**Schooling and learning deficits: a simple unified measurement framework**

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*Abstract*

There exists no unified measurement framework that encompasses and integrates schooling and learning deficits – arguably the two most important education challenges in most developing countries. This paper offers a methodology that fills this gap. Using the notions of age-appropriate grade, actual grade, and effective grade for a school-age child, we develop an integrated framework offering a range of schooling, learning and education deprivation measures which also build in distributional considerations. The paper illustrates the value-added of the measurement framework for education policy and evaluation with an application to recent data for India.

JEL codes: I2; O15.

Keywords: schooling deficit; learning deficit; education deprivation; India

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**Schooling and learning deficits: a simple unified measurement framework**

## 1. Introduction

Getting children into school and ensuring that they learn adequately at school are arguably the two most important educational challenges for most developing countries. The vast literature on education, especially in a developing country context, is related to or motivated by one or both of these challenges. These two challenges could also be thought of as the "quantity" challenge of schooling deficits and the "quality" challenge of learning deficits. The former refers to the problems of (a) children out of school, who either have never attended school or have dropped out of school; and (b) children lagging behind or straggling – those in school but attending grades that are below what is appropriate for their age. Learning deficits, by contrast, refer to the problem of children learning below, sometimes well below, what is appropriate for the grade they are attending.

While both these challenges have been extensively referred to in the literature and have been focal points of nearly all major policy discussions on improving educational outcomes in developing countries, it is somewhat surprising that when it comes to measuring these outcomes there exists no unified framework that encompasses and integrates the two types of deficit. Thus, on the one hand, we have measures such as gross and net enrolment rates, school life expectancy, mean years of schooling, dropout and retention rates. Numerous studies use such measures to characterize different facets of schooling deficits, drawing upon data from diverse sources such as population censuses, school censuses or household surveys.[1] On the other hand, we have measures such as those based on test scores – including internationally-benchmarked ones such as the Programme for International Student Assessment (PISA) and the Trend in International Mathematics and Science Study (TIMSS) – that aim to capture learning achievements of in-school children.[2] With the adoption of the Sustainable Development Goals by member countries of the United Nations, there is added emphasis on measuring learning outcomes of all school-age children,[3] and recent rounds of the Multiple Indicators Cluster Survey (MICS), for instance, have already moved in this direction by incorporating modules on measuring learning levels. However, there is no common metric that permits a joint consideration of these two types of measures. Moreover, these measures often do not have an explicit deprivation focus as they are frequently limited to measuring average outcomes without a benchmark against which varying shortfalls in schooling and learning can be assessed.

The conspicuous lack of a unified measurement framework focused on education deprivation that integrates the two types of deficits is unsatisfactory, not only methodologically but also at a practical and policy level. The primary goal of this paper is to fill this gap by offering a methodology that integrates schooling and learning deficits into a common measurement framework, and provides an overall measure of education deprivation that naturally builds in consideration of both types of deficits. From this perspective, the first-order concern is one of

[1] There is a vast literature on the construction and use of such schooling indicators; see, for instance, Kominski (1990), Barro and Lee (1993), Ahuja and Filmer (1996), Filmer and Pritchett (2001), Hannum (2002), Case et al. (2004), Kingdon (2007), Desai and Kukarni (2008), UNESCO (2012) for some typical examples. Also see UNESCO (2009) for definitions of a wide range of such indicators.

[2] PISA and TIMSS have been widely used to measure learning achievements across a wide range of countries. The quality of the labour force as measured by standardized test scores has often been shown to be important in explaining cross-country growth performance; see for instance, Hanushek and Kimko (2000), Hanushek and Woessmann (2008, 2012).

[3] Also see Pritchett (2013) for a detailed discussion of learning shortfalls across a range of countries including those that have achieved significant improvements in access to schooling.

education deficits viewed as children learning below their age-appropriate learning levels, and schooling and learning deficits feed into this education deficit.

Our framework utilizes three primitives, viz. the age-appropriate grade for a child, the actual grade the child is attending, and the child's effective grade corresponding to the child's level of learning. Schooling deficit is then conceptualized as the shortfall of the actual grade from the age-appropriate grade and learning deficit as the shortfall of the effective from the actual grade. The overall education deficit for a child can then be seen as the shortfall of their effective grade from their age-appropriate grade. In this setup, schooling and learning deficits contribute to education deficits, although the existence of either a schooling or a learning deficit need not necessarily imply an education deficit. Nor may schooling, learning or education deficits always move in the same direction.

The three primitives lay the basis for defining a new range of schooling, learning and education deprivation measures. The measures parameterize schooling, learning and education shortfalls, drawing upon the poverty measurement literature, in particular, the class of measures introduced by Foster, Greer and Thorbecke (1984). Analogous to the Foster-Greer-Thorbecke (FGT) measures, our measures allow for aversion to inequality in schooling and learning achievements amongst the deprived. Embedding the unified framework within the poverty measurement methodology not only brings a natural deprivation focus to our measure, but also ensures that our measures satisfy a number of desirable axioms that have been emphasized in the poverty measurement literature. It also directly builds into all our measures a distributional dimension typically lacking in the conventional education indicators.[4] In this regard, even our

[4] Distributional considerations have been relatively neglected in the education measurement literature. One exception is the illiteracy measure in Denny (2002) which also utilizes the FGT structure. There has also been recent interest in inequality of education opportunity which has tended to focus on inequality in the learning dimension using test scores (for instance, Ferreira and Gignoux, 2014). But, our framework is far more general, as it integrates both schooling and learning deficits in a common measurement methodology. Moreover, measures such as Denny's illiteracy measure are more applicable to an adult population and are not well-suited to measuring age-appropriate learning outcomes for children.

schooling and learning deprivations, taken by themselves, offer a significant generalization of existing measures.

The value-added of the unified framework comes from the additional insights it can offer as a diagnostic and analytical tool for education policy and evaluation, in turn related to the central features of the measurement framework itself. The paper highlights three main ways in which the framework matters by presenting an application to rural India using data for 2008 and 2012. First, it shows that the framework can be important for targeting insofar as conventional schooling and learning indicators by themselves can be poor guides to the prevailing levels of education deprivation. Changes in these indicators are not necessarily good guides to changes in education deprivation either. While we also show (in section 3.2) that several of the conventional measures are analytically related to and can be derived from the unified framework, our framework is more general. The reason why conventional schooling and learning measures may often fail to be good targeting indicators is that they are at best partial indices of overall education deprivation.

Second, partial indices they may be, schooling and learning deficits are nonetheless key constitutive elements of education deprivation, and a policy question of interest is the relative contribution of these two elements to overall education deprivation. The unified framework allows a natural decomposition of the overall level (or changes in) education deprivation into components representing schooling and learning deficits. The framework thus offers a natural way of quantifying the relative importance of the quantity and quality challenges in education at a given point in time and over time.

Third, our framework also helps assess how much does inequality in the distribution of schooling and learning levels, as opposed to their low average levels, matter for observed education deprivation. While variance in education outcomes has been the subject of some attention in the literature, such as Hanushek and Woessman (2006), Ferreira and Gignoux (2014), our framework explicitly incorporates dispersion in schooling and learning deficits, and yields a direct measure of their contribution to education deprivation. Variations in this contribution offer an indication of how far the policy focus may need to be on addressing inequalities in schooling and learning opportunities relative to raising the average standard in different contexts.

While the primary purpose of the application is illustrative, it is also of some independent interest. India is home to 124 million – almost one-fifth – of the 652 million primary school-age children in the world.[5] The Indian application thus also has some relevance for global education challenges. It is also of added interest in light of recent debates around educational progress in India following the passage of the Right of Children to Free and Compulsory Education Act of 2009. Using data for 2008 and 2012, the application offers at least a "before-after" comparison of the education situation. From an India-specific perspective, key findings from the application include: (i) high levels of education deprivation amongst primary school-age children in rural India, with more than half of them educationally deprived; (ii) learning deficits accounting for about 60% of the overall education deprivation; (iii) a significant deterioration (increase) in education deprivation between 2008 and 2012 which was almost entirely driven by higher learning deprivation, while schooling deficits remained largely unchanged; and (iv) a high contribution of inequality in schooling and learning outcomes to education deprivation, such that if inequality in actual and effective grades could be eliminated across children of a given age within states of India, overall education deprivation in the country could be cut by more than half.

[5] The numbers are for 2011 as reported in UNESCO (2014), Annex, Statistical Table 4.

The paper is organized as follows. Section 2 introduces the concepts of schooling and learning deficits illustrated with country examples, and then goes on to formalize these concepts using notions of age-appropriate, actual and effective grades for school-age children, which are the main building blocks of our framework. Section 3 presents our unified measurement framework and its main properties. Section 4 presents its empirical implementation for rural India, while section 5 discusses ways in which the unified framework can matter for education policy and evaluation. Our concluding observations are noted in the final section.

## 2. The building blocks

### *2.1 Schooling deficits*

The basic idea of schooling deficits is well-known, though attention has been mostly directed to whether school-age children are enrolled in school or not. Our notion of schooling deficit extends this to also consider whether children in school are attending the right grade for their age or whether they have a "grade deficit". The potential significance of such grade deficits is readily illustrated with some examples. For instance, the official starting age for grade 1 is 6 years in Nepal and Bhutan, and 7 years in Afghanistan. Thus, in an ideal world, a 14-year old in Nepal and Bhutan should be in grade 9, and in grade 8 in Afghanistan. The reality, however, stops well short of this ideal. For instance, in 2010 only 23% of the 14-year-olds were enrolled in grade 9 (or above) in Nepal, and only 12% in Bhutan. Similarly, only 19% of the 14-year-olds were enrolled in grade 8 (or above) in Afghanistan (Table 1). More than half of the 14-year-olds in Afghanistan, about 18% in Bhutan and 14% in Nepal, were not enrolled at all; this comprised those who had never attended school or had dropped out. The rest – 30% in Afghanistan, 70% in Bhutan, and 63% in Nepal, though in school were lagging behind their age-appropriate grade by one to eight years.

[Table 1 here]

These examples illustrate the key point that an adequate assessment of schooling deficits in any empirical context needs to take into account not only of whether school-age children are enrolled in school, but equally of what grade they are attending. In some contexts (such as conflict-ridden Afghanistan) the biggest challenge could be children out of school, in others (Nepal and Bhutan) it may be that while most children are in school, the vast majority are lagging behind. Hence, the need for a framework that explicitly measures the varying extent of schooling deficits and takes into account how these deficits are distributed across school-age populations.

### *2.2 Learning deficits*

Getting children into school even into the right grades does not by itself ensure that they will learn adequately. Schooling is indeed of little value if not much learning takes place at schools. Learning deficits are rife across the developing world, and have been the focus of increasing attention. For instance, one of the Sustainable Development Goals recently endorsed by member countries of the United Nations explicitly targets "inclusive and equitable quality education". Calculations from the recent Annual Status of Education Report (ASER) 2012 survey for rural India are illustrative of the nature of this challenge (Table 2).

[Table 2 here]

The nationwide survey, for instance, shows that: 61% of all children enrolled in grade 3 could not read a grade 1 level text, 38% could not even read a word; 53% of children in grade 5 could not read a grade 2 text; 75% of those in grade 5 could not do simple division problems; and 46% in grade 5 could not solve simple two-digit subtraction problems with borrowing.

### *2.3 The age-appropriate, the effective and the actual grade*

The above discussion leads us to introduce the elementary building blocks of the proposed measurement methodology that seeks to integrate these two types of deficits within a common framework. The building blocks relate to the simple notions of the age-appropriate grade, the actual grade, and the effective grade of a school-age child, denoted as:

- Age-appropriate grade: $g_j^p$ = the grade child $j$ *should be attending* given her/ his age (and the officially-endorsed starting age for school);
- Actual grade: $g_j$ = the grade child $j$ *is actually attending*;
- Effective grade: $g_j^e$ = the grade child $j$ *is effectively in* given her/ his level of learning.

Thus, schooling deficits manifest as the difference between the age-appropriate grade and the actual grade, and learning deficits as the difference between the actual grade and the effective grade. Accordingly, education deprivation may be viewed as the difference between the age-appropriate and the effective grade, thus encompassing both schooling and learning deficits. Typically, we will have $g_j^e \leq g_j \leq g_j^p$, though not always so. Indeed, even within this simple construct, an array of schooling and learning deficits is possible, as shown in the matrix below:

**Matrix of possible combinations of schooling and learning deficits**

| | | | | **Super-performers** |
|---|---|---|---|---|
| | | **No learning deficit** $\boldsymbol{g_j^e = g_j}$ | **Learning deficit** $\boldsymbol{g_j^e < g_j}$ | **Learning surplus** $\boldsymbol{g_j^e > g_j}$ |
| | **No schooling deficit** $\boldsymbol{g_j = g_j^p}$ | (I) $g_j^e = g_j = g_j^p$ | (III) $g_j^e < g_j = g_j^p$ | (V) $g_j^e > g_j = g_j^p$ |
| | **Schooling deficit** $\boldsymbol{g_j < g_j^p}$ | (II) $g_j^e = g_j < g_j^p$ | (IV) $g_j^e < g_j < g_j^p$ | (VI) $g_j^e > g_j,\ g_j < g_j^p$ |
| **Super-performers** | **Schooling surplus** $\boldsymbol{g_j > g_j^p}$ | (VII) $g_j^e = g_j > g_j^p$ | (VIII) $g_j^e < g_j,\ g_j > g_j^p$ | (IX) $g_j^e > g_j > g_j^p$ |

*Note*: $g_j^e$, $g_j$, $g_j^p$ respectively represent the effective grade, the actual grade and the age-appropriate grade for child $j$.

The above distinguishes nine different cases. While cases I-IV will be the ones of main interest, it is useful to comment briefly on cases V through IX which relate to the possibilities of there being a schooling surplus or a learning surplus or both. It is possible for children to be sometimes enrolled in grades that are above their age-appropriate norm due to an early start or grade acceleration. However, these are relatively uncommon. Similarly, there may be children whose learning standards are above those expected for the grade they are in, which may reflect the children's higher ability, or better quality of educational inputs including parental input. We dub these children with a schooling or learning surplus as "super-performers". Numerically, they are unlikely to be very substantial in a developing country context, but the measurement framework needs to recognize this possibility. Recognition of this possibility does however have an implication for the measurement of education deficit, viewed here as the difference between the age-appropriate grade and the effective grade $(g_j^p - g_j^e)$. An education deficit arises in cases II, III and IV; it does not arise in cases I, V, VII and IX; and in cases VI and VIII, it may or may not arise depending upon whether the schooling (learning) deficit is compensated by the learning (schooling) surplus or not. Put differently, the presence of either a schooling or a learning deficit is a necessary condition for the existence of an education deficit, but the presence of either deficit is not a sufficient condition for a child to experience an education deficit.

## 3. The measurement framework

### *3.1 Schooling, learning and education deprivation measures*

Based on the foregoing development, we now introduce our measures of schooling, learning and education deprivation for an individual child and for the population of children. The schooling deficit for child $j$ can be defined as:

$$d_{Sj}(\alpha) = \left(\frac{g_j^p - g_j}{g_j^p}\right)^{\alpha} I(g_j^p - g_j > 0) \quad \text{for } \alpha \geq 0 \tag{1}$$

where the difference $(g_j^p - g_j)$ is a measure of the child's schooling deficit (the extent to which her actual grade falls short of her age-appropriate grade) which is normalized by the age-appropriate grade; $I(g_j^p - g_j > 0)$ is an indicator function which takes the value 1 whenever a child's actual grade is less than her age-appropriate grade, and zero otherwise; and $\alpha$ is a non-negative number that parameterizes aversion to inequality in schooling deprivation amongst those so deprived, with higher values of $\alpha$ indicative of greater aversion.

Similarly, the learning deficit for child $j$ is defined as:

$$d_{Lj}(\alpha) = \left(\frac{g_j - g_j^e}{g_j}\right)^{\alpha} I(g_j - g_j^e > 0) \quad \text{for } \alpha \geq 0 \tag{2}$$

Note that the learning gaps are normalized by the actual grade; this seems appropriate as learning deficits measure the shortfall of the effective grade from the actual grade. One could however also normalize these with age-appropriate grades, though the resulting measure in that case will not necessarily attain the upper bound of 1 even with an effective grade of zero. In light of this, normalization by the actual grade seems preferable, which is the direction pursued here.

And finally the education deficit for child $j$ is defined as:

$$d_{Ej}(\alpha) = \left(\frac{g_j^p - g_j^e}{g_j^p}\right)^{\alpha} I(g_j^p - g_j^e > 0) \quad \text{for } \alpha \geq 0 \tag{3}$$

Note that for an education deficit to arise there must be either a schooling or a learning deficit or both, but the existence of a schooling or learning deficit alone is not sufficient for there to be an education deficit.

The above individual deficit measures in (1)-(3) in turn lead to the following aggregate measures of schooling, learning and education deprivation:

$$D_K(\alpha) = \frac{1}{n}\sum_{j=1}^{n} d_{Kj}(\alpha) \quad \text{for } \alpha \geq 0 \text{ and } K = S, L, E \tag{4}$$

where $n$ is the size of the school-age population with each child in the population indexed by $j$.

The $D_K(\alpha)$ measures draw upon the well-known Foster-Greer-Thorbecke (FGT) family of poverty measures, and can be interpreted along similar lines (Foster, Greer and Thorbecke, 1984).[6] For instance, for $\alpha = 0$, the $D_E(\alpha)$ measure collapses to the proportion of school-age children with any education deficit, and could be thought of as an education deprivation headcount. For $\alpha = 1$, $D_E(\alpha)$ measures the average proportionate education gap for the school-age population. Note that the proportionate education gap captures the shortfall of the effective grade from the age-appropriate grade normalized by the age-appropriate grade, with the shortfall evaluated as zero whenever effective grade equals or exceeds the age-appropriate grade. Values of $\alpha > 1$ introduce convexity in the $D_E(\alpha)$ measure such that higher levels of deprivation are accorded greater weight in aggregating to an overall measure of deprivation for the school-age population. In the empirical illustration for India (discussed below), we will work with values of $\alpha = 0$, 1 and 2.

The schooling and learning deprivation measures, $D_S(\alpha)$ and $D_L(\alpha)$, are of independent interest in their own right and can be interpreted in analogous fashion. They can also be viewed as conditional valuations of the general education deprivation measure:

[6] The FGT approach has indeed been extended to multidimensional poverty measurement where one of the dimensions often is education. See Aaberge and Brandolini (2015) for a recent survey of the large and growing literature on multidimensional poverty. But this literature is not geared to looking at the education outcomes as a special focus, even when more than one education indicator is used in such applications. By contrast, the major focus of this paper is on educational deprivation with schooling and learning deficits as the key elements of a unified measurement framework.

$$D_S(\alpha) = D_E(\alpha) \,\middle|\, \left(g_j = g_j^e, \forall j\right); \quad D_L(\alpha) = D_E(\alpha) \,\middle|\, \left(g_j = g_j^p, \forall j\right) \tag{5}$$

In other words, abstracting for the moment from the super-performers (those with schooling or learning surpluses), the education deprivation measure collapses to the schooling (learning) deprivation measure if there are no learning (schooling) deficits.

As the $D_K(\alpha)$ deprivation measures belong to the FGT class of poverty measures, they share all their properties including symmetry, focus, normalization, boundedness between 0 and 1, population invariance, scale invariance, subgroup decomposability, continuity and monotonicity for $\alpha > 0$, and transfer principle for $\alpha > 1$.[7]

In applying this framework, it is important to note that our learning and education deprivation measures crucially depend on the specification of learning standards appropriate for different grades that go into defining effective grades. Setting these standards is similar to the exercise of setting poverty lines in the context of poverty measurement, and will inevitably require a deliberative process to arrive at appropriate judgements on acceptable standards. Many countries already have established standardized tests for particular grades. Norms underlying these tests can provide readily-usable benchmarks for specifying effective grades at a national level. Internationally too, there are precedents such as PISA and TIMSS which use learning assessment instruments tailored to specific age-groups. Building consensus on age- and grade-appropriate learning standards for international comparisons may be challenging, but the experience for instance with the setting of international poverty lines (e.g. the purchasing power parity-based $1.90 a day line) for global poverty monitoring, suggests that this is a feasible task.

[7] See Foster, Greer and Thorbecke (1984) and Foster et al (2013) for a discussion of these properties.

### *3.2 Relationship to some conventional measures*

Several conventional education indicators can be related to the measurement framework proposed above and some can be viewed as special cases. For instance, UNESCO (2016) defines the adjusted net enrolment ratio (ANER) as the "enrolment of the official age group for a given level of education either at that level or the levels above, expressed as a percentage of the population in that age group". It is readily seen that ANER for any particular age $y$ is related to the schooling deprivation measure for $\alpha = 0$ for that age as:

$$ANER^{(y)} = 1 - D_S^{(y)}(0) \tag{6}$$

Similarly, the proportion of children who have never been to school and the drop-out rate can be seen as subindices of the schooling deprivation incidence measures for $\alpha = 0$, upon noting that those with schooling deficits comprise of three mutually exclusive groups: (i) those who have never attended school, (ii) those who have attended school in the past, but have currently dropped out, and (iii) the stragglers, those who are currently attending school but are lagging behind their age-appropriate grade. Denoting these groups as "NA", "DO" and "ST", it follows that

$$D_S(\alpha) = D_S^{NA}(\alpha) + D_S^{DO}(\alpha) + D_S^{ST}(\alpha) \tag{7}$$

In particular, $D_S^{NA}(0)$ and $D_S^{DO}(0)$ measure the never-been-to-school rate and the drop-out rate respectively. The sum, $D_S^{NA}(0) + D_S^{NA}(0)$, measures the current out-of-school rate, another often-used education indicator.

Likewise, age-specific enrolment ratio (AER), which measures the enrolment rate for a given age $y$ regardless of the level of education, can be written as:

$$AER^{(y)} = 1 - D_S^{(y)}(0) + D_S^{ST(y)}(0) \tag{8}$$

which also leads to the school-life expectancy (SLE) measure for a child of age $y_0$ as[8]:

$$SLE^{(y_0)} = \sum_{y=y_0}^{y_{max}} \left[1 - D_S^{(y)}(0) + D_S^{ST(y)}(0)\right] \tag{9}$$

Equations (6)-(9) show how many conventional indicators are related to the proposed measurement framework. They also highlight that generalizations of some of these conventional indicators are possible for values of $\alpha > 0$ that can further build in considerations related to the depth and severity of schooling deficits.

### *3.3 Decompositions*

The definition of the schooling and learning deprivation measures naturally motivates an important decomposition, namely, the decomposition of the aggregate education deprivation measure into schooling and learning deprivation components. Note however that the education deprivation measure $D_E(\alpha)$ is not additively decomposable into schooling and learning components. However, we can implement a decomposition using Shapley decomposition methods (Shorrocks, 2013). This involves constructing two counterfactual education deprivation measures corresponding to: (i) eliminating learning deficits while holding schooling deficits constant, and conversely, (ii) eliminating schooling deficits while holding learning deficits constant. Supressing the argument $\alpha$ to simplify notation, let the two counterfactuals be denoted $D_E|_{d_{Lj}=0}$ and $D_E|_{d_{Sj}=0}$ respectively. Two pathways to decomposition can thus be identified: eliminating the learning deficits first followed by removal of schooling deficits, or vice versa.

Using the first counterfactual measure $D_E|_{d_{Lj}=0}$, the difference $(D_E - D_E|_{d_{Lj}=0})$ shows the reduction in education deprivation as a result of removing learning deficits, thus giving us a

[8] School life expectancy is defined as the total number of years of schooling which a child of a certain age can expect to receive, assuming that the probability of him/ her being enrolled at any particular age is given by the current enrolment rate for that age (UNESCO, 2009).

measure of the contribution of learning deficits to education deprivation; the rest, $D_E|_{d_{Lj}=0}$ itself, is what remains on account of the unchanged schooling deficits. Analogously, using the second counterfactual, $D_E|_{d_{Sj}=0}$, the difference $(D_E - D_E|_{d_{Sj}=0})$ shows the contribution of schooling deficits to education deprivation while $D_E|_{d_{Sj}=0}$ gives the contribution of learning deficits. Averaging over the two possible pathways then gives the following exact decomposition:

$$D_E = \widetilde{D}_S + \widetilde{D}_L \quad \text{where}$$

$$\widetilde{D}_S = \frac{1}{2}\left[D_E + (D_E|_{d_{Lj}=0} - D_E|_{d_{Sj}=0})\right] \tag{10}$$

$$\widetilde{D}_L = \frac{1}{2}\left[D_E - (D_E|_{d_{Lj}=0} - D_E|_{d_{Sj}=0})\right]$$

The decomposition offers a useful device to assess the relative contributions of schooling and learning deficits to overall education deprivation in any given empirical setting. In interpreting the decomposition, however, it is worth noting one respect in which the decomposition may understate the contribution of the learning component. This is because when using the second counterfactual involving the elimination of schooling deficits, the learning deficits are assumed to remain unchanged. In other words, when the actual grade of children is raised up to their age-appropriate grade, it is assumed that they carry their existing learning deficits (or surpluses) with them to the higher actual grade. However, absent any change in educational inputs by schools or parents, it is likely that a rise in actual grades is not accompanied by a commensurate rise in effective grades, in turn implying a likely increase in learning deficits. To the extent that this occurs, the decomposition in (6) will understate the contribution of the latter to education deprivation.[9]

[9] The likely impact of a reduction in schooling deficits on learning deficits is difficult to estimate, and hence, the decomposition treats the elimination of learning and schooling deficits symmetrically.

A simple extension of (6) also allows us to assess changes over time. Thus, the contribution of changes in schooling and learning deficits to an observed change in education deprivation can be evaluated as:

$$\Delta D_E = \Delta\widetilde{D}_S + \Delta\widetilde{D}_L \tag{11}$$

Another set of decompositions follow from the subgroup decomposability property of the $D_K(\alpha)$ measures. By construction, the property holds for schooling, learning as well as education deprivation measures, and it can be stated as follows. If a school-age population of size $n$ can be partitioned into $k$ mutually exclusive groups of sizes $(n_1, n_2, \dots n_k)$ with $\sum_{i=1}^{k} n_i = n$, then

$$D_K(\alpha) = \sum_{i=1}^{k} \left({}^{n_i}/_{n}\right) D_K^i(\alpha) \text{ for } K = S, L, E \tag{12}$$

where $D_K^i(\alpha)$ is the schooling/ learning/ education deprivation measure for subgroup $i$. Thus, for instance, the aggregate education deprivation measure can be written as the subpopulation-weighted average of the education deprivation measures of the sub-groups. This property lends itself to a number of practical applications. For instance, with the subgroups distinguishing girls from boys, it is possible to look at the gender composition of educational deprivation. Similarly, one could look at how rural and urban education deprivations contribute to national deprivation, or indeed the relative contributions of different regions or socio-economic groups (not to mention using such decompositions for inter-country comparisons). Another interesting subgroup-decomposition is by children of different age-groups; thus, for instance, the contribution of lower and upper primary school-age children could be compared with those of post-primary age to locate which shortfalls contribute most to overall education deprivation. It is worth noting that these different decompositions can also be combined with each other. For instance, the framework allows one to answer more detailed questions, such as how much do the learning shortfalls of rural upper-primary school-age girls contribute to the national educational deficit and whether that contribution has changed over time.

Finally, we can also use this framework to quantify the contribution of inequality in actual and effective grades (and, by implication, inequality in schooling and learning deficits) conditional on any age to overall education deprivation, by constructing counterfactual education deprivation measures in the absence of such inequality. Such a decomposition shows how much the dispersion in actual or effective grades as opposed to low average levels of actual or effective grades matters for observed education deprivation.

## 4. Putting the unified framework into action for rural India

We apply the above measurement framework using data from two rounds of the Annual Status of Education Report (ASER) surveys for 2008 and 2012 for rural India.

### *4.1 ASER data and empirical methods*

ASER is a large-scale nationwide survey of school enrolment and learning levels of children in rural India. The ASER Centre and the nongovernmental organization *Pratham* together with over 25,000 volunteers from local partner organizations across the country have been conducting this survey annually since 2005. The 2012 survey[10] covered nearly 597,000 children aged 3-16 years in over 331,000 households in 567 districts of rural India. ASER is a household-based rather than a school-based survey. It collects information on schooling status for all 3-16 year old children living in sampled households. All children aged 5-16 years, including those who have never attended school or have currently dropped out, are tested in basic reading and basic arithmetic. The testing is done at home rather than at school which has

[10] This was the latest round available at the time of conducting this study. More recent rounds have subsequently become available.

two significant advantages: it allows children out of school to be tested, and it also mitigates probable biases due to the influence of teachers or the school environment.

The ASER survey tests basic learning levels of all 5-16 year olds using a reading and an arithmetic tool.[11] The reading test, conducted in the local language of each Indian state[12], has four categories: (i) *letter recognition* using a set of commonly used letters of the alphabet; (ii) *word recognition* using common familiar words with two letters and one or two *matras* (vowel signs); (iii) *grade 1 text reading,* using a set of four simple linked sentences, each having no more than 4-5 words; these words or their equivalent are in the grade 1 textbook of the respective Indian state; (iv) *grade 2 text reading*, using a short story with 7-10 simple sentences with common words in a familiar context; these words (or their equivalent) are in the grade 2 textbooks of respective states. The arithmetic test also has four categories: (i) *single-digit number recognition* with randomly chosen numbers between 1 and 9; (ii) *two-digit number recognition* with randomly chosen numbers between 11 and 99; (iii) *subtraction*: two-digit numerical problems with borrowing; and (iv) *division*: numerical problems with division of a three-digit number by a single-digit number.[13]

In order to implement the measurement framework of section 3, we need to identify the age-appropriate, actual and effective grades for each sample child. We use the following procedures for this with the ASER data. The age-appropriate grade for a child is directly determined by the age of the child; in particular, for child $j$, $g_j^p = age_j - 5$, since the officially recommended start-age for grade 1 is 6 years. If a child is currently attending school, their actual grade is directly available from the survey data. If a child has never attended school,

[11] Other tools have also been used in some of the ASER surveys. However, we limit our focus to these two tools as they have been consistently deployed in all ASER rounds.
[12] In 2012, this test was administered in 16 regional languages.
[13] For further details on how these tests are administered, see ASER (2013), chapter 2.

their actual grade is taken to be zero. If a child has currently dropped out of school, the last grade attended by the child is reported in the survey, which is then taken to be their actual grade.

The determination of the effective grade of a child is more complex as the ASER surveys are not designed to directly elicit information on effective grades. As mentioned above, the surveys administer reading and arithmetic tests. We thus construct mappings from reading and arithmetic test outcomes to effective grades which approximate the grade norms underlying the reading and arithmetic tools used in the ASER surveys. Note that the highest level of reading tested corresponds to what is expected by completion of grade 2 or an effective grade of 3.[14] Similarly, the highest level of the arithmetic test corresponds to what is expected by completion of grade 4 or an effective grade of 5. This limits the effective grades that can be estimated with ASER data to the range of grades 1-5. In light of this, we limit our analysis to children aged 7-10 years only, whose age-appropriate grades range between grades 2 and 5.

Our mapping scheme for effective grades involves essentially two steps. First, each level of learning in the reading test is assigned an effective reading grade ($g_j^e(reading)$) and similarly each level in the arithmetic test is assigned an effective arithmetic grade ($g_j^e(arithmetic)$), as shown in Table A1.1.[15] This leads to the second step with two possible alternatives for determining the overall effective grade for a child determined as the maximum or the minimum of her effective reading grade and her effective arithmetic grade[16]:

$$g_j^e = \max\{g_j^e(reading),\ g_j^e(arithmetic)\} \tag{13}$$

[14] This is based on the notion that someone currently in grade 3 who has the reading ability expected upon the completion of grade 2 does not have a learning deficit, or in other words has an effective grade of 3.
[15] Table A1.1 also shows the specific competencies associated with each learning level.
[16] Reading and arithmetic learning levels are highly correlated. Representing the lowest to the highest levels by numbers 1 to 5, the weighted sample correlation between the two is 0.83 for 5-16 year olds (0.77 for 7-10 year olds) for 2012. To be sure, the “max” and “min” are not the only mapping schemes possible; any weighted average of effective reading and arithmetic grades could also be a potential weighting scheme.

or

$$g_j^e = \min\{g_j^e(reading),\ g_j^e(arithmetic)\} \quad (14)$$

By using the higher of the reading or arithmetic effective grade, the "max" mapping scheme, shown in Table A1.2, errs on the side of overestimating learning levels, and thus provides more conservative estimates of learning deficits. The "min" scheme, shown in Table A1.3, on the other hand uses a more stringent definition of effective grade requiring minimum proficiency in *both* reading and arithmetic.[17] We present our main results using the more conservative "max" mapping scheme. Supplementary Tables in Appendix 2 also provide results for the alternative "min" mapping scheme.

### *4.2 Age-appropriate, actual and effective grades*

Table 3 shows the mean age-appropriate, actual and effective grades for 7-10 year old children in rural India for 2008 and 2012. The means are presented for all children within the age group, and also for the educationally deprived amongst them (those with $g_j^e < g_j^p$).

[Table 3 here]

Several features of the estimates in Table 3 are noteworthy, focusing first on the estimates for the more recent year 2012:

(i) The average age-appropriate grade for all 7-10 year old rural children in India is 3.6, while their average actual grade is 3.3 and their average effective grade is 2.9. In other words, the average educational deprivation amongst this young cohort is 0.7 of a grade, which is made up of an average schooling gap of 0.3 of a grade and an average learning gap of 0.4 of a grade.

[17] See Appendix 1 for a detailed discussion of the two mapping schemes.

(ii) Not all the 7-10 year olds are educationally deprived. Amongst those who are so deprived, the mean age-appropriate, actual and effective grades are 4.1, 3.4 and 2.4 respectively. The higher average age-appropriate grade amongst this group relative to 3.6 for all 7-10 year olds signifies that the educationally deprived on average tend to be older by half a year. Their actual and effective grades imply a schooling deficit of 0.7 grades and a learning deficit of 1 grade, and added together a large education deficit of 1.7 grades.[18]

(iii) For this age-cohort, there do not seem to be any sizeable differences between girls and boys with respect to their average actual or effective grades, implying quantitatively similar average schooling and learning gaps. On average, girls have marginally lower schooling deficits (by 0.1 grade) and marginally higher learning deficits (also by 0.1 grade) than boys. The differences though small are nonetheless statistically significant at the national level.

(iv) Both schooling and learning gaps increase with age. Thus, the mean schooling gap increases from 0.1 of a grade for age 7 to 0.6 of a grade by age 10. There is in fact a mean learning surplus at age 7, but a significant learning deficit of one full grade emerges by age 10. The increase of these deficits with age is suggestive of the cumulative nature of disadvantages in schooling and learning.

Turning to comparisons over time, there is a marginal (though statistically significant) increase from 3.2 to 3.3 in the overall average actual grade between 2008 and 2012. However, by contrast, there is a notable deterioration in the average effective grade which declines from 3.2

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[18] With a more stringent definition of effective grade based on the "min" mapping scheme, the educational status of rural Indian children looks considerably more dismal. For instance, the mean effective grade for all 7-10 year olds is 2, implying an average learning gap of 1.3 grades and an education gap of 1.6 grades. Amongst the educationally deprived, the corresponding gaps are 1.7 and 2.2 grades. See Appendix 2, Table A2.1.

in 2008 to 2.9 in 2012. Thus, while there was little change in the average schooling gap, the average learning gap appears to have widened over this period.

### *4.3 Schooling, learning and education deprivation measures*

Mean grades (actual or effective) do not convey much information on the nature and extent of schooling, learning or education deprivations. For these, we need to turn to the deprivation measures which are reported in Table 4. As a stark example, the near equality of the mean actual and effective grades in 2008 (both about 3.2) may suggest that learning deprivations are not a significant concern. The estimates of learning deprivations in Table 4 however show how misleading such an inference would be. For instance, the $D_L(0)$ measure for 2008 shows that almost one-third of the 7-10 year old children experienced learning deprivations with their effective grades falling short of their actual grades.

There was also a high incidence of schooling deprivation in 2008 with about 42% of the 7-10 year olds' in grades lagging behind their age-appropriate grades. The prevailing schooling and learning shortfalls are in turn also reflected in a high proportion (45%) of children with education deprivations.

Comparison across boys and girls also reveals a notable pattern. Schooling deprivation measures for girls in this age group are in fact significantly lower than those for boys, but their learning deprivation levels are significantly higher. Thus, while education deprivation measures for girls are significantly higher than those for boys, this is not owing to their higher schooling deprivation. This holds for all values of $\alpha = 0$, 1 and 2. These estimates suggest that to address the gender disparity in education deprivation, it will be important to address the disparity in learning deprivations between girls and boys.

[Table 4 here]

Table 4 also shows the estimates for 2012 which indicate some striking changes over time. While schooling deprivation declined between 2008 and 2012, both learning and education deprivation increased significantly. In terms of the incidence measures ($\alpha = 0$), the proportion of the 7-10 year old children in rural India with schooling deprivation declined from 42% to 40%, while the proportion with learning deprivation increased from 33% to 42% and those education deprivation increased from 45% to 53%. Similar pattern of a decline in schooling deprivation and an increase in learning and education deprivation is also observed for $\alpha = 1$ and 2. All changes are statistically significant.

## 5. Does the unified framework matter?

We discuss three principle ways in which the unified framework can matter for education policy and evaluation.

### *5.1 Targeting and tracking performance*

One of ways in which the unified measurement framework matters is that conventional schooling and learning measures on their own need not track education deprivation very well. This applies to both the levels of education deprivation as well as changes in levels. For levels, this is illustrated in Table 5 for the education deprivation measure with $\alpha = 0$, which measures the proportion of children with effective grades lagging behind their age-appropriate grades. Forming deciles of India's 568 districts on the basis of $D_E(0)$, the Table reports the proportion of districts in the same decile when alternatively ranked by conventional schooling or learning indicators. The results show that this proportion is relatively small for both 2008 and 2012. For instance, when ranked by decreasing net enrolment rate (NRR) or increasing incidence of schooling deprivation ($D_S(0)$), the extent of overlap is limited to only 11-15% of all districts. Recall that $D_S(0)$ is closely related the adjusted net enrolment rate (section 3.2); hence, its similar performance to NER is not surprising. The overlap across deciles formed with learning measures[19] – such as the average learning score (which we measure by the ratio of mean effective grade to the mean actual grade for the district) or the incidence of learning deprivation ($D_L(0)$) – is higher but still limited to 26-30% of districts. (Note that for these data, the average learning score and $D_L(0)$ perform similarly in tracking education deprivation.) Thus, if we want to target education policy by levels of overall education deprivation, the conventional schooling or learning measures, by themselves, can be a poor guide to such targeting.

[Table 5 here]

How far do changes in conventional schooling and learning indicators offer good guides to changes in education deprivation? Figure 1 plots changes in education deprivation incidence against changes in incidence of schooling and learning deprivation between 2008 and 2012 across India's districts.[20] The Figure shows a sharp contrast: changes in schooling deprivation have virtually no relationship with changes in education deprivation, while changes in learning deprivation track changes in education deprivation rather well.

[Figure 1 here]

This is not a general result, but one specific to the country and the context. The larger point is that schooling and leaning deprivation measures are partial indices, and there is no reason to expect that by themselves they will track either levels or changes in education deprivation well. The finding in Figure 1 that movements in education deprivation are well-tracked by movements in learning deprivation reflects a particular feature of the Indian context for this period where schooling deficits changed little while there was widespread deterioration in

[19] These measures are constructed for only those children who are currently enrolled in school, consistent with conventional test scores-based learning measures which are typically defined for in-school children.

[20] Plots of changes in education deprivation incidence against changes in NER or changes in average learning score are very similar to corresponding plots against changes in $D_S(0)$ or $D_L(0)$ in Figure 1, and hence are not shown.

learning deficits. This takes us to the second potential policy value of the unified measurement framework.

### *5.2 Assessing relative contributions of schooling and learning deficits to education deprivation*

While both schooling and learning deficits contribute to observed education deficits, the unified framework allows us to quantify their relative contributions. Insofar as interventions needed for getting children into school and attending the right grades may be different from those needed to ensure adequate learning in the grades they are attending, a measure of the relative contributions of schooling and learning deficits to overall education deprivation is a useful statistic for policymakers to know.

Following the methodology outlined in section 3.3, the results of the decomposition of education deprivation into schooling and learning components are shown in Table 6. For 2008, the results indicate the schooling and learning components contributed more or less equally to education deprivation. The contribution of the learning component to education deprivation was between 50 to 53 percent. However, by 2012 the learning component's contribution rose substantially to 58-62%. The results also show that the share of the learning component tended to be higher for higher values of $\alpha$. This is suggestive of relatively larger deterioration in learning for those with greater education shortfalls.

[Table 6 here]

The last four columns of Table 6 show the decomposition of the change in education deprivation between 2008 and 2012. As noted earlier, there was a significant deterioration (increase in) in the level of education deprivation for the 7-10 year old children in rural India over this period. The decomposition over time shows that this was entirely driven by the deterioration in learning deprivation; the change in the learning components accounts for virtually all of the change in education deprivation, for all values of $\alpha$, and for both boys and girls. This is indeed the reason why in Figure 1 changes in $D_L(0)$ tracked changes in $D_E(0)$ so well, while changes in $D_S(0)$ did not.

### *5.3 Are average schooling and learning levels too low or is there too much inequality in schooling and learning?*

The third way in which the unified framework offers a useful insight for education policy and evaluation is by assessing how far is education deprivation a matter of low average levels of schooling and learning versus inequality in their distribution. The unified framework directly incorporates information on the distribution of schooling and learning deficits into an overall measure of education deprivation, and thus makes such an assessment possible.

Thus, within our framework one could also ask: how much of the observed levels of education deprivation are on account of the inequality in the distribution of actual or effective grades across children of a given age? We explore this across different states in India by constructing counterfactual education deprivation measures where every child of a particular age in the state is assumed to have the mean actual grade and the mean effective grade for that particular age and state. Table 7 shows the results for measures with $\alpha = 2$; note that measures with $\alpha < 2$ can *increase* with the elimination of inequality in actual and effective grades, and thus not well-suited to quantifying the contribution of such inequality.

The estimates in Table 7 show that for rural India as a whole, inequality in the distribution of actual and effective grades matters a lot. With equalized actual and effective grades in each state-age category, the education deprivation measure for $\alpha = 2$ for rural India is reduced by more than half.[21] The declines in corresponding schooling and learning deprivation measures are even larger. These estimates underscore the importance of reducing the inequality in actual and effective grades, and suggest that an improvement in mean schooling and learning performance may not do enough.

[Table 7 here]

The estimates also show a great deal of variation across states in the contribution of such inequality to education deprivation, ranging from 33 and 40 percent in case of Dadra & Nagar Haveli and Pondicherry to 77 and 75 percent in case of Himachal Pradesh and Punjab. The variation is indicative of the varying importance of improving average schooling and learning levels relative to addressing their unequal distribution for alleviating education deprivation in different contexts, which in turn has implications for tailoring the policy mix to the nature of the problem at hand.

## 6. Conclusion

We see the main contribution of this paper as two-fold. First, it has sought to offer a unified framework for measuring schooling and learning deficits. From such a unified perspective, the key problem in education can be viewed as one of education deficits, i.e. children learning below their age-appropriate learning level. This key problem can be broken into two components, viz. children attending grades that lag behind their age-appropriate grades (schooling deficits), and children learning less than they should be learning in the grades they are actually attending (learning deficits). This simple construct immediately yields a convenient decomposition of education deficits into schooling and learning deficits, which allows us to quantify how much of the education deprivation in any given context is due to one

[21] Note that this stops short of full equalization as differences in mean actual and effective grades across states are still maintained.

type of deficit or another. This is useful information for assessing the nature of the key problem in education in diverse contexts as well as for devising remedial actions to address it.

Second, by casting it within a poverty measurement methodology, our framework explicitly builds in concerns with inequality of schooling and learning outcomes insofar as they impinge on the extent of education deprivation. From this perspective, education indicators based on mean levels of schooling and learning achievements can be deceptive. In many empirical contexts, low (or even zero) mean schooling and learning deficits can coexist with high levels of education deprivation because these deficits for many children are not low. The unified framework directly incorporates this distributional dimension, which again has implications for both assessment and treatment.

The paper has sought to illustrate these contributions and related uses of the measurement framework with an application to rural India. While the application is mainly for illustrative purposes, it highlights several distinctive features of the education problems in one empirical context. We find that more than half of the 7-10 year old children in rural India are educationally deprived, facing either schooling or learning deficits (using fairly conservative learning standards). Learning deficits contributed 58-62% of the overall education deprivation in 2012. Our measures show a significant increase in education deprivation between 2008 and 2012, which was almost entirely driven by the increase in learning deprivation (with little change in schooling deprivation) over this period. The education challenges in the country appear to have worsened since the passage of the Right to Education Act in 2009. The illustration also highlights that dispersion in schooling and learning deficits can matter a great deal for education deprivation; if every child had the mean actual and mean effective grade in their age-group in each state, more than half of the observed education deprivation amongst 7-10 year olds in rural India would be wiped out. There is also evidence of considerable regional diversity in these patterns, which again is important for both education policy and evaluation.

While of independent policy interest for India, the main point of referring to these findings from the perspective of this paper is to illustrate that the measurement methodology lends itself to uncovering such findings in any empirical context. They cannot be generated by conventional education indicators. Only a unified distribution-sensitive measurement framework such as the one proposed in this paper can accomplish this task.

Finally, we note that the implementation of this measurement framework requires a mapping of effective grades from assessed performance in learning tasks, together with a specification of learning standards appropriate to each grade. There would inevitably be some contextual specificity and room for judgement in this specification. It is not our intention to defend the particular mapping schemes deployed in our application as sacrosanct, though they are arguably reasonable. Rather, once a particular mapping scheme is agreed upon, the measurement framework could be put into action to gain insights into how schooling and learning deficits jointly shape education deprivation. Insofar as the framework is deemed useful, it does however have an implication for future data collection in that the learning assessment tasks could be explicitly tailored to the agreed grade-appropriate standards. The ASER and MICS surveys have already moved in that direction, and have also taken the important step of assessing learning for both in-school and out-of-school children (the latter feature distinguishing them from PISA and TIMSS). Future data collection along similar lines can considerably enhance the ready application of the unified measurement framework.

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**Table 1: Distribution of 14-year-olds by current grade**

| Grade | Afghanistan, 2010 | Bhutan, 2010 | Nepal, 2010 |
|---|---|---|---|
| Not enrolled | 50.8% | 17.6% | 13.5% |
| 1 | 0.1% | 0.2% | 0.0% |
| 2 | 0.5% | 0.7% | 0.7% |
| 3 | 1.4% | 1.7% | 2.4% |
| 4 | 2.5% | 4.7% | 4.0% |
| 5 | 5.5% | 8.3% | 7.5% |
| 6 | 8.9% | 17.8% | 12.6% |
| 7 | 11.2% | 18.7% | 17.2% |
| 8 | 11.2% | 18.3% | 18.6% |
| 9 | 5.3% | 8.1% | 15.7% |
| 10 or above | 2.6% | 3.8% | 7.7% |
| Total | 100.0% | 100.0% | 100.0% |

*Note*: Calculations based on data sourced from the Multiple Indicator Cluster Survey IV for Afghanistan, the Multiple Indicator Cluster Survey IV for Bhutan, and the Nepal Living Standards Survey III for 2010.

**Table 2: Learning deficits of children in rural India, 2012**

| Grade | READING (% of children who …) | | | |
|---|---|---|---|---|
| | Cannot read | | | |
| | letters | words | Grade I text | Grade II text |
| **III** | 11.9 | 38.1 | 61.3 | 78.5 |
| **IV** | 7 | 24.6 | 44.5 | 65.4 |
| **V** | 4.6 | 16.6 | 31.9 | 53.3 |
| **VI** | 2.9 | 11.2 | 22 | 40.9 |
| **VII** | 1.7 | 7.3 | 15.1 | 30.9 |
| **VIII** | 1.6 | 5.7 | 11.3 | 23.7 |
| | **ARITHMETIC** (% of children who …) | | | |
| | Can not recognize numbers | | Can not | Can not |
| | 1 - 9 | 10 - 99 | subtract | divide |
| **III** | 8.7 | 39 | 73.7 | 93.3 |
| **IV** | 4.9 | 25.7 | 57.7 | 84.8 |
| **V** | 3.2 | 17.9 | 46.5 | 75.2 |
| **VI** | 2 | 12.2 | 38.4 | 67 |
| **VII** | 1.3 | 7.9 | 30.6 | 58.4 |
| **VIII** | 1.3 | 6.4 | 26.4 | 52.1 |

*Note*: Sourced from ASER Centre (2013). See Appendix 1 for details of the reading and arithmetic tool administered during the survey.

**Table 3: Mean age-appropriate, actual and effective grades for 7-10 year old children in rural India, 2008 and 2012**

| | 2008 | | | | | | 2012 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Age-app. grade** | | **Actual grade** | | **Effective grade** | | **Age-app. grade** | | **Actual grade** | | **Effective grade** | |
| **Mean for all** | | | | | | | | | | | | |
| **Age** | | | | | | | | | | | | |
| **7** | 2 | | 1.93 | (0.006) | 2.51 | (0.008) | 2 | | 1.95 | (0.006) | 2.37 | (0.008) |
| **8** | 3 | | 2.70 | (0.007) | 2.95 | (0.007) | 3 | | 2.75 | (0.007) | 2.74 | (0.008) |
| **9** | 4 | | 3.53 | (0.007) | 3.40 | (0.008) | 4 | | 3.59 | (0.008) | 3.14 | (0.009) |
| **10** | 5 | | 4.34 | (0.008) | 3.67 | (0.007) | 5 | | 4.44 | (0.008) | 3.38 | (0.008) |
| **Boys** | 3.60 | (0.004) | 3.19 | (0.007) | 3.20 | (0.006) | 3.59 | (0.005) | 3.23 | (0.007) | 2.98 | (0.006) |
| **Girls** | 3.58 | (0.004) | 3.21 | (0.007) | 3.13 | (0.007) | 3.59 | (0.005) | 3.29 | (0.007) | 2.89 | (0.007) |
| **Total** | 3.59 | (0.003) | 3.20 | (0.006) | 3.17 | (0.006) | 3.59 | (0.003) | 3.26 | (0.006) | 2.93 | (0.006) |
| **Mean for educationally deprived** | | | | | | | | | | | | |
| **Age** | | | | | | | | | | | | |
| **7** | 2 | | 1.45 | (0.012) | 1.00 | . | 2 | | 1.57 | (0.013) | 1.00 | . |
| **8** | 3 | | 2.23 | (0.011) | 1.71 | (0.004) | 3 | | 2.46 | (0.011) | 1.71 | (0.004) |
| **9** | 4 | | 3.23 | (0.010) | 2.47 | (0.006) | 4 | | 3.39 | (0.010) | 2.43 | (0.006) |
| **10** | 5 | | 4.11 | (0.010) | 3.12 | (0.007) | 5 | | 4.30 | (0.010) | 2.96 | (0.007) |
| **Boys** | 4.10 | (0.006) | 3.26 | (0.011) | 2.52 | (0.007) | 4.08 | (0.006) | 3.41 | (0.010) | 2.43 | (0.007) |
| **Girls** | 4.06 | (0.006) | 3.29 | (0.011) | 2.46 | (0.007) | 4.04 | (0.006) | 3.47 | (0.011) | 2.35 | (0.007) |
| **Total** | 4.08 | (0.004) | 3.27 | (0.009) | 2.49 | (0.006) | 4.06 | (0.004) | 3.44 | (0.008) | 2.39 | (0.005) |

*Note*: Calculations based on ASER 2008 and 2012 data, and using the "max" mapping scheme for effective grades. See section 2 for an explanation of age-appropriate, actual and effective grades, and section 4.1 and Appendix 1 for discussion of the "max" mapping for effective grades. Standard errors in parentheses allow for sample stratification (district-level) and clustering (village-level).

**Table 4: Schooling, learning and education deprivation measures for 7-10 year olds in rural India, 2008 and 2012**

| | 2008 | | | 2012 | | |
|---|---|---|---|---|---|---|
| | $D_S(0)$ | $D_L(0)$ | $D_E(0)$ | $D_S(0)$ | $D_L(0)$ | $D_E(0)$ |
| **Boys** | 0.430 | 0.316 | 0.446 | 0.410 | 0.401 | 0.518 |
| | (0.0026) | (0.0022) | (0.0024) | (0.0027) | (0.0025) | (0.0026) |
| **Girls** | 0.407 | 0.338 | 0.463 | 0.381 | 0.443 | 0.544 |
| | (0.0027) | (0.0024) | (0.0025) | (0.0027) | (0.0027) | (0.0027) |
| **Total** | **0.419** | **0.326** | **0.453** | **0.397** | **0.421** | **0.531** |
| | (0.0023) | (0.0019) | (0.0021) | (0.0022) | (0.0021) | (0.0021) |
| | $D_S(1)$ | $D_L(1)$ | $D_E(1)$ | $D_S(1)$ | $D_L(1)$ | $D_E(1)$ |
| **Boys** | 0.170 | 0.114 | 0.176 | 0.162 | 0.156 | 0.212 |
| | (0.0013) | (0.0009) | (0.0012) | (0.0012) | (0.0012) | (0.0013) |
| **Girls** | 0.161 | 0.126 | 0.186 | 0.149 | 0.178 | 0.230 |
| | (0.0013) | (0.0011) | (0.0013) | (0.0013) | (0.0013) | (0.0014) |
| **Total** | **0.165** | **0.120** | **0.181** | **0.156** | **0.167** | **0.221** |
| | (0.0011) | (0.0009) | (0.0011) | (0.0010) | (0.0010) | (0.0011) |
| | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ |
| **Boys** | 0.083 | 0.049 | 0.082 | 0.078 | 0.071 | 0.101 |
| | (0.0009) | (0.0005) | (0.0007) | (0.0008) | (0.0007) | (0.0008) |
| **Girls** | 0.079 | 0.055 | 0.088 | 0.072 | 0.083 | 0.113 |
| | (0.0009) | (0.0006) | (0.0008) | (0.0009) | (0.0008) | (0.0009) |
| **Total** | **0.081** | **0.052** | **0.085** | **0.075** | **0.077** | **0.107** |
| | (0.0008) | (0.0005) | (0.0007) | (0.0007) | (0.0006) | (0.0007) |

*Note*: Calculations based on ASER 2008 and 2012 data, and using the "max" mapping scheme for effective grades. See section 3 for definition of the schooling, learning and education deprivation measures, and section 4.1 and Appendix 1 for discussion of the "max" mapping for effective grades. Standard errors reported in parentheses allow for sample stratification (district-level) and clustering (village-level).

**Table 5: Schooling, learning and education deprivation measures for 7-10 year olds in rural India, 2008 and 2012**

| **For deciles of districts ranked by $D_E(0)$, the proportion of districts in the same decile when ranked by …** | | **2008** | **2012** |
|---|---|---|---|
| *Schooling measures* | | | |
| Net enrolment rate (decreasing) | *NER* | 0.149 | 0.122 |
| Incidence of schooling deprivation (increasing) | $D_S(0)$ | 0.142 | 0.113 |
| *Learning measures* | | | |
| Average learning score (decreasing) | $\overline{g^e}/\overline{g^a}$ | 0.267 | 0.301 |
| Incidence of learning deprivation (increasing) | $D_L(0)$ | 0.271 | 0.299 |

*Note*: Calculations based on ASER 2008 and 2012 data, and using the "max" mapping scheme for effective grades. The learning measures are calculated for only those currently enrolled in a class.

**Table 6: Decomposition of education deprivation into schooling and learning components for 7-10 year old children in rural India, 2008 and 2012**

| | 2008 | | | | 2012 | | | | Change in | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $D_E(0)$ | $\tilde{D}_S(0)$ | $\tilde{D}_L(0)$ | % share of $\tilde{D}_L(0)$ | $D_E(0)$ | $\tilde{D}_S(0)$ | $\tilde{D}_L(0)$ | % share of $\tilde{D}_L(0)$ | $D_E(0)$ | $\tilde{D}_S(0)$ | $\tilde{D}_L(0)$ | % share of $\tilde{D}_L(0)$ |
| **Boys** | 0.446 | 0.227 | 0.219 | 49.2 | 0.518 | 0.225 | 0.293 | 56.5 | 0.072 | -0.002 | 0.073 | 102.2 |
| **Girls** | 0.463 | 0.222 | 0.240 | 51.9 | 0.544 | 0.217 | 0.327 | 60.1 | 0.082 | -0.005 | 0.087 | 106.7 |
| **Total** | **0.454** | **0.225** | **0.229** | **50.4** | **0.531** | **0.222** | **0.309** | **58.2** | **0.077** | **-0.003** | **0.080** | **103.8** |
| | $D_E(1)$ | $\tilde{D}_S(1)$ | $\tilde{D}_L(1)$ | % share of $\tilde{D}_L(1)$ | $D_E(1)$ | $\tilde{D}_S(1)$ | $\tilde{D}_L(1)$ | % share of $\tilde{D}_L(1)$ | $D_E(0)$ | $\tilde{D}_S(1)$ | $\tilde{D}_L(1)$ | % share of $\tilde{D}_L(1)$ |
| **Boys** | 0.176 | 0.087 | 0.089 | 50.7 | 0.212 | 0.087 | 0.126 | 59.3 | 0.036 | 0.000 | 0.037 | 101.1 |
| **Girls** | 0.186 | 0.087 | 0.100 | 53.4 | 0.230 | 0.086 | 0.144 | 62.6 | 0.044 | -0.001 | 0.044 | 101.8 |
| **Total** | **0.181** | **0.087** | **0.094** | **51.9** | **0.221** | **0.087** | **0.134** | **60.8** | **0.040** | **0.000** | **0.040** | **100.7** |
| | $D_E(2)$ | $\tilde{D}_S(2)$ | $\tilde{D}_L(2)$ | % share of $\tilde{D}_L(2)$ | $D_E(2)$ | $\tilde{D}_S(2)$ | $\tilde{D}_L(2)$ | % share of $\tilde{D}_L(2)$ | $D_E(2)$ | $\tilde{D}_S(2)$ | $\tilde{D}_L(2)$ | % share of $\tilde{D}_L(2)$ |
| **Boys** | 0.082 | 0.040 | 0.042 | 51.3 | 0.101 | 0.040 | 0.061 | 60.6 | 0.019 | 0.000 | 0.019 | 101.1 |
| **Girls** | 0.089 | 0.041 | 0.048 | 53.8 | 0.113 | 0.041 | 0.072 | 63.6 | 0.024 | 0.000 | 0.024 | 99.6 |
| **Total** | **0.085** | **0.041** | **0.045** | **52.5** | **0.107** | **0.041** | **0.066** | **62.0** | **0.022** | **0.000** | **0.022** | **99.5** |

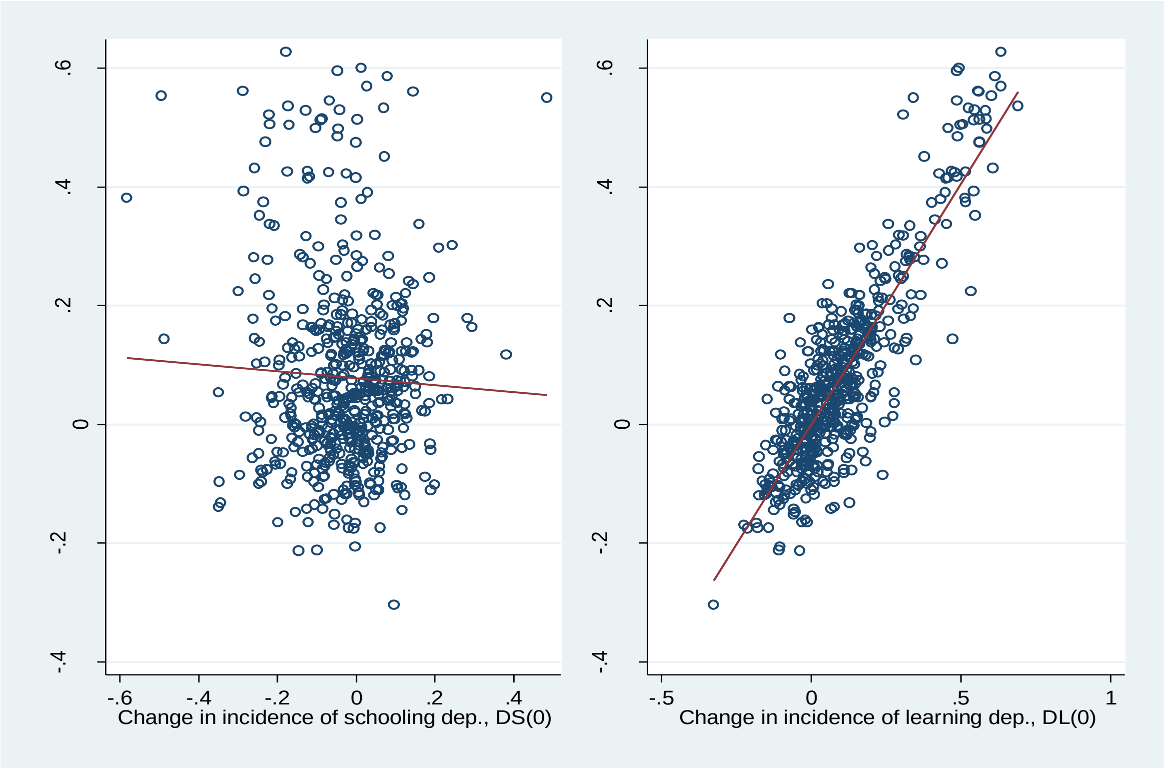
*Note*: Calculations based on ASER 2008 and 2012 data. See sections 3 for an explanation of the decomposition of education deprivation into schooling and learning components; see section 4.1 for discussion of the “max” and “min” mappings for effective grades.

**Table 7: Reduction in schooling, learning and education deprivation with equalized actual and effective grades within each state-age group, 2012**

| State/ Union Territory | Actual | | | With equalized actual and effective grades | | | %age change with equalized actual and effective grades | | |
|---|---|---|---|---|---|---|---|---|---|
| | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ |
| Assam | 0.078 | 0.078 | 0.113 | 0.013 | 0.028 | 0.059 | -83.7 | -63.8 | -48.3 |
| Andhra Pradesh | 0.053 | 0.026 | 0.034 | 0.005 | 0.004 | 0.011 | -91.2 | -86.2 | -68.8 |
| Arunachal Pradesh | 0.061 | 0.033 | 0.044 | 0.003 | 0.004 | 0.013 | -94.4 | -87.1 | -70.7 |
| Bihar | 0.104 | 0.081 | 0.130 | 0.014 | 0.015 | 0.048 | -86.6 | -80.9 | -62.9 |
| Chhattisgarh | 0.053 | 0.082 | 0.113 | 0.009 | 0.036 | 0.066 | -82.1 | -56.1 | -41.4 |
| Dadra & Nagar Haveli | 0.018 | 0.125 | 0.135 | 0.001 | 0.084 | 0.091 | -97.2 | -32.8 | -32.7 |
| Daman & Diu | 0.011 | 0.100 | 0.107 | 0.000 | 0.041 | 0.045 | -96.3 | -59.4 | -58.0 |
| Gujarat | 0.019 | 0.092 | 0.098 | 0.000 | 0.041 | 0.047 | -97.9 | -55.2 | -51.6 |
| Goa | 0.061 | 0.025 | 0.049 | 0.026 | 0.006 | 0.022 | -56.9 | -74.1 | -54.7 |
| Haryana | 0.059 | 0.053 | 0.060 | 0.002 | 0.008 | 0.016 | -96.6 | -84.4 | -73.8 |
| Himachal Pradesh | 0.025 | 0.033 | 0.038 | 0.000 | 0.008 | 0.009 | -99.6 | -76.1 | -76.6 |
| Jammu & Kashmir | 0.100 | 0.040 | 0.061 | 0.025 | 0.008 | 0.028 | -74.6 | -81.2 | -53.9 |
| Jharkhand | 0.092 | 0.081 | 0.117 | 0.010 | 0.021 | 0.050 | -89.2 | -74.3 | -57.8 |
| Karnataka | 0.066 | 0.048 | 0.081 | 0.024 | 0.012 | 0.035 | -62.9 | -75.9 | -56.4 |
| Kerala | 0.025 | 0.028 | 0.029 | 0.000 | 0.007 | 0.008 | -98.4 | -76.4 | -71.1 |
| Madhya Pradesh | 0.049 | 0.126 | 0.138 | 0.001 | 0.066 | 0.076 | -97.6 | -47.6 | -44.7 |
| Maharashtra | 0.067 | 0.058 | 0.096 | 0.028 | 0.017 | 0.049 | -58.0 | -71.6 | -49.1 |
| Manipur | 0.143 | 0.017 | 0.046 | 0.058 | 0.000 | 0.021 | -59.3 | -100.0 | -55.7 |
| Meghalaya | 0.200 | 0.031 | 0.101 | 0.106 | 0.000 | 0.055 | -47.1 | -100.0 | -45.1 |
| Mizoram | 0.118 | 0.013 | 0.040 | 0.039 | 0.000 | 0.016 | -66.6 | -100.0 | -60.1 |
| Nagaland | 0.113 | 0.018 | 0.044 | 0.036 | 0.000 | 0.017 | -67.9 | -99.4 | -61.9 |
| Orissa | 0.033 | 0.109 | 0.119 | 0.001 | 0.038 | 0.046 | -97.9 | -64.9 | -61.7 |
| Punjab | 0.071 | 0.033 | 0.046 | 0.010 | 0.003 | 0.011 | -86.6 | -91.7 | -75.2 |
| Pondicherry | 0.021 | 0.055 | 0.058 | 0.000 | 0.035 | 0.035 | -100.0 | -36.1 | -39.7 |
| Rajasthan | 0.066 | 0.096 | 0.114 | 0.001 | 0.038 | 0.047 | -98.3 | -60.6 | -59.4 |
| Sikkim | 0.097 | 0.015 | 0.034 | 0.020 | 0.000 | 0.014 | -79.6 | -97.3 | -58.8 |
| Tamil Nadu | 0.012 | 0.072 | 0.070 | 0.000 | 0.033 | 0.032 | -100.0 | -54.2 | -54.6 |
| Tripura | 0.099 | 0.028 | 0.074 | 0.064 | 0.008 | 0.036 | -36.0 | -72.9 | -50.6 |
| Uttar Pradesh | 0.128 | 0.100 | 0.158 | 0.025 | 0.030 | 0.082 | -80.9 | -69.9 | -48.0 |
| Uttaranchal | 0.062 | 0.070 | 0.086 | 0.003 | 0.015 | 0.027 | -94.7 | -79.1 | -68.0 |
| West Bengal | 0.068 | 0.061 | 0.086 | 0.007 | 0.016 | 0.032 | -89.7 | -74.3 | -62.5 |
| **India** | **0.075** | **0.077** | **0.107** | **0.012** | **0.025** | **0.049** | **-83.5** | **-67.8** | **-54.4** |

*Note*: Calculations based on ASER 2012 data.

**Figure 1: Changes in the incidence of education, schooling and learning deprivation between 2008 and 2012 across Indian districts**




Note: Based on ASER data for 2008 and 2012.

## Appendix 1: Mapping ASER reading and arithmetic tools into effective grades

To understand the mapping scheme from reading and arithmetic test outcomes to effective grades, first note that the effective grade is defined in "current" terms to ensure temporal consistency with the notion of the current actual grade. Thus, for instance, it is presumed that a child who is currently in grade 5 should at least have the learning level expected at the completion of grade 4. Or, put differently, a child whose actual grade is 5 is assumed to have no learning deficit if she has at least the learning level expected by the end of grade 4; hence in this case, her effective grade is taken to be grade 5. If however she demonstrates a learning competence equivalent of grade 2, then her effective grade is taken to be 3 implying a two-year learning deficit. Finally, it is worth reiterating that because ASER also tested children who are currently not in school, we can define their effective grades in a similar way.

**Table A1.1: Achievement levels for reading and arithmetic tests and associated effective grades**

| | | | | | |
|---|---|---|---|---|---|
| **Reading level:** | **Beginner level** | **Letter level** | **Word level** | **Paragraph level** | **Story level** |
| | Can not correctly recognize at least 4 out of 5 letters shown | Can recognize letters but can not correctly read at least 4 out of 5 words shown | Can read words but can not correctly read a Std I text | Can read a Std I text but can not correctly read a Std II text | Can correctly read a Std II text |
| **Effective reading grade** | 1 or less than 1 | 1 or less than 1 | 1 | 2 | 3 |
| **Arithmetic level:** | **Beginner level** | **One-digit number recognition (1-9) level** | **Two-digit number recognition (11-99) level** | **Subtraction level** | **Division level** |
| | Can not correctly identify at least 4 out of 5 numbers (1-9) shown | Can identify 1-9 numbers but can not correctly identify at least 4 out of 5 numbers (11-99) shown | Can identify 11-99 numbers but can not correctly solve two subtraction problems | Can solve subtraction problems but can not correctly solve a division problem | Can correctly solve a division problem |
| **Effective arithmetic grade** | 1 | 2 | 3 | 4 | 5 |

*Note*: Based on description of reading and arithmetic tests in ASER Centre (2013).

The reading and arithmetic tools administered in the ASER surveys each have five possible levels of achievement, as shown below in Table A1. By administering these tools, the ASER surveys thus assign to each child a reading and arithmetic learning level ranging from the lowest (beginner) level to the highest (story/division) level.

Table A1 also shows the reading and arithmetic effective grades that may correspond to the respective levels of reading and learning achievements. Thus, for instance, the highest story level for the reading test corresponds to the ability to correctly read a grade 2 text; and hence, it may be surmised that a child at the story level has a current reading effective grade of 3, following the logic that a child who has a demonstrated learning level of grade 2 is "qualified" to be currently attending grade 3. Working backwards from the highest level, the effective grades for lower levels of reading ability could be similarly assigned as shown in Table A1. The effective grades for arithmetic are also similarly determined, starting with the highest level of division corresponding to learning level of grade 4 and hence an effective arithmetic grade of 5, and working backwards to lower levels of arithmetic ability.

Next, we combine the reading and arithmetic effective grades into an overall effective grade for a particular child. Note that, given the nature of tests administered by ASER, the range for $g_j^e(arithmetic)$ is 1 to 5, while the range for $g_j^e(reading)$ is 1 to 3 since the maximum degree of difficulty in the reading test was limited to being able to read a grade 2 text. This delimits a 1-5 range for the overall effective grade ($g_j^e$). It also has the further implication that for a 6-year old, by construction, there will be no observed learning deficit because 6-year olds have an age-appropriate grade ($g_j^p$) of 1 and the minimum value of $g_j^e$ for *any* child is 1. At the other end, we also cannot correctly identify learning deficits children age 11 and above, since $g_j^p$ for an 11-year old is 6 while the tests only allow us to identify effective grades up to maximum of grade 5. For this reason, our application is limited to 7-10 year old children only.

For children of age 7-10 years, we use two variations on the mapping scheme, as discussed in the text. The "max" mapping scheme follows the simple rule that the overall effective grade is taken to be the higher of either the effective reading or the effective arithmetic grade. Thus, in case the two effective grades differ for a child, the procedure amounts to conferring the benefit of doubt in favour of a higher level of learning for that child as given by the higher of the two effective grades. This procedure leads to the mapping scheme for effective grades in Table A2.

**Table A1.2: Mapping reading and arithmetic tests into effective grades: the "max" scheme**

| | | READING | | | | |
|---|---|---|---|---|---|---|
| | | **Beginner level** | **Letter level** | **Word level** | **Paragraph level** | **Story level** |
| **ARITHMETIC** | | | | | | |
| | **Effective grade** | **1** | **1** | **1** | **2** | **3** |
| **Beginner level** | **1** | 1 | 1 | 1 | 2 | 3 |
| **Number recognition (1-9) level** | **2** | 2 | 2 | 2 | 2 | 3 |
| **Number recognition (11-99) level** | **3** | 3 | 3 | 3 | 3 | 3 |
| **Subtraction level** | **4** | 4 | 4 | 4 | 4 | 4 |
| **Division level** | **5** | 5 | 5 | 5 | 5 | 5 |

*Note*: The "max" scheme defines a child's effective grade as the maximum of their effective reading grade and their effective arithmetic grade, based on Table A1.1.

The "min" mapping scheme adopts more stringent learning standards and follows the rule of the overall effective grade defined as the minimum of effective reading grade and the effective arithmetic grade. However, as also noted in the text, this "min" rule can only be consistently applied if the effective reading grade is less than three. This is because a child with an effective reading grade of 3 (who passes the story level in Table A1) may in fact have an effective reading grade of 3 or higher, as she could have passed higher levels of reading ability were they tested for higher levels by the ASER survey. But since they were not, we use a modified "min" rule where if the effective reading grade is 3 *and* the effective arithmetic grade is higher than 3, then the higher arithmetic grade is taken to be the best estimate of the child's effective reading grade too, which then renders the overall effective grade equal to the effective arithmetic grade in such cases. This modified "min" scheme is shown in Table A3. While the "min" scheme imposes higher learning standards, it is worth bearing in mind that even the "min" estimates of education deprivation may be considered conservative; being able to do simple division and read a grade 2 text is not exactly setting a high bar for grade 5.

**Table A1.3: Mapping reading and arithmetic tests into effective grades: the "min" scheme**

| | | READING | | | | |
|---|---|---|---|---|---|---|
| | | **Beginner level** | **Letter level** | **Word level** | **Paragraph level** | **Story level** |
| **ARITHMETIC** | | | | | | |
| | **Effective grade** | **1** | **1** | **1** | **2** | **3** |
| **Beginner level** | **1** | 1 | 1 | 1 | 1 | 3 |
| **Number recognition (1-9) level** | **2** | 1 | 1 | 1 | 2 | 3 |
| **Number recognition (11-99) level** | **3** | 1 | 1 | 1 | 2 | 3 |
| **Subtraction level** | **4** | 1 | 1 | 1 | 2 | 4 |
| **Division level** | **5** | 1 | 1 | 1 | 2 | 5 |

*Note*: The "min" scheme defines a child's effective grade as the minimum of their effective reading grade and their effective arithmetic grade, based on Table A1.1.

## Appendix 2: Supplementary Tables

**Table A2.1: Mean age-appropriate, actual and effective grades for 7-10 year old children in rural India, 2008 and 2012: "Min" mapping: Effective grade as minimum of effective reading and effective arithmetic grades**

| | 2008 | | | | | | 2012 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Age-app. grade | | Actual grade | | Effective grade | | Age-app. grade | | Actual grade | | Effective grade | |
| **Mean for all** | | | | | | | | | | | | |
| **Age** | | | | | | | | | | | | |
| **7** | 2 | | 1.93 | (0.006) | 1.42 | (0.007) | 2 | | 1.95 | (0.006) | 1.36 | (0.007) |
| **8** | 3 | | 2.70 | (0.007) | 1.82 | (0.008) | 3 | | 2.75 | (0.007) | 1.70 | (0.008) |
| **9** | 4 | | 3.53 | (0.007) | 2.39 | (0.011) | 4 | | 3.59 | (0.008) | 2.14 | (0.011) |
| **10** | 5 | | 4.34 | (0.008) | 2.83 | (0.010) | 5 | | 4.44 | (0.008) | 2.48 | (0.011) |
| **Boys** | 3.60 | (0.004) | 3.19 | (0.007) | 2.17 | (0.008) | 3.59 | (0.005) | 3.23 | (0.007) | 1.95 | (0.008) |
| **Girls** | 3.58 | (0.004) | 3.21 | (0.007) | 2.13 | (0.008) | 3.59 | (0.005) | 3.29 | (0.007) | 1.96 | (0.008) |
| **Total** | 3.59 | (0.003) | 3.20 | (0.006) | 2.15 | (0.006) | 3.59 | (0.003) | 3.26 | (0.006) | 1.95 | (0.006) |
| **Mean for educationally deprived** | | | | | | | | | | | | |
| **Age** | | | | | | | | | | | | |
| **7** | 2 | | 1.78 | (0.006) | 1.00 | . | 2 | | 1.85 | (0.007) | 1.00 | . |
| **8** | 3 | | 2.56 | (0.007) | 1.28 | (0.003) | 3 | | 2.65 | (0.008) | 1.20 | (0.003) |
| **9** | 4 | | 3.34 | (0.009) | 1.51 | (0.005) | 4 | | 3.46 | (0.009) | 1.46 | (0.006) |
| **10** | 5 | | 4.13 | (0.010) | 2.03 | (0.008) | 5 | | 4.32 | (0.009) | 1.94 | (0.008) |
| **Boys** | 3.56 | (0.005) | 2.98 | (0.007) | 1.48 | (0.004) | 3.59 | (0.005) | 3.11 | (0.008) | 1.43 | (0.004) |
| **Girls** | 3.55 | (0.005) | 3.01 | (0.008) | 1.48 | (0.004) | 3.60 | (0.005) | 3.19 | (0.008) | 1.44 | (0.005) |
| **Total** | 3.56 | (0.003) | 3.00 | (0.006) | 1.48 | (0.003) | 3.59 | (0.004) | 3.15 | (0.006) | 1.43 | (0.003) |

*Note*: Calculations based on ASER 2008 and 2012 data. See section 2 for an explanation of age-appropriate, actual and effective grades, and section 4.1 and Appendix 1 for the "min" mappings for effective grades. Standard errors in parentheses allow for sample stratification (district-level) and clustering (village-level).

**Table A2.2: Schooling, learning and education deprivation measures for 7-10 year olds in rural India, 2008 and 2012: "Min" mapping: Effective grade as minimum of effective reading and effective arithmetic grades**

| | 2008 | | | 2012 | | |
|---|---|---|---|---|---|---|
| | $D_S(0)$ | $D_L(0)$ | $D_E(0)$ | $D_S(0)$ | $D_L(0)$ | $D_E(0)$ |
| **Boys** | 0.430 | 0.647 | 0.756 | 0.410 | 0.697 | 0.807 |
| | (0.0026) | (0.0023) | (0.0022) | (0.0027) | (0.0024) | (0.0021) |
| **Girls** | 0.407 | 0.663 | 0.765 | 0.381 | 0.709 | 0.807 |
| | (0.0027) | (0.0024) | (0.0022) | (0.0027) | (0.0025) | (0.0022) |
| **Total** | **0.419** | **0.654** | **0.760** | **0.397** | **0.703** | **0.807** |
| | (0.0023) | (0.0020) | (0.0019) | (0.0022) | (0.0020) | (0.0018) |
| | $D_S(1)$ | $D_L(1)$ | $D_E(1)$ | $D_S(1)$ | $D_L(1)$ | $D_E(1)$ |
| **Boys** | 0.170 | 0.347 | 0.434 | 0.162 | 0.395 | 0.476 |
| | (0.0013) | (0.0015) | (0.0015) | (0.0012) | (0.0016) | (0.0016) |
| **Girls** | 0.161 | 0.358 | 0.439 | 0.149 | 0.403 | 0.474 |
| | (0.0013) | (0.0015) | (0.0015) | (0.0013) | (0.0017) | (0.0016) |
| **Total** | **0.165** | **0.352** | **0.436** | **0.156** | **0.399** | **0.475** |
| | (0.0011) | (0.0013) | (0.0013) | (0.0010) | (0.0014) | (0.0013) |
| | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ | $D_S(2)$ | $D_L(2)$ | $D_E(2)$ |
| **Boys** | 0.083 | 0.204 | 0.270 | 0.078 | 0.244 | 0.303 |
| | (0.0009) | (0.0010) | (0.0011) | (0.0008) | (0.0012) | (0.0012) |
| **Girls** | 0.079 | 0.211 | 0.272 | 0.072 | 0.249 | 0.301 |
| | (0.0009) | (0.0011) | (0.0012) | (0.0009) | (0.0013) | (0.0013) |
| **Total** | **0.081** | **0.207** | **0.271** | **0.075** | **0.246** | **0.302** |
| | (0.0008) | (0.0009) | (0.0010) | (0.0007) | (0.0010) | (0.0010) |

*Note*: Calculations based on ASER 2008 and 2012 data. See sections 3 and 4.1 and Appendix 1 for an explanation of the deprivation measures, and the “min” mapping for effective grades. Standard errors in parentheses allow for sample stratification (district-level) and clustering (village-level).