantile

Decomposition of gender-gap in scores: Cross-sections by quantiles

Dependent variable	LANGUAGE									
Cohort:	Younger cohort					Older cohort				
Age:	At 5 years	At 8 years				At 12 years	At 15 years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	Mean	5th	50th	95th	Mean	Mean	5th	50th	95th
Boys' score	0.02	0.02	-0.94***	-0.30***	2.45***	0.06	0.19***	-1.64***	0.37***	1.44***
	(0.06)	(0.06)	(0.02)	(0.05)	(0.12)	(0.05)	(0.06)	(0.08)	(0.09)	(0.04)
Girls' score	-0.02	-0.02	-0.98***	-0.44***	1.94***	-0.05	-0.19***	-1.83***	-0.10	1.28***
	(0.06)	(0.06)	(0.02)	(0.03)	(0.14)	(0.05)	(0.06)	(0.08)	(0.09)	(0.05)
Difference in scores	0.04	0.04	0.03	0.13***	0.50***	0.10**	0.38***	0.19	0.47***	0.16**
	(0.04)	(0.04)	(0.02)	(0.04)	(0.15)	(0.05)	(0.07)	(0.12)	(0.11)	(0.06)
Explained difference	0.01	0.01	-0.00	0.05*	0.10	0.03**	0.36***	0.25***	0.52***	0.14***
	(0.03)	(0.03)	(0.01)	(0.03)	(0.09)	(0.01)	(0.06)	(0.06)	(0.08)	(0.03)
Unexplained differenc	0.02	0.02	0.03	0.09**	0.40***	0.08	0.02	-0.06	-0.05	0.03
	(0.04)	(0.04)	(0.02)	(0.04)	(0.16)	(0.06)	(0.04)	(0.13)	(0.08)	(0.06)
Constant	-0.56	-0.56	-0.09	0.60	1.88	1.48	-0.98	-1.08	-3.54	1.73
	(0.54)	(0.54)	(0.62)	(0.90)	(3.64)	(1.80)	(1.70)	(5.60)	(3.24)	(2.25)
Observations	1,920	1,920	1,900	1,900	1,900	962	942	942	942	942

Dependent variable	MATH									
Cohort:	Younger cohort					Older cohort				
Age:	At 5 years	At 8 years				At 12 years	At 15 years			
Boys' score	0.01	0.01	-1.42***	0.04	1.93***	0.05	0.19***	- [5.]	0.27***	2.14***
	(0.05)	(0.05)	(0.04)	(0.06)	(0.10)	(0.05)	(0.06)	-	(0.10)	(0.12)
Girls' score	-0.00	-0.00	-1.51***	0.04	1.97***	-0.04	-0.18***	-	-0.18**	1.49***
	(0.05)	(0.05)	(0.06)	(0.08)	(0.10)	(0.05)	(0.05)	-	(0.07)	(0.11)
Difference in scores	0.01	0.01	0.09	-0.00	-0.04	0.09	0.36***	-	0.45***	0.65***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)	(0.06)	(0.06)	-	(0.10)	(0.15)
Explained difference	0.02	0.02	-0.08***	-0.13***	-0.22***	0.02**	0.19***	-	0.08	0.07
	(0.02)	(0.02)	(0.03)	(0.04)	(0.07)	(0.01)	(0.05)	-	(0.06)	(0.08)
Unexplained differenc	-0.01	-0.01	0.16***	0.13**	0.18	0.07	0.17***	-	0.37***	0.58***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.12)	(0.06)	(0.05)	-	(0.09)	(0.15)
Constant	-0.57	-0.57	-1.69	0.99	0.67	2.44	0.44	-	-3.03	6.44
	(0.72)	(0.72)	(1.39)	(1.37)	(3.26)	(1.88)	(2.14)	-	(3.99)	(6.33)
Observations	1,922	1,922	1,903	1,903	1,903	971	973	-	973	973

1. Robust village clustered standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level

2.Covariates shown in Table 2 are included

3.Unconditional quantiles regressions estimated as per Fipro et al. (2009)

4. Pooled decomposition models are estimated

5. The 5th percentile for the older cohort in math was not estimated

Table 4. Decomposition of the change in the boy-advantage over time

Decomposition of the gender-gap in change in scores: Panels by quantiles

Dependent variable	LANGUAGE							
Children included:	**Younger cohort (At 5 and 8 years)**				**Older cohort (At 12 and 15 years)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean	**5th**	**50th**	**95th**	**Mean**	**5th**	**50th**	**95th**
Change in boys' score	0.06**	-0.95***	-0.28***	2.48***	0.12***	-1.76***	0.33***	1.34***
	(0.03)	(0.01)	(0.02)	(0.10)	(0.04)	(0.06)	(0.06)	(0.03)
Change in girls' score	-0.06***	-0.98***	-0.39***	2.18***	-0.12***	-1.91***	0.05	1.25***
	(0.02)	(0.01)	(0.02)	(0.10)	(0.04)	(0.08)	(0.05)	(0.02)
Difference in change	0.12***	0.03*	0.11***	0.29**	0.24***	0.16	0.28***	0.09**
	(0.04)	(0.02)	(0.03)	(0.14)	(0.05)	(0.10)	(0.07)	(0.03)
Explained	0.07***	0.00	0.04***	0.17**	0.22***	0.11***	0.32***	0.10***
	(0.02)	(0.01)	(0.02)	(0.07)	(0.04)	(0.04)	(0.06)	(0.02)
Unexplained	0.05*	0.03*	0.06**	0.12	0.02	0.04	-0.04	-0.01
	(0.03)	(0.02)	(0.03)	(0.13)	(0.03)	(0.10)	(0.05)	(0.03)
Constant	-0.03	0.27	-0.04	0.79	-0.21	0.17	0.26	-1.02***
	(0.22)	(0.20)	(0.23)	(1.00)	(0.31)	(0.89)	(0.52)	(0.34)
Observations	3,820	3,820	3,820	3,820	1,904	1,904	1,904	1,904

Dependent variable	MATH							
Children included:	**Younger cohort (At 5 and 8 years)**				**Older cohort (At 12 and 15 years)**			
	Mean	**5th**	**50th**	**95th**	**Mean**	**5th**	**50th**	**95th**
Change in boys' score	0.00	-1.57***	0.02	1.76***	0.12***	-1.37***	0.43***	1.80***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.06)	(0.09)
Change in girls' score	-0.00	-1.61***	0.02	1.75***	-0.11***	-1.40***	0.14**	1.31***
	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)	(0.03)	(0.05)	(0.06)
Difference in change	0.01	0.04	0.00	0.01	0.23***	0.03	0.29***	0.49***
	(0.04)	(0.05)	(0.05)	(0.07)	(0.05)	(0.04)	(0.08)	(0.11)
Explained	0.02	0.03*	0.02	-0.01	0.05	-0.02	0.06	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.05)
Unexplained	-0.01	0.01	-0.02	0.02	0.18***	0.04	0.23***	0.36***
	(0.03)	(0.05)	(0.04)	(0.07)	(0.04)	(0.04)	(0.07)	(0.09)
Constant	0.03	0.66	-0.03	0.72	-1.14***	0.38	-1.41**	-5.16***
	(0.30)	(0.49)	(0.38)	(0.63)	(0.41)	(0.54)	(0.68)	(1.25)
Observations	3,825	3,825	3,825	3,825	1,945	1,945	1,945	1,945

1. Robust child clustered standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level

2.Covariates shown in Table 2 are included

3.Unconditional quantiles regressions estimated as per Fipro et al. (2009)

4. Pooled decomposition models are estimated

Table 5A. Decomposition of change in scores over time: Language

Decomposition of changes in scores, by gender and cohort

Dependent variable:	LANGUAGE											
	Panel A : Decompositions overview											
	Younger cohort						*Older cohort*					
	Girls			Boys			Girls			Boys		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	5th	**50th**	**95th**	**5th**	**50th**	**95th**	**5th**	**50th**	**95th**	**5th**	**50th**	**95th**
Wave 1	-0.96***	-0.33***	2.44***	-0.93***	-0.27***	2.55***	-2.06***	0.16***	1.25***	-1.85***	0.34***	1.23***
	(0.02)	(0.02)	(0.22)	(0.02)	(0.02)	(0.17)	(0.17)	(0.06)	(0.04)	(0.10)	(0.06)	(0.03)
Wave 2	-0.98***	-0.44***	1.94***	-0.94***	-0.30***	2.45***	-1.83***	-0.10	1.28***	-1.64***	0.37***	1.44***
	(0.02)	(0.02)	(0.12)	(0.02)	(0.03)	(0.09)	(0.07)	(0.07)	(0.05)	(0.08)	(0.07)	(0.03)
Change in scores	-0.02	-0.11***	-0.49**	-0.01	-0.03	-0.11	0.22	-0.26***	0.02	0.21*	0.04	0.21***
	(0.02)	(0.03)	(0.24)	(0.02)	(0.04)	(0.19)	(0.17)	(0.08)	(0.06)	(0.11)	(0.08)	(0.04)
Explained change	0.14	0.54***	2.32**	0.24**	0.83***	3.26***	-0.03	0.22	0.44**	-0.34	0.70***	0.50***
	(0.11)	(0.13)	(0.91)	(0.10)	(0.15)	(0.74)	(0.72)	(0.28)	(0.20)	(0.44)	(0.25)	(0.18)
Unexplained change	-0.16	-0.65***	-2.81***	-0.25**	-0.86***	-3.36***	0.25	-0.48*	-0.42**	0.55	-0.67***	-0.29
	(0.11)	(0.14)	(0.96)	(0.10)	(0.15)	(0.81)	(0.73)	(0.29)	(0.20)	(0.46)	(0.26)	(0.19)
Constant	-0.27	-0.03	4.72	-0.89	0.95	8.73***	5.68	2.31	-1.06	-3.42	-3.40	1.37
	(0.47)	(0.66)	(4.52)	(0.67)	(0.75)	(3.30)	(6.69)	(2.67)	(1.92)	(3.99)	(2.39)	(1.50)
Observations	1,788	1,788	1,788	2,032	2,032	2,032	966	966	966	938	938	938
	Panel B: Detailed decompositions											
Explained change/ composition effects												
Child	0.11	0.40***	1.23	0.20**	0.57***	2.20***	-0.30	-0.07	0.33*	-0.76*	0.04	0.39**
	(0.11)	(0.13)	(0.91)	(0.10)	(0.15)	(0.73)	(0.72)	(0.27)	(0.19)	(0.45)	(0.25)	(0.18)
Parent	-0.00	-0.01	0.05	-0.00	-0.01	0.06	-0.00	-0.00	0.00	-0.02	0.02*	0.01
	(0.01)	(0.01)	(0.08)	(0.01)	(0.01)	(0.05)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
Household	0.01	-0.01	-0.02	0.00	-0.02*	-0.04	0.07	-0.01	0.00	0.04**	0.00	-0.01
	(0.01)	(0.01)	(0.06)	(0.01)	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
School	0.01**	0.01**	0.05***	0.01	0.01**	0.08***	0.07**	0.06***	0.01*	0.11**	0.08***	0.02**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)	(0.04)	(0.02)	(0.01)
Unexplained change/ coefficient effects												
Child	-0.01	-0.59	-4.33	0.12	-1.52**	-10.70***	-3.02	-2.68	0.42	3.75	2.68	-1.64
	(0.42)	(0.60)	(4.58)	(0.47)	(0.66)	(3.74)	(7.01)	(2.57)	(1.80)	(4.14)	(2.32)	(1.44)
Parent	-0.00	-0.17	-0.16	-0.02	-0.25*	0.17	-0.21	-0.02	0.11	-0.04	-0.18***	-0.02
	(0.08)	(0.11)	(0.82)	(0.09)	(0.13)	(0.69)	(0.23)	(0.10)	(0.08)	(0.12)	(0.07)	(0.04)
Household	0.26**	0.18	-0.73	0.10	-0.11	0.90	-1.15	-0.24	0.47	1.02*	-0.03	0.05
	(0.11)	(0.19)	(1.52)	(0.13)	(0.19)	(1.00)	(0.93)	(0.34)	(0.30)	(0.57)	(0.32)	(0.24)
School	-0.17	-0.09	-0.88**	0.39	-0.03	-1.11***	-0.55	-0.23*	-0.12	-1.12**	0.13	-0.05
	(0.21)	(0.19)	(0.36)	(0.41)	(0.26)	(0.33)	(0.49)	(0.12)	(0.08)	(0.43)	(0.13)	(0.06)
Caste	0.03	0.05	-0.34	0.03	0.08	-0.53	-0.12	0.19	-0.25**	-0.05	0.08	0.03
	(0.04)	(0.07)	(0.68)	(0.04)	(0.07)	(0.42)	(0.28)	(0.13)	(0.12)	(0.17)	(0.14)	(0.11)
Early childhood	-0.01	-0.00	0.06	0.01	-0.01	-0.09						
	(0.01)	(0.01)	(0.07)	(0.01)	(0.01)	(0.07)						

1. Child clustered standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level

2.Unconditional quantiles regressions estimated as per Fipro et al. (2009)

3. Pooled decomposition models are estimated

4. Covariates base PPVT, caste and early childhood composition effects and not shown since they are zero

Table 5B. Decomposition of change in scores over time: Math

Decomposition of changes in scores, by gender and cohort

Dependent variable:	MATH									
	Panel A : Decomposition overview									
	Younger cohort						*Older cohort*			
	Girls			Boys			Girls		Boys	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	5th	**50th**	**95th**	**5th**	**50th**	**95th**	**50th**	**95th**	**50th**	**95th**
Wave 1	-1.50***	0.28***	1.68***	-1.62***	0.29***	1.66***	0.43***	1.43***	0.56***	1.46***
	(0.05)	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)	(0.04)
Wave 2	-1.51***	0.04	1.97***	-1.42***	0.04	1.93***	-0.18***	1.49***	0.27***	2.14***
	(0.04)	(0.05)	(0.09)	(0.03)	(0.04)	(0.07)	(0.06)	(0.10)	(0.08)	(0.11)
Change in	-0.01	-0.24***	0.30***	0.20***	-0.25***	0.27***	-0.61***	0.05	-0.29***	0.68***
scores	(0.06)	(0.06)	(0.10)	(0.06)	(0.05)	(0.08)	(0.07)	(0.10)	(0.08)	(0.11)
Explained	0.17	1.48***	1.82***	0.91***	1.66***	2.15***	0.06	0.95**	0.30	0.32
change	(0.25)	(0.23)	(0.41)	(0.28)	(0.24)	(0.36)	(0.30)	(0.41)	(0.32)	(0.40)
Unexplained	-0.17	-1.72***	-1.52***	-0.72***	-1.91***	-1.87***	-0.67**	-0.90**	-0.59*	0.36
change	(0.25)	(0.24)	(0.41)	(0.27)	(0.24)	(0.34)	(0.31)	(0.40)	(0.33)	(0.40)
Constant	-1.24	-2.09*	-5.06**	0.61	-3.17***	-6.19***	2.31	-6.34	-2.69	-2.15
	(1.72)	(1.23)	(2.53)	(1.49)	(1.03)	(1.91)	(2.83)	(3.89)	(2.94)	(4.21)
Observations	1,793	1,793	1,793	2,032	2,032	2,032	983	983	962	962
	Panel B: Detailed decompositions									
Explained change/ composition effects										
Child	0.14	1.43***	1.81***	0.89***	1.57***	2.03***	-0.07	0.90**	-0.01	0.19
	(0.25)	(0.24)	(0.41)	(0.28)	(0.24)	(0.36)	(0.31)	(0.41)	(0.34)	(0.41)
Parent	0.01	-0.01	0.02	-0.02	0.00	0.01	-0.00	0.00	0.00	-0.00
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.02)
Household	-0.02	0.02	-0.02	0.00	-0.01	-0.01	0.00	-0.03	-0.03*	-0.01
	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
School	0.03	0.02**	-0.01	0.01	0.02	-0.01	0.13***	0.08***	0.19***	0.06***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Unexplained change/ coefficient effects										
Child	-1.06	-0.33	1.58	-1.74	-0.08	3.75**	-3.00	4.53	0.64	0.81
	(1.26)	(1.12)	(2.18)	(1.49)	(1.01)	(1.71)	(2.84)	(3.50)	(2.71)	(3.92)
Parent	0.34	0.16	0.39	0.33	-0.20	0.24	0.08	0.09	0.03	0.10
	(0.21)	(0.20)	(0.39)	(0.26)	(0.20)	(0.29)	(0.10)	(0.14)	(0.09)	(0.12)
Household	-0.26	1.26***	2.24***	0.44	1.21***	0.84*	0.06	1.00*	0.14	1.73**
	(0.29)	(0.31)	(0.67)	(0.34)	(0.29)	(0.50)	(0.38)	(0.53)	(0.41)	(0.67)
School	1.86	0.04	-0.12	-0.37	0.76***	0.32	-0.40***	-0.06	0.35**	-0.04
	(1.14)	(0.47)	(0.33)	(0.29)	(0.24)	(0.27)	(0.15)	(0.11)	(0.14)	(0.12)
Caste	0.01	-0.21*	-0.05	-0.08	-0.16	-0.47**	-0.27**	-0.54**	-0.06	-0.49
	(0.08)	(0.13)	(0.31)	(0.12)	(0.10)	(0.22)	(0.13)	(0.26)	(0.15)	(0.31)
Early childhood	-0.04	-0.01	0.02	0.00	-0.01	-0.03				
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)				

1. Child clustered standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level

2.Unconditional quantiles regressions estimated as per Fipro et al. (2009)

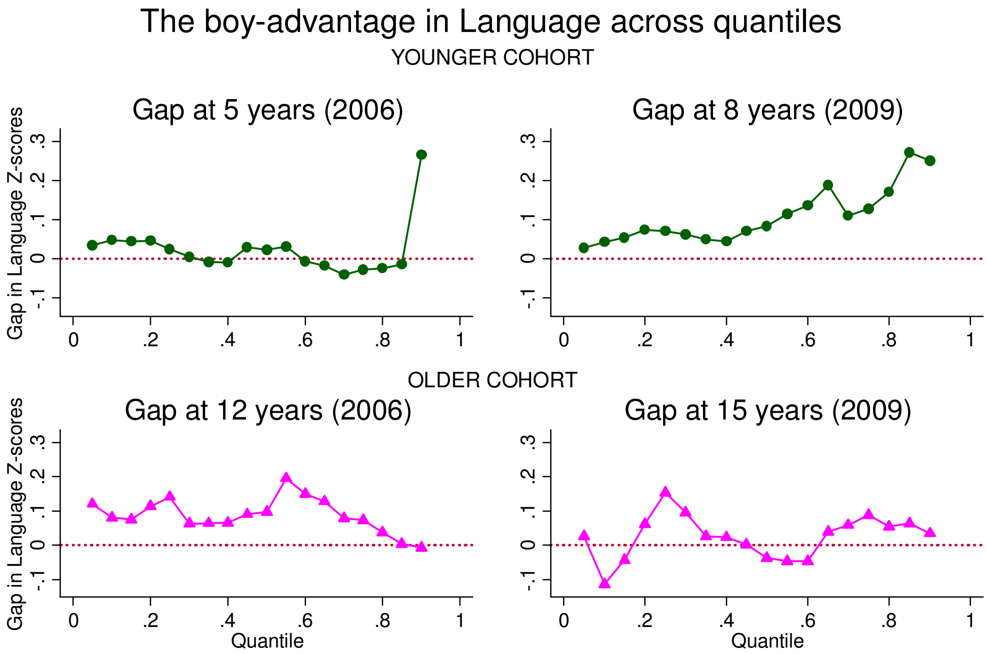
3. Pooled decomposition models are estimated

4. Covariates caste and early childhood composition effects and not shown since they are zero

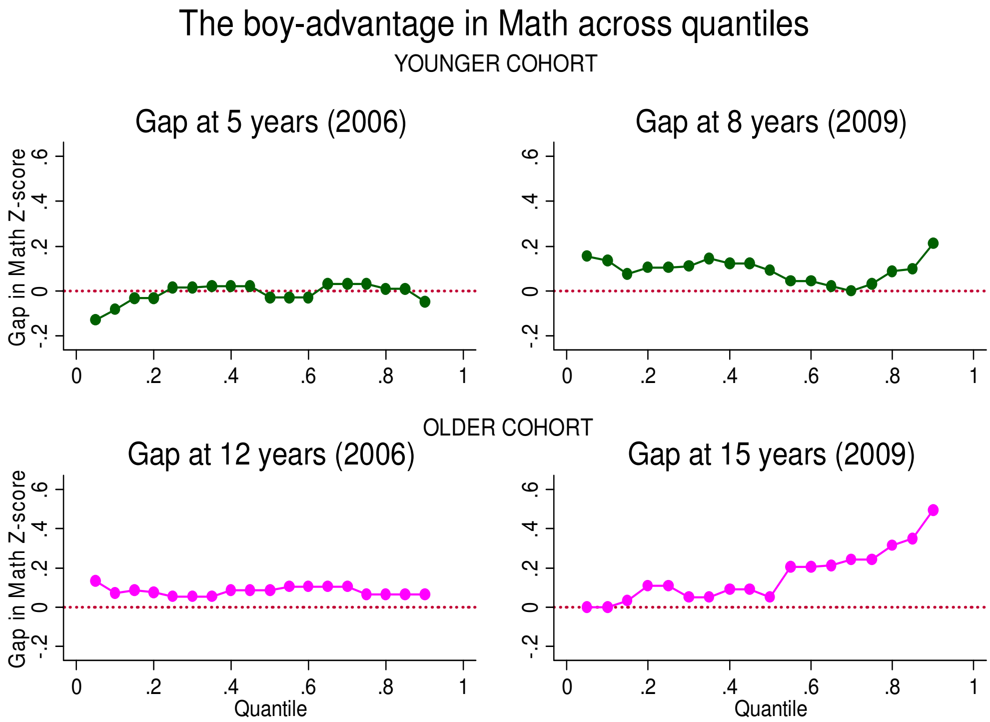
FIGURES

Decomposition results

Figure 1: Quantile regressions, by outcome and cohort



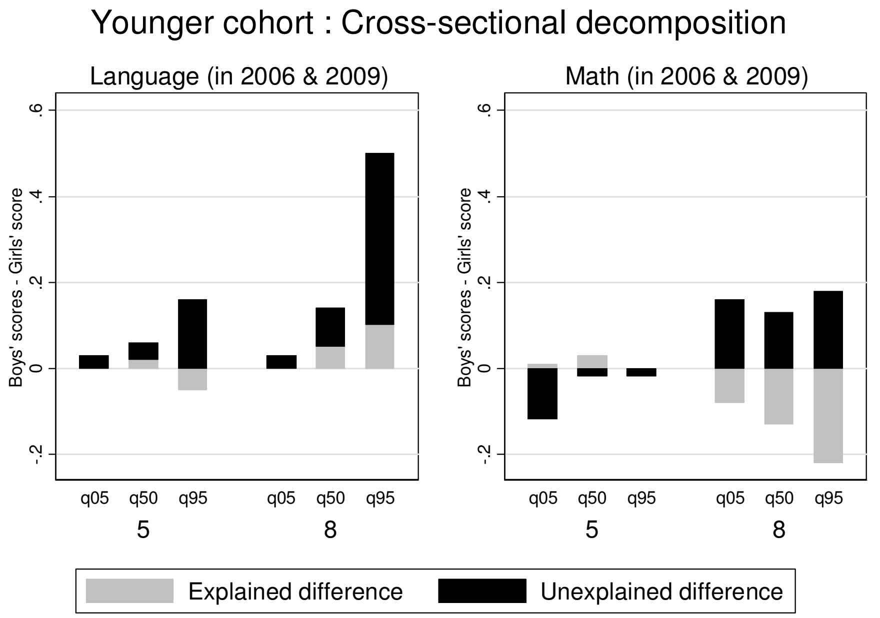
Note: Adjusted models shown. Recentered influence regressions implemented.



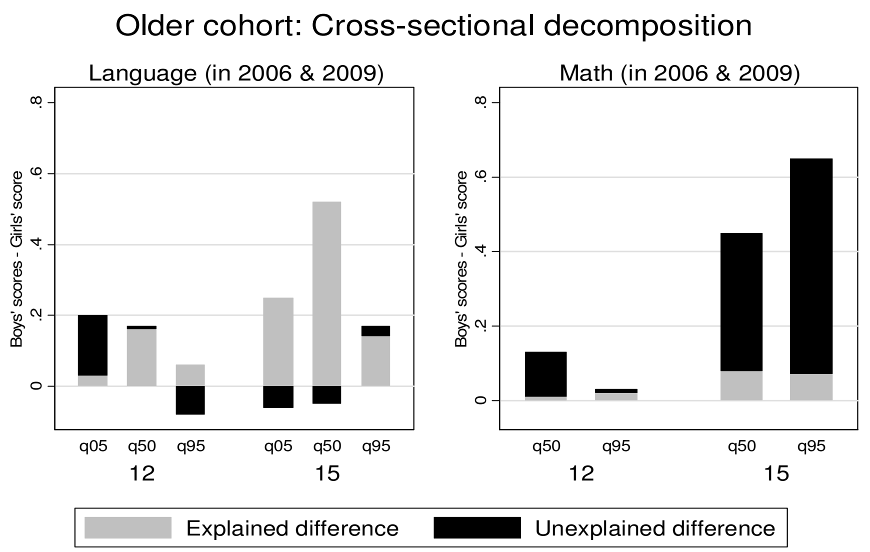
Note: Adjusted models shown. Recentered influence regressions implemented.

Figure 2: Differences that explain the gender-gap in cognitive outcomes

a. **Cross-sectional models**



Note: Recentered influence regressions used for each quantile. Pooled decomposition over gender. per Table 3.



Note: Recentered influence regressions used for each quantile. Pooled decomposition over gender per Table 3.

Figure 3: Differences that explain the change in the gender-gap in cognitive outcomes

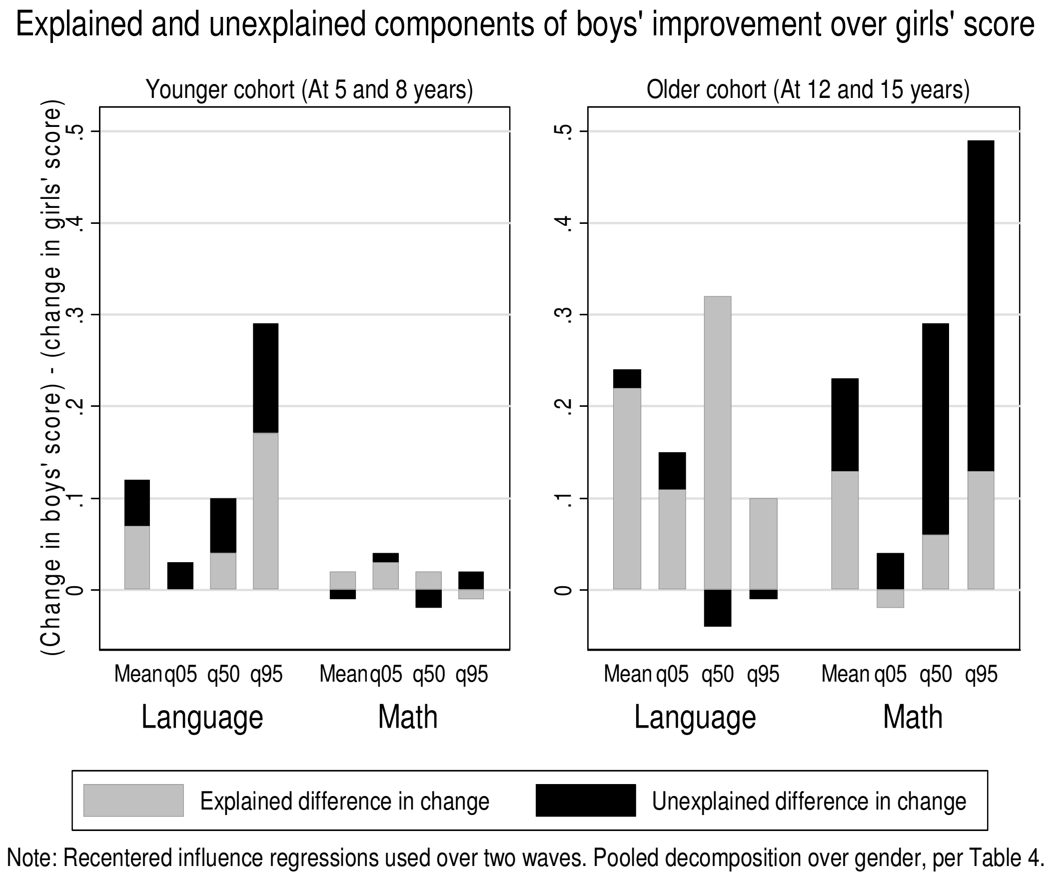


Figure 4a: Aggregate decomposition of change in cognitive outcomes by gender

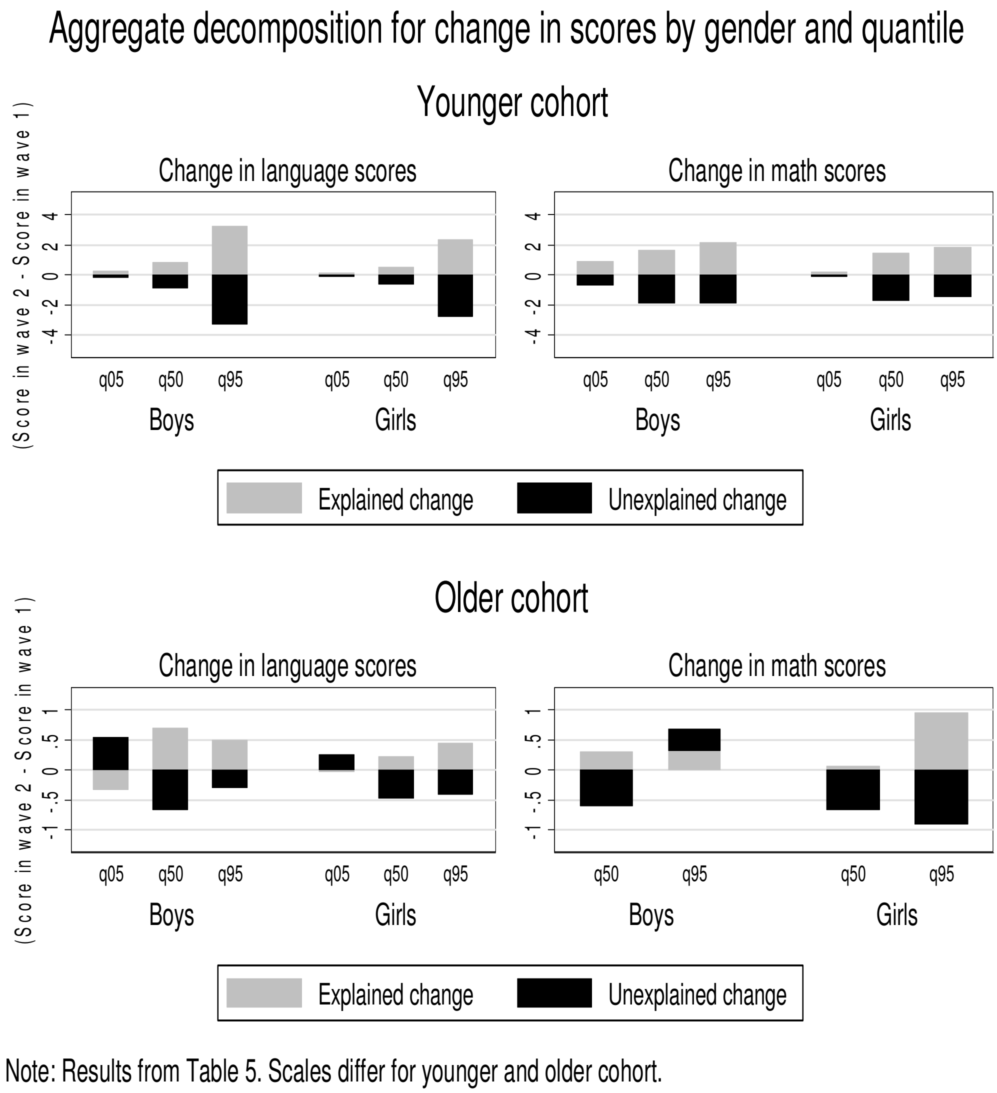
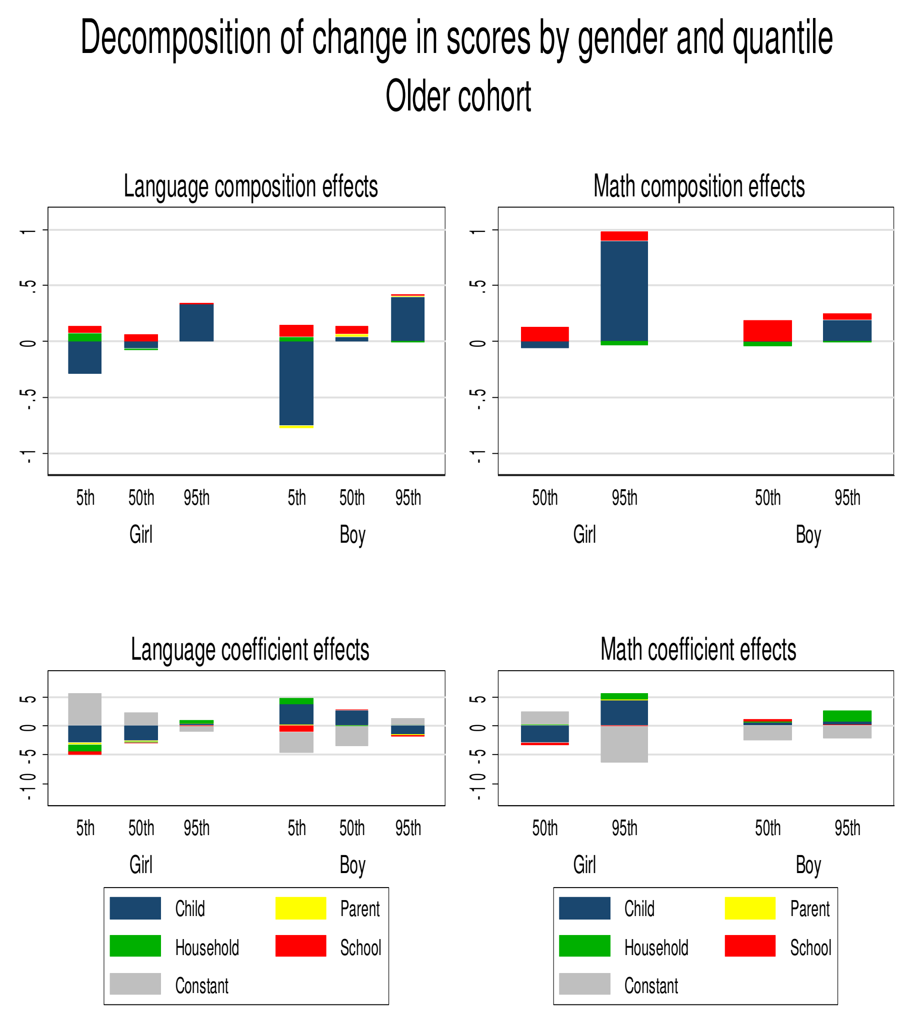


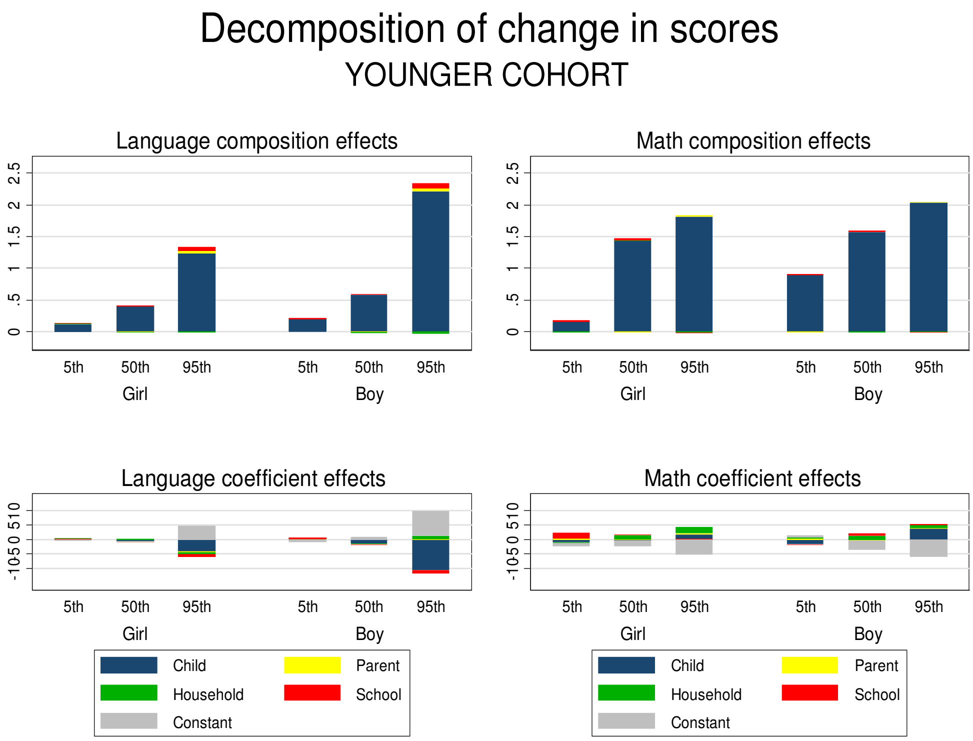
Figure 4b: Detailed decomposition of change in cognitive outcomes by gender

a. **Older cohort**



Note: Results are from Table 5. Scales differ for composition and coefficient effects.

b. Younger cohort



Note: Results are from Table 5. Scales differ for coefficient and composition effects.

How Girls Fall Behind On Cognitive Performance: Quantile Decomposition Evidence from Andhra Pradesh, India

Cognitive competence is a fragile construct and a range of factors influence whether individuals perform above or below their ability. Using rich longitudinal data collected by Young Lives from the state of Andhra Pradesh, India (2002-2009), this paper studies two cohorts of children at two points in time (at 5 and 8 years, and 12 and 15 years of age) and examines gender inequality in performance in language and math tests. Newly developed quantile estimation techniques in conjunction with traditional Blinder-Oaxaca decompositions are applied to examine the boy-advantage (and changes over time) in these test scores.

The evidence suggests that indeed, looking at average differences can be misleading since substantial heterogeneity exists across quantiles. In addition, the production function (determinants) for language and math are different. Specifically, a widening of the boy-advantage takes place across quantiles and over time for the younger cohort in language, and for the older cohort in math. This pattern is most pronounced for girls in math at 15 years, where the largest gap (and change in gap) is at the 95th percentile. Unexplained effects are found to contribute most to these gaps, which is often interpreted in the literature as evidence of gender discrimination. Additionally, child-level factors contribute most to these unexplained gaps. This highlights the possible influence of characteristics such as self-efficacy on the relatively poor test performance of (the brightest) girls in the current context.

Young Lives
An International Study of Childhood Poverty

About Young Lives

Young Lives is an international study of childhood poverty, involving 12,000 children in 4 countries over 15 years. It is led by a team in the Department of International Development at the University of Oxford in association with research and policy partners in the 4 study countries: Ethiopia, India, Peru and Vietnam.

Through researching different aspects of children's lives, we seek to improve policies and programmes for children.

Young Lives Partners

Young Lives is coordinated by a small team based at the University of Oxford, led by Professor Jo Boyden.

- *Ethiopian Development Research Institute, Ethiopia*
- *Pankhurst Development Research and Consulting plc*
- *Save the Children (Ethiopia programme)*
- *Centre for Economic and Social Sciences, Andhra Pradesh, India*
- *Save the Children India*
- *Sri Padmavathi Mahila Visvavidyalayam (Women's University), Andhra Pradesh, India*
- *Grupo de Análisis para el Desarollo (GRADE), Peru*
- *Instituto de Investigación Nutricional, Peru*
- *Centre for Analysis and Forecasting, Vietnamese Academy of Social Sciences, Vietnam*
- *General Statistics Office, Vietnam*
- *University of Oxford, UK*

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