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Learning in India's primary schools: How do disparities widen across the grades?



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ABSTRACT

Using a large-scale household survey, we investigate how disparities in learning change over the primary school cycle. Even controlling for other factors, household wealth and parental schooling drive sizeable gaps in learning, increasing in magnitude over the school grades. Gender gaps also widen, although only among the poorest. In contrast to other countries, overage status is positively associated with learning early on, but its importance dissipates by later grades. While the importance of factors varies across states, household wealth predominates. The analysis highlights the importance of tackling disadvantage associated with poverty early, to avoid its effects on learning becoming entrenched.

1. Introduction

The growth in enrolment in many low- and lower middle-income countries over the past 15 years has been accompanied by an uncomfortable realisation: attending school does not guarantee learning. Of the estimated 250 million children not learning the basics, around half have spent at least four years in school (UNESCO, 2014). In order to rectify this, it is essential to identify the key sources of learning disparities to better identify and support those being left behind.

Studies from wealthier countries demonstrate that learning disparities develop from the earliest years and become increasingly entrenched over time. However, evidence on disparate learning trajectories from low- and middle-income countries is less readily available. We contribute to this body of research by analysing how determinants of learning change over the primary school cycle in rural India. As the world's second most populous country and home to low levels of learning among its poorest households, rectifying educational opportunities in India will be essential to attaining the global sustainable development goals on education.

We model the power of five characteristics – household wealth, gender, mothers' schooling, fathers' schooling, and overage status – in predicting how learning disparities change over the primary school grades. By accounting for the intersecting nature of these characteristics, we are able to assess their importance relative to one another. This has important implications for practice because identifying how factors change over the primary school cycle can help policymakers focus on those that exacerbate gaps over time, rather than those that dissipate.

We find that poverty supersedes all other characteristics as a predictor of learning disparities. Even when controlling for other sources of disadvantage, the gap between the poorest and richest widens through the primary school grades. First-generation school-goers and girls also increasingly fall behind over the primary cycle, although the latter is true predominantly among poorer children. In contrast to research on sub-Saharan Africa, overage status is linked to higher learning levels early on, but this relationship dissipates by the later primary school grades. Given India's internal heterogeneity, with the exception of household wealth, these factors vary in importance across states.

The paper proceeds as follows: Section 2 reviews key literature on how learning disparities develop in childhood with respect to children's background characteristics as a means to inform our research questions. Section 3 describes the data that we analyse, and Section 4 outlines our methodological approach. We then present results (Section 5), and follow this with a discussion of their implication for research and policy (Section 6).

2. Framing the research: evidence on the causes of learning disparities

Among wealthier countries, there is clear evidence that the early years are crucial to disparities in children's cognitive development (Carneiro and Heckman, 2002, 2003). In the UK, on average, five year-olds from richer households are already 15 months ahead of those from poorer households in vocabulary development (Blanden and Machin, 2010). Looking earlier on, longitudinal data from the US (Cunha et al., 2010) and UK (Jerrim and Vignoles, 2013) demonstrate that learning

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disparities are visible before children start school, even detecting socio-economic gaps in cognitive development by age 22 months (Feinstein, 2003). While research varies between claiming that learning disparities then widen throughout schooling (Feinstein, 2003; Goodman et al., 2009) or are simply maintained (Duncan and Magnuson, 2011; Reardon, 2011), there is a consensus that gaps are sizeable and do not diminish.

By comparison, we know far less about disparities in learning trajectories in low- and lower-middle income countries. Evidence on trajectories for student populations on average though make clear that overall levels of progress are disappointing (Asadullah and Chaudhury, 2015; Das, 2013; Muralidharan and Zieleniak, 2013; Pritchett and Beatty, 2015; Singh, 2014). More than half of children in grade 5 are unable to read a text at a level expected in grade 2 (ASER India, 2014). Research on a student cohort in Andhra Pradesh, India, found that most foundational learning happens in grades 1 and 2, meaning that those who had yet to learn foundational skills by this early stage were unlikely to catch up (Muralidharan and Zieleniak, 2013). This point is corroborated by data from a range of learning assessments across India indicate that only around one in 10 of those who lack a basic literacy or numeracy skill are able to gain this skill after an additional year of schooling (Bhattacharjea et al., 2011; Educational Initiatives, 2010; Pritchett and Beatty, 2015).

Unfortunately, progress among the most disadvantaged children is likely to be far worse than these average levels, given the body of evidence exploring educational inequalities in low- and lower-middle income countries. In India, as with many other countries, prior research has identified considerable disparities in access to primary schooling (see, for example, Kingdon 2002; Agrawal, 2014; Asadullah et al., 2013; Asadullah and Yalonetzky, 2012) and in differential access to private and government provision (for example, Alcott and Rose, 2015; Bangay and Latham, 2013; Chudgar and Creed, 2016; Kelly et al., 2016; Maitra et al., 2011; French and Kingdon, 2010; Woodhead et al., 2013a, 2013b; Singh and Bangay, 2014; Singh and Sarkar, 2015).

Increasingly, studies in India have been complemented by research focusing on the extent and determinants of disparities of learning more specifically (for example, Borooah, 2012; Kingdon, 2007; Rolleston and James, 2015; Woodhead et al., 2013a). Poverty is found to be one of the key drivers of learning gaps across country contexts. Findings on disparities in sub-Saharan Africa (for example, Jones and Schipper, 2012; Spaul and Kotze, 2015; UNESCO, 2014) are mirrored in India, where poorer children are far less likely to learn foundational literacy and numeracy skills (Borooah, 2012; Rolleston and James, 2015). For example, across rural India, fewer than 25% of poorer children aged 11–13 are in school and have learned the basics, just half the rate of wealthier children (Rose et al., 2016). Like other countries included in the Young Lives study (Ethiopia, Peru and Vietnam), in Andhra Pradesh, India, the richest quartile made a greater improvement than did the poorest quartile in maths between ages 5 and 8 (Rolleston et al., 2014).

Gender is another key predictor of disparities, as unequal access to educational opportunities (Aslam, 2009; Azam and Kingdon, 2013; Maitra et al., 2011; Srivastava, 2006) has translated into considerable learning disparities across South Asia (Alcott and Rose, 2015; Asadullah and Chaudhury, 2015; Borooah, 2012; Kingdon, 2002). Among poorer households in Uttar Pradesh, for example, by age 10 girls have fallen 10 percentage points behind boys in developing basic numeracy skills (UNESCO, 2014). Such patterns are heavily entrenched, as Indian census data show that gender inequalities in literacy rates have remained consistent for decades (Kingdon, 2007).

Parental education is also important to children's learning. Among a range of predictors including wealth, occupation, religion, and caste, Chaudhuri and Roy (2009) emphasise parental education as the key household determinant of demand for education and a means for redressing gender disparities in access to schooling in India, although Pal (2004) argues that maternal education alone matters for girls. For those

children in India who do access school, parental education is a key predictor of the type of school attended (Muralidharan and Kremer, 2008; Muralidharan and Sundararaman, 2013). Parents with low levels of education are also less likely to be as aware as other parents of their children's progress (Banerjee et al., 2007), and evidence from Andhra Pradesh shows clear links between gaps in learning outcomes and parental education levels (Woodhead et al., 2013a).

Overage enrolment is another frequently identified source of educational disparities in the research literature. However, most of this research focuses on sub-Saharan Africa. In eastern and southern African countries, learning is lower among children in classes with more overage children, although this does not disproportionately hinder the poorest (Hungu and Thuku, 2010; Jones, 2014). Overage children perform worse in the later primary school grades in Kenya, even after controlling for pupil background factors and school characteristics (Hungu et al., 2014). In francophone Africa especially, this concern is exacerbated by the common practice of grade repetition (20% of primary school children repeat grades on average), which is detrimental to learning outcomes and occurs primarily among poorer children, thus deepening socioeconomic gaps in learning (Glick and Sahn, 2010).

There is not yet commensurate research on the impact of overage enrolment in India, although it may play a different role. On average, overage status is less common in India than in sub-Saharan Africa. These lower rates may be largely attributable to the policy of automatic promotion implemented in India 2009, although this is not always fully implemented (Bhattacharjea et al., 2013). Even so, according to ASER data, overage rates in rural primary schools in India for the lowest wealth quintile are comparable to national overage rates in countries such as Namibia, Zimbabwe and Niger (UNESCO, 2015).

Each of the identified factors – gender, wealth, mothers' schooling, fathers' schooling, and overage enrolment – has been identified in the past literature as a driver of learning disparities in low and lower-middle income countries. We take this forward by presenting evidence from large-scale data that assesses whether the importance of these factors changes over the primary school cycle. We estimate inferential models that account for key confounding variables models with recent data from rural India with the aim of identifying how learning disparities change over the primary school cycle. Our goal is not to try to identify causal relationships – e.g. that poverty 'causes' low levels of learning – but to identify those facing the greatest barriers to learning. To achieve this, we address the following research questions:

1. Which prior characteristics – gender, wealth, mothers' schooling, fathers' schooling, and overage enrolment – are associated with learning gaps in India, even when controlling for other sources of disadvantage?
2. Which of these characteristics increase gaps in learning trajectories over the primary school cycle?
3. To what extent does the importance of these characteristics across the primary school cycle differ across states?

3. Data and descriptive statistics

3.1. Data source

To investigate our research questions, we analyse data from the Annual Status of Education Reports (ASER) in rural India. Established by Pratham, a non-governmental organization, ASER is an annual household survey conducted by volunteers in every rural district in India, the primary focus of which is collecting information on enrolment, literacy levels, and numeracy levels among 5–16 year-olds (Chavan and Banerji, 2013; Results for Development, 2015). ASER uses a stratified random-sampling survey design: every district in the country is surveyed, and then, within each district, 20 villages from the previous two years are re-surveyed and 10 more are selected at random. Within each of these 30 villages, the ASER team members selected and

surveyed 20 households. We account for this survey design in all subsequent analyses by using the appropriate population weights and clustering standard errors with Stata's `—svyset—` command.

In order to assess changes in learning over time, we use data from the five consecutive ASER surveys conducted between 2009 and 2013, inclusive. Because this paper's focus is learning progress amongst primary-school attending children, we restrict our sample to children in class Grades 1–5 in each year. We recognize that this potentially underestimates the overall low levels of learning if out-of-school children were also to be taken into account. However, the proportion of children who are out of school in the ASER sample in India is, in any case, reasonably low (Rose and Alcott, 2015). In addition, given the different practices in madrasa schools and how small the fraction of sampled children was that attend these schools (less than 1%), we exclude this subsample from our analysis so as to maintain focus on conditions for the majority of children.

Our analysis combines comparable data from ASER India over six years, enabling us to construct quasi-longitudinal data on school cohort groups, e.g., a cohort who is in Grade 1 in 2009, Grade 2 in 2010, and so forth. We construct multiple cohorts within the time span, using controls to account for the different conditions that the various cohorts may have faced. We recognize that this is not true longitudinal data, as we are not following the same children across the grades. Nonetheless, ASER's sampling frame ensures that samples are representative at the district level, and thus, by extension, at the state and national levels. Given the absence of data of a truly longitudinal nature at a comparable scale, we believe that these factors make this the best available approach to studying the dynamic nature of learning disparities over time.

3.2. Outcome variable

Our key outcome of interest is learning. In this paper, we focus on numeracy. We chose to focus on numeracy because there may be concerns over the comparability of the literacy tests across different languages used in the ASER India survey (Results for Development, 2015). Even so, we analysed both literacy and numeracy outcomes and find similar patterns in each.¹

The ASER assessment tools are designed to be straightforward for data collection, providing information that is easy to communicate (ASER Centre, 2014). Accordingly, the ASER surveys assess numeracy using the tool shown in Fig. 1. Children are tested individually for their ability at each level sequentially until they reach a level they cannot complete; i.e., if they can recognize numbers but cannot perform subtraction, they are not tested for the ability to perform division.

As a tool for measuring learning, ASER shows high inter-rater reliability and concurrent validity with more extended measures such as the Fluency Battery and the Read India literacy and math tests, as well as with early grade reading and mathematics assessments (Vagh, 2010; Results for Development, 2015). Further, in contrast with government data such as the National Achievement Survey, ASER tests basic foundational skills (ASER India, 2014). This is more befitting of the low levels of learning among children in India. These factors, combined with ASER's sampling frame and scale, are likely to make it the most robust means available for assessing learning disparities in rural India.

Given our focus on primary education, we focus in particular on whether the child completes the subtraction task.² Although official expectations of learning are not clear in India (Banerji, 2013), the ability to perform subtraction is implicitly expected by the end of their second year of schooling (ASER India, 2014; Bhattacharjee et al., 2011). More specifically, the assessment task consists of subtracting one two-

digit number from another with borrowing (e.g., solving 56–37). Children attempt two subtractions and must complete each successfully to be considered able to subtract.

3.3. Explanatory variables

For our independent variables, we focus on three background characteristics highlighted by prior policy research: gender, socioeconomic status, and mothers' and fathers' education. We also include overage status, which might itself be influenced by these background characteristics. For gender, the adult administering the survey assesses whether the given child is male or female. To assess socioeconomic status, for each household we calculate a wealth index. A similar method is used in the Demographic and Health Survey (see, for example, Rutstein and Johnson, 2004), and Filmer and Pritchett (2001) have demonstrated the robustness of such approaches. Following the example of Saeed and Zia (2014) using ASER Pakistan data, we generate this index through a factor analysis of the following indicators: type of house (mud, brick and mud, or mud and cement), whether the house has electricity, a mobile phone, and a television.³ We then reweight these scores to have a minimum of zero (the poorest households, i.e. those living in a mud house with no electricity, mobile phone or television) and a maximum of one (the wealthiest households, i.e. those living in mud and cement homes with electricity, a mobile phone and a television). To identify whether children are first-generation learners, we assess parental education according to two dichotomous variables: whether the child's mother attended school and whether the child's father attended school, each of which is based on the given parent's self-report.

We define overage status as a child being two or more years above the official age for the given class grade, i.e., in Grade 1 and aged 9 or older, in Grade 2 and aged 10 or older, and so forth. Given the cross-sectional nature of the data, we are unable to determine whether a given overage child was overage when they began primary school and/or has been held back, i.e. taken more than one year to complete a school grade.

In addition to our key independent variables, we also control for class grade, whether each child attends a government or private school, whether they receive private tutoring, and the state and district in which they live. We account for private schooling and tuition because of the body of research suggesting that they may influence learning outcomes, even when accounting for disparities in access to each (see, for example, Alcott and Rose, 2015; Aslam and Atherton, 2012; Dongre and Tewary, 2014; French and Kingdon, 2010; Goyal, 2009). We also account for state and district because educational outcomes are likely to depend at least partly on regional variations in demographics, school provision, education policies, local infrastructure, and job opportunities (Chaudhuri and Roy, 2009; Kingdon and Theopold, 2008; Pandey et al., 2009; Wadhwa, 2013, 2014).


One factor that we are not able to directly control for is caste, since ASER surveys do not collect household information on this variable. We recognize, however, that this is a deeply embedded element of Hindu societies in India. Caste, along with tribal and religious status, is associated with disparities in educational opportunities (Borooah, 2012; Borooah, 2012; Asadullah et al., 2014), and is closely linked to socioeconomic status (Härmä, 2010). We would argue that the absence of a direct control for caste does not undermine our substantive findings, especially because the deeply embedded nature of socioeconomic status and caste makes disentangling them more a measurement challenge than a substantive means for informing policy.

Table 1 provides descriptive information on our sample, in the form

¹ Results of the analysis for literacy are available from the authors on request.

² We also found similar patterns in relative learning rates for the survey's other numeracy tasks, although as expected absolute rates were higher for number recognition and lower for division.

³ The one difference between our index and Saeed and Zia's is that we do not also consider home ownership, since this information was not collected in the 2009–2013 ASER India surveys.



MATH TEST SAMPLE (1)

Number recognition 1–9	Number recognition 10–99	Subtraction 2 digit with borrowing	Division 3 digit by 1 digit
<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">3</div> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">7</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">65</div> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">38</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="text-align: right; margin-right: 10px;"> $\begin{array}{r} 51 \\ - 35 \\ \hline \end{array}$ </div> <div style="text-align: right;"> $\begin{array}{r} 67 \\ - 48 \\ \hline \end{array}$ </div> </div>	$7 \overline{)918}$
<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">1</div> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">4</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">92</div> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">23</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="text-align: right; margin-right: 10px;"> $\begin{array}{r} 84 \\ - 49 \\ \hline \end{array}$ </div> <div style="text-align: right;"> $\begin{array}{r} 73 \\ - 36 \\ \hline \end{array}$ </div> </div>	$6 \overline{)769}$
<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">8</div> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">9</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">47</div> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">72</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="text-align: right; margin-right: 10px;"> $\begin{array}{r} 56 \\ - 37 \\ \hline \end{array}$ </div> <div style="text-align: right;"> $\begin{array}{r} 31 \\ - 13 \\ \hline \end{array}$ </div> </div>	$8 \overline{)987}$
<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">5</div> <div style="border: 1px solid black; padding: 5px; width: 40px; height: 40px; text-align: center; margin: 5px;">2</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">56</div> <div style="border: 1px solid black; padding: 5px; width: 60px; height: 40px; text-align: center; margin: 5px;">87</div> </div>	<div style="display: flex; justify-content: space-around;"> <div style="text-align: right; margin-right: 10px;"> $\begin{array}{r} 45 \\ - 18 \\ \hline \end{array}$ </div> <div style="text-align: right;"> $\begin{array}{r} 43 \\ - 24 \\ \hline \end{array}$ </div> </div>	$4 \overline{)513}$

Ask the child to recognise any 5 numbers. Atleast 4 must be correct.

Ask the child to recognise any 5 numbers. Atleast 4 must be correct.

Ask the child to do any 2 subtraction problems. Both must be correct.

Ask the child to do any 1 division problem. It must be correct.

Fig. 1. Sample mathematics learning measure used in ASER surveys.
Source: ASER Centre, <http://www.asercentre.org/p/142.html>.

Table 1
Descriptive statistics for the sample.

	(1) Full sample n = 1,266,332	(2) Those who can subtract n = 431,981	(3) Those who cannot subtract n = 834,351
Can subtract (%)	33	–	–
Female (%)	46	45	47
Most privileged (%)	20	27	17
Least privileged (%)	11	8	13
Mother attended school (%)	48	58	44
Father attended school (%)	65	71	63
Overage (%)	7	9	7
Attend private school (%)	25	31	22
Receives private tuition (%)	26	37	21

Note: we define the most privileged children as those living in a mud and cement house possessing electricity, a phone and a television. We define the least privileged children as those living in a mud house with none of the aforementioned possessions.

of mean values for each of our key background characteristics of interest, as well as school type and private tuition. As the first row in column (1) shows, just a third of children in primary school are able to subtract, despite that the fact that this is expected of at least three fifths of our sample (those in Grades 3–5). Comparing columns (2) and (3), the ability to perform subtraction varies according to each of the key characteristics of interest. For the first three characteristics – gender,

socioeconomic status, and parental education – this variation is consistent with past research. In other words, boys are more likely to be able to subtract than are girls, wealthier children are more likely to be able to subtract, and children whose mothers and fathers attended school are more likely to be able to subtract than those whose parents did not. In contrast, our fourth key characteristic of interest – overage status – runs counter to prior research: children who are overage for their grade are more likely to be able to subtract than are those in age-appropriate grades.⁴

Besides our key policy variables, we also account for other factors that are likely to influence learning outcomes: survey year, state, and district. It is important to control for the year in which each survey was taken because conditions are likely to have varied somewhat across years.⁵ State and district variables are important because of the large heterogeneity in conditions within India (Bhattacharjea, et al., 2011; Wadhwa, 2014). Between states, average values for learning outcomes and each of the policy variables differ considerably (Fig. 2). For example, primary-school children in Mizoram are over twice as likely to be able to subtract as primary-school children in Uttar Pradesh. Children in Kerala are three times more likely than children in Rajasthan to

⁴ Since the apparent relationship between overage and learning is at odds with the literature, we examined its distribution among children according to other characteristics, namely class grade and wealth to get a better understanding of overage patterns. We found no clear pattern for overage status according to class grade, but it is clear that overage status is unevenly distributed according to socioeconomic status: children in the poorest wealth quintile are three times more likely than children in the wealthiest quintile to be overage.

⁵ ASER India (2015a,b) provide more information on how learning outcomes varied over the years.

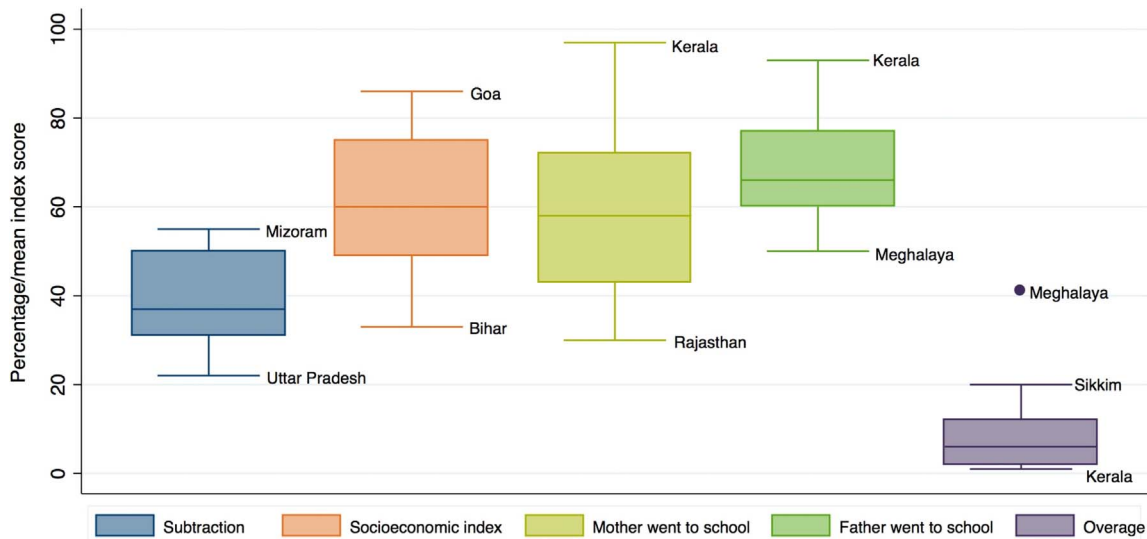


Fig. 2. Variation in characteristics across states. Source: ASER India 2009–2013.

have a mother who went to school.

Furthermore, the trajectory of learning disparities varies greatly by state. Focusing on 3 of the more populous states (Fig. 3), different patterns in the trajectory of learning gaps are apparent with percentage-point disparities in Grade 2 ranging from 27 (Orissa) to 1 (Tamil Nadu) and in Grade 5 from 27 (Orissa and Gujarat) to 15 (Tamil Nadu). One way of articulating this variation across states is to view them as following one of three main trends across the primary school years: wide → wide, narrow → wide, and narrow → narrow. To demonstrate how this pattern varies, we group the 12 most populous states according to which of these patterns they follow (Table 2). Such heterogeneity in conditions across states further demonstrates the need for statistical models and policy recommendations to account for this variation.

4. Methodology

We use ordinary least-squares (OLS) regression to estimate all of the

Table 2 Indian states by pattern of socioeconomic disparities in primary school. Source: ASER India 2009–2013.

Grade 2	Wide	Grade 5 Wide Orissa Assam Haryana Bihar	Narrow –
	Narrow	Uttar Pradesh Gujarat Madhya Pradesh Jharkand Rajasthan	Maharashtra Karnataka Tamil Nadu

inferential models presented in this paper. Our dependent variable of interest – whether a child can perform subtraction – is dichotomous, and, in recent years, the convention in many social-science fields has been to estimate logistic regression models for outcomes of this nature

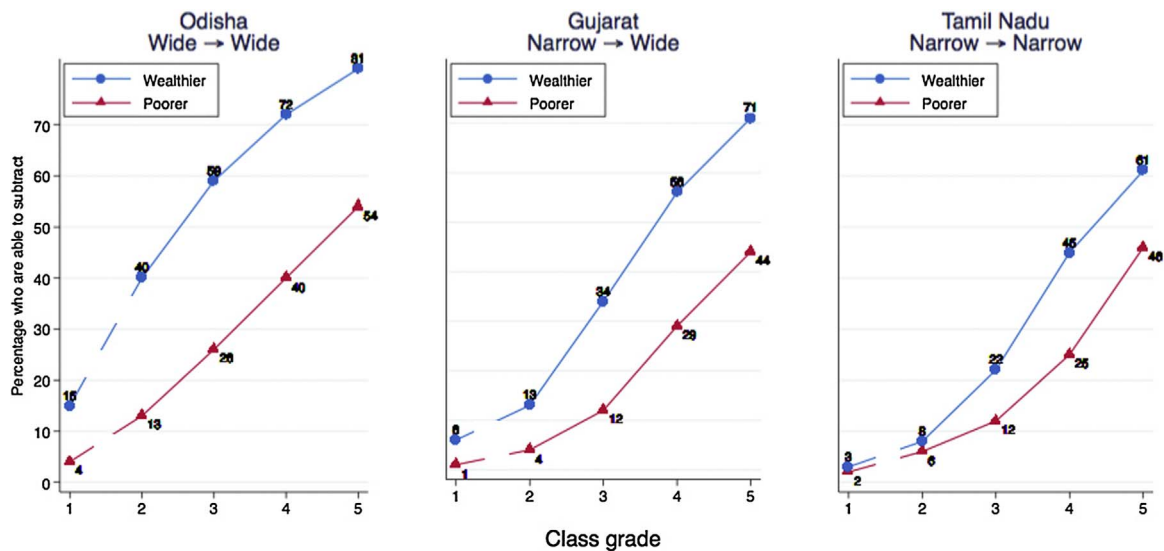


Fig. 3. Comparison of patterns in learning disparities in three large states, rural India. Note: wealthier children are those from the highest socioeconomic quintile and poorer children are those from the poorest socioeconomic quintile. Dotted line between Grades 1 and 2 reflect the fact that children are not expected to be able to subtract until Grade 2. Source: ASER India 2009–2013.

(Hellevik, 2009; Mood, 2010). However, we prefer to use OLS regression for this study, as countervailing evidence suggests that OLS is comparable to logistic regression terms of the accuracy of model predictions and preferable in terms of the intuitiveness with which one can interpret each model’s estimated coefficients (Angrist and Pischke, 2008; Hellevik, 2009). While we would argue that the interpretation of analytical models should always be a primary concern when writing for a policymaking audience, this is an especially pertinent issue when estimating models with interaction terms. Whereas the interpretation of interaction effects in OLS is relatively straightforward, in logistic regression models it is more precarious (Ai and Norton, 2003; Norton et al., 2004). Given that interaction terms are an essential component of the strategy used to address our second research question, this provides further grounds for us to prefer OLS in this study. As a further check, we ran all models as logistic regressions instead of OLS. The significance levels and relative magnitude of the predictors remain the same.

OLS regression analyses the impact of an independent variable on the probability of a categorical outcome whilst holding constant the impact of the other independent variables included in the model. As such, our regression models enable us to establish whether the predictive power of each factor still holds once controlling for a range of other variables. Letting Y_i denote our learning outcome of interest for student i , i.e., whether child i can perform subtraction, we estimate the following model:

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + \varepsilon_i, \tag{1}$$

where X_1 to X_k refer to the explanatory variables described above, each β parameter represents the average change in Y associated with a one-unit increase in the given explanatory variable when controlling for all other explanatory variables in the model, and the error term ε_i is normally distributed with a mean of zero.

Then, in order to assess whether the predictive strength of our key explanatory variables differ between the earlier and later primary school years, we estimate an additional model that takes formula (1) and adds an interaction term between class grade and each of the key explanatory variables (gender, socioeconomic status, parental education and overage status). For example, taking the variable X_1 to represent class grade, X_2 to represent gender, and X_3 to represent socioeconomic status, the expression for Y_i is now

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 (X_{1i} X_{2i}) + \beta_4 X_{3i} + \beta_5 (X_{1i} X_{3i}) + \dots + \beta_k X_{ki} + \varepsilon_i \tag{2}$$

We control for a range of factors that past research has identified as important to children’s learning, enabling us to establish relationships between the identified explanatory and outcome variables. However, we recognize that there are limitations to our analysis given the data available. First, the cross-sectional nature of the ASER data means that we cannot be certain about the temporal precedence of our explanatory and control variables. For example, in order to assess the impact of household wealth on learning, it is important also to control for the influence of private tuition; however, we cannot be certain about the direction in which the relationship between household wealth and tuition is working. Household wealth influences a family’s ability to pay for private tuition, but expenditure on private tuition also reduces the ability of households to afford the items from which we derive our wealth index. Second, as the ASER dataset is household-based, it does not include some variables that are likely to be relevant for explaining learning outcomes. Notably, school factors are likely to be important, such as teacher qualifications and experience and class size. This means that our estimates are prone to omitted variable bias, as is typical of OLS estimates based on survey data.

5. Results

Model results (Table 3) indicate that each of the key characteristics

Table 3
OLS model estimates of ability to subtract.

	(1) Base model	(2) Add schooling	(3) Poorest quintile only	(4) Wealthiest quintile only
Female	-0.03** (0.00)	-0.02** (0.00)	-0.03** (0.00)	0.00 (0.00)
SES	0.16** (0.00)	0.12** (0.00)	- (0.00)	- (0.00)
Father attended school	0.07** (0.00)	0.06** (0.00)	0.04** (0.00)	0.04** (0.00)
Mother attended school	0.04** (0.00)	0.04** (0.00)	0.05** (0.00)	0.07** (0.00)
Overage	0.07** (0.00)	0.06** (0.00)	0.05** (0.00)	0.10** (0.00)
Attend private school		0.09** (0.00)	0.13** (0.00)	0.11** (0.00)
Receives private tuition		0.12** (0.00)	0.10** (0.00)	0.06** (0.00)
Observations	1,194,281	884,124	184,037	178,306
R-squared	0.28	0.29	0.25	0.31

Note: Standard errors in parentheses. Coefficients for state, district, year, and class-grade controls not shown.

** p < 0.01.

associated with our first research question predicts learning disparities. In the first model (column 1), each of the estimates is a significant predictor of learning. Holding other variables in the model constant, the drop in the likelihood of being able to subtract is 16 percentage points for children from the poorest households (in comparison to children from the wealthiest households), three percentage points for girls, four percentage points for those whose mother did not attend school, and seven percentage points for those whose father did not attend school. Combining these estimates, on average, a girl from one of the poorest households and whose mother and father did not go to school is 30 percentage points less likely to be able to subtract than a boy from one of the wealthiest households whose parents did attend school. However, while the differences associated with gender, wealth, and parental education are commensurate with prior literature, overage status is a significant predictor but in the opposite direction to that found in past research: when controlling for the other variables, overage children are, on average, seven percentage points more likely to be able to subtract than children who are not overage.

In column (2), we add variables for whether children attend a private school and receive private tuition to establish whether the effects of prior characteristics dissipate. The coefficient estimates suggest this is not the case: all of the four key characteristics remain significant. The coefficients for gender, parental education, and overage status each change by a single percentage point or less, indicating that the extent to which they predict learning gaps is largely unaffected by school type and tuition. The coefficient for socio-economic status drops more in absolute terms, from 16 to 12 percentage points, suggesting that disadvantages tied to socioeconomic wealth are relatively less independent of school type and tuition, as might be expected, although its influence remains relatively strong overall.

Given the sizeable importance of socioeconomic index scores in column (1) and column (2), we also analysed whether the other drivers of learning disparities in our model varied in their impact among wealthier and poorer children. To do this, we estimated two more models with the same variables but restricted samples: for the poorest quintile, shown in column (3), and the wealthiest quintile, shown in column (4). These model estimates suggest that, whereas the impact of parental education is similar across poorer and wealthier children, the role of gender and overage status differ. Regarding gender, after

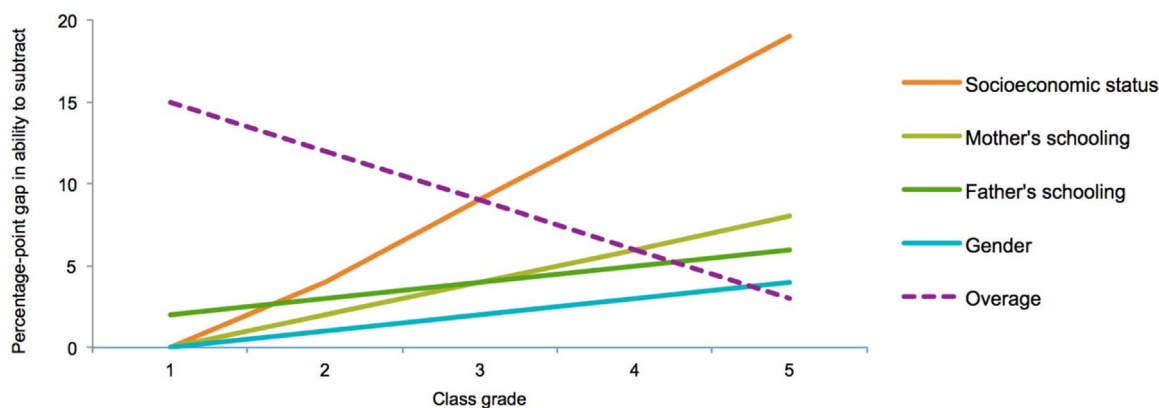


Fig. 4. Changing predictive power of characteristics over primary school grades. Source: ASER India 2009–2013.

controlling for all other model variables, poorer girls are significantly less likely to be able to subtract than are poorer boys, by three percentage points, but there is no significant difference between wealthier girls and wealthier boys. While overage status is still positively linked to learning for both groups, the associated increase in the likelihood of being able to subtract is lower for poorer children (5 percentage points) than it is for wealthier children (10 percentage points). With the ASER survey data, we are unable to identify whether the reasons for overage status differ between poorer and wealthier children; for example, care responsibilities or access to pre-primary education may differ considerably between the groups. Whatever the reasons though, the apparent benefit of overage status for wealthier children is twice that for poorer children.

Building on this analysis, we are able to answer our second research question, namely which of the predictors of learning gaps are more influential in the widening of disparities over the primary school cycle. As per formula (2), we expand the OLS model from Table 3, column (2), to include an interaction effect between each key background characteristic and the given child's school grade. All of these interactions are significant at the $p < 0.01$ level, which suggests that the predictive strength of each characteristic changes between the beginning and end of primary school (Fig. 4).

The predictive strength of socioeconomic status, gender and parental education all increase between the beginning and end of primary school. Three of these – socioeconomic status, gender and mother's schooling – are non-significant predictors during grade 1. By grade 5 though, all are significant, with the effect of socioeconomic status being the strongest: holding the model's other variables constant, the drop in the likelihood of being able to subtract is 19 percentage points for children from the poorest households (in comparison to children from the wealthiest households),⁶ four percentage points for girls, eight percentage points for those whose mother did not attend school, and six percentage points for those whose father did not attend school. Overage status follows a distinctive pattern. It is a far stronger predictor of the ability to subtract in the earlier primary-school grades than it is in the later grades. Holding the other model variables constant, the magnitude of the overage coefficient in grade 1 (15 percentage points) is almost as great as the difference between the poorest and richest children in grade 5 (18 percentage points).

To help visualise how these factors drive divergent trajectories, we plot model estimates for the likelihood of being able to subtract for four different groups of children – advantaged girls, advantaged boys, disadvantaged girls, and disadvantaged boys – across the primary school grades (Fig. 5).⁷ This depiction shows that the disparity between the

most advantaged children (green lines) and the least advantaged (red lines) widens over the school grades. Between grade 1 and grade 5 the gap doubles, from 15 to 29 percentage points. Amongst the least advantaged children, almost none (1%) are able to subtract in grade 1, suggesting they have had no exposure to learning before entering school, while the proportion of more advantaged children who can already subtract in grade 1 (16%) is comparable to the proportion of disadvantaged children who can subtract in grade 3.

The other clear difference between more and less advantaged children is that there is a clear gender disparity between disadvantaged boys (red dotted line) and disadvantaged girls (full red line). While next to no children from disadvantaged households are able to do subtraction in grade 1, rates improve more slowly among girls such that there is a 7 percentage-point gap by grade 5 (47% compared to 40%). In contrast, there is near gender parity among advantaged children in terms of how many are able to subtract, as the trajectories for advantaged girls (full blue line) and advantaged boys (dotted blue line) map almost directly on top of one another.

In order to answer our third research question, we also estimate the model with interaction terms separately for each state. Given the diversity of conditions across India, it is perhaps unsurprising to find that some of the key variables have a more consistent impact across states than others (Table 4). The most constant predictors of disparity are socioeconomic status (significant in 25 of the 34 states) and parental education (23 and 19 for maternal and paternal, respectively). By contrast, the impact of gender varies: holding other model variables constant, girls do worse than boys in 11 states, but in 3 states girls outperform boys. Overage status is a significant positive predictor of learning in 24 states, albeit, as for the model on the whole of rural India, only in the earlier school grades.

6. Discussion

Education systems should redress disparities in learning according to inherited disadvantage associated with poverty, gender and parental education. Yet in India, as in so many countries, our paper shows that learning gaps associated with these factors widen over the primary school cycle. These determinants of disparities remain significant, and change little in magnitude, even when controlling for differences in private school attendance and tuition received.

Even when controlling for other sources of disparities, the magnitude of wealth as a predictor of learning gaps is considerable. This is all the more important since it drives the widening of learning gaps over the primary school cycle. The fact that the wealth gap still remains after controlling for private school attendance and tuition, two of the most

⁶ Socioeconomic status still has the strongest impact even when making the more modest comparison between all children above the median wealth and all children below.

⁷ Also, given that gender matters to learning far more among poorer than among

(footnote continued)

wealthier households, we include an interaction effect between wealth and gender.

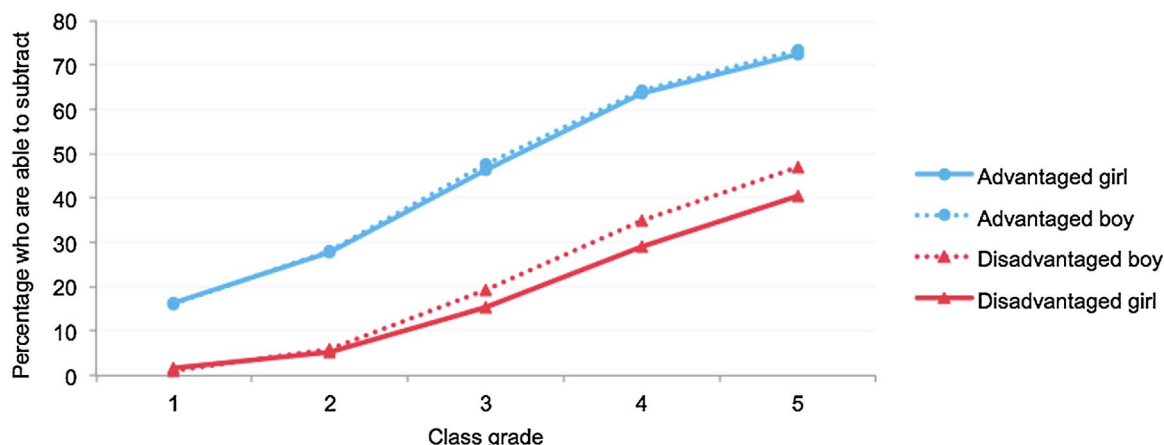


Fig. 5. Likelihood of being able to subtract over the primary school grades, comparing more and less advantaged boys and girls. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Note: we define advantaged children as those who have a mother and father who both went to school, and whose houses have electricity, a phone, a television, and brick or cement walls and a roof. We define disadvantaged children as those who do not have a parent who attended school, and who live in a mud house with none of the aforementioned possessions.

Source: ASER India 2009–2013

Table 4

Overview of model results for each state.
Source: ASER India 2009–2013.

Policy focus	Number of states where the variable is significant (out of 34)	Notes
Gender	14	In three of these states, girls do significantly better than boys: Kerala, Punjab, and Tamil Nadu
Socioeconomic	25	There were no states in which poorer children outperformed wealthier children
Mother's schooling	23	Mother's education is more important than father's education in all states except Tripura
Father's schooling	19	–
Overage	24	There were no states in which overage children did significantly worse

commonly cited sources of learning disparities, indicates that wealth is generating learning disparities in additional ways. Future research could add to our understanding of this disparity by exploring the underlying mechanisms that propel this relationship.

Although not as powerful a predictor as wealth, model estimates show a clear gap in learning trajectories between boys and girls. However, this gender disparity is occurring primarily among children from poorer households, indicating that disadvantages associated with gender and poverty reinforce one another. Further, the fact that gender disparities are apparent in some states but not others corroborates prior research emphasising heterogeneity of conditions across India (Bhattacharjea et al., 2011; Wadhwa, 2014). It also has important implications for policy research. First, it implies both that efforts to redress gender inequalities will be of most use if targeted regionally. Second, it suggests that caution should be taken when extrapolating evidence from specific states to India as a whole.

Overage status is associated with improved learning in the early primary school grades, although any benefit dissipates and becomes non-significant in the later grades. The finding of a positive relationship runs counter to prior research in eastern Africa, which has warned of the negative effects of overage status on learning (Hungu et al., 2014; Hungu and Thuku, 2010; Jones, 2014). Our findings, that overage status is linked to higher levels of learning in the early primary school years in rural India, suggest that overage status plays a rather different role in children's learning than in other contexts. This demonstrates the pitfall of relying on claims made in other country contexts, and thus merits additional research on the reasons for the apparent positive impact of overage status on learning in India in the early grades. There appears to be a greater boost for more privileged children, which may be attributable to greater levels of pre-schooling. Further, if it were the case that overage children have received supplementary education prior to entering grade 1, this might corroborate critiques arguing that

curricular pace, rigidity, and elitism fail the majority of schoolchildren in India (e.g., Chavan, 2015; Mukerji and Walton, 2012; Pritchett and Beatty, 2015). As such, our findings give further support to the need for policy to ensure that early-grades curricula are set at the pace of disadvantaged students who are most at risk of not learning. Otherwise, these children have little chance of catching up.

Our research demonstrates the dynamic nature of learning gaps over the school cycle, highlighting the need for interventions to begin from the early years. The findings also provide an important contribution to the on-going, heated debate on the stage at which the education Sustainable Development Goal should track progress in learning (Rose, 2015). Given the evidence that gaps begin from the early grades of primary school and subsequently widen, we would argue that it is vital to start to track progress from the early grades. There is otherwise a danger that these gaps will be left unaddressed before it is too late to tackle them.

From a methodological perspective, the paper points to the need for better longitudinal data. As noted, our models control for a range of important variables, but these are not exhaustive and are collected cross-sectionally. Longitudinal data would strengthen our ability to identify causal patterns because we would then be able to untangle the role of interrelated factors according to which preceded others. In particular, baseline learning levels would enable us to estimate progress in learning among particular subgroups, e.g. rates of improvement among the most low-achieving poor children. The Young Lives study is the strongest example to date of longitudinal survey in low- and middle-income countries, but it has been collected on a somewhat narrower geographical scale than is desirable to shape national education policy. Such data could also offer a more nuanced understanding of learning gaps than is currently possible by collecting data on other likely determinants of disadvantage, such as disability and caste.

In this paper, we go some way to analysing the nature of disparities

in learning at the national scale in India. However, if research is to move from depicting learning gaps to offering means to redress these gaps, it is essential to turn our focus to the role of formal education. In order to do this, future surveys should seek to link household data with administrative data. This would make it possible to analyse the role of different school policies (e.g. school funding, teacher training, class size, and ability tracking) in lessening or exacerbating learning disparities. Such information could inform policymaking, and, ultimately, teaching practices in the classroom.

7. Summary

Disparities in learning remain a key concern for education policymakers worldwide. While research in wealthier countries indicates that learning gaps among children with different background characteristics are apparent and widen over the school cycle, there is less evidence on whether similar patterns exist in many developing countries. We add to this literature by analysing conditions in rural India over the recent years. Using data from the Annual Survey of Education Report, we model learning outcomes across child ages according to four key concerns in the research literature: gender, socioeconomic status, parental education and overage status. We also test the durability of each concern across the primary school cycle. This distinction enables us to examine whether each characteristic is tied to widening disparities during the early years of schooling.

We find that, although each of the key predictors prove significant, wealth is not only the strongest determinant of learning disparities, but importantly that its importance grows over the primary school grades. This suggests the need to focus policy attention on ways to alleviate the impact of poverty on learning, even before children start school. Gender gaps also increase across the school grades, but primarily within the poorest households, and their prevalence varies across states. This suggests that resources to improve opportunities for girls should be targeted, focusing on those areas and households in which gender gaps are the most pronounced. The effect of being overage is contrary to that found in other contexts, namely that, in rural India, those who are not in the expected age for their grade appear to be more likely to be learning, although this pattern dissipates after the early grades. This could be due to a variety of factors, such as whether overage children have had exposure to prior learning via pre-schooling, for example, and deserves further investigation. Finally, our findings contribute to global debates on the stage at which to track learning in order to assess progress towards the education Sustainable Development Goal. We identify the need to include a target for learning in the early grades, disaggregated by wealth, gender and other markers of disadvantage, in order to be aware of whether progress is being made before it is too late.

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