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How to Improve Education Outcomes Most Efficiently? A Review of the Evidence Using a Unified Metric

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Abstract

Many low- and middle-income countries lag far behind high-income countries in educational access and student learning. Policymakers must make tough choices about which investments to make to improve education with limited resources. Although hundreds of education interventions have been rigorously evaluated, making comparisons between the results is challenging. This paper provides the most recent and comprehensive review of the literature on effective education programs, with a novel emphasis on cost-effectiveness. We analyze the effectiveness and cost-effectiveness of interventions from over 200 impact evaluations across 52 countries. We use a unified measure—learning-adjusted years of schooling (LAYS)—that combines access and quality and compares gains to an absolute, cross-country standard. The results identify programs and policies that can be up to an order of magnitude more cost-effective than business-as-usual approaches, enabling policymakers to improve education outcomes substantially more efficiently.

KEYWORDS
Education; Cost-Benefit Analysis; Government Policies; Impact Evaluations

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How to Improve Education Outcomes Most Efficiently? A Review of the Evidence Using a Unified Metric

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1 Introduction

The average child in a low-income country is expected to attend 5.6 fewer years of school than a child in a high-income country (World Bank, 2020).[1] Moreover, by the age of 10, 90 percent of children in low-income countries still cannot read with comprehension (Azevedo et al., 2021). With limited resources, policymakers must make tough choices about what to invest in to improve education outcomes, with options ranging from constructing schools to improving school management to deploying new educational software. Making these investment decisions requires comparable data on both the benefits and costs of alternative approaches.

However, the impacts of educational interventions are often reported in ways that make these comparisons difficult. For example, policymakers must choose between interventions that increase the number of years a child stays in school and investments that deliver increased learning during those years, without a good way of comparing progress against these alternative outcomes. Yet the returns to education are often a function of both education quantity and quality (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2015; Psacharopoulos & Patrinos, 2018, 2004). And policymakers want a combination of the two. Politicians and advocates have called for an increase in the number of "years of quality education," a single concept that incorporates both quality and quantity dimensions (Crawfurd, Evans, Hares, & Moscoviz, 2020; McKeever, 2020). There is evidence that some of the benefits of education, including economic growth, are more closely associated with learning (Angrist, Djankov, Goldberg, & Patrinos, 2021), whereas others are associated with years of schooling (Baird, McIntosh, & Özler, 2011; De Neve, Fink, Subramanian, Moyo, & Bor, 2015; Duflo, Dupas, & Kremer, 2021). These two dimensions of education cannot be considered entirely separately. Improving the quality of education has more impact if more children go to school for longer, and programs that increase years of schooling lead to more learning if the underlying education system is of a higher quality.

In this paper, we analyze over 200 educational policies and interventions across 52 countries, identifying the most efficient approaches to improve education outcomes using a unified education measure—Learning-Adjusted Years of Schooling (LAYS)—that combines improvements in both access and quality. By doing so, we make it possible to compare the effectiveness of a broad range of education interventions using a concrete and policy-salient metric.[2] For a subset of interventions for which cost data are available, we include cost-effectiveness analysis and comparisons, which is critical to assessing the most efficient policies to invest in.

We find that while many interventions are not cost-effective, some of the most cost-effective interventions can deliver the equivalent of over three years of high-quality education (i.e., three years of learning in a high-performing country such as Singapore) for as little as $100 per child.

[1] We calculate this based on a measure of expected years of schooling using source data from the UNESCO Institute for Statistics (UIS) compiled for the World Bank Human Capital Index 2020.

[2] In previous work, the concept of LAYS has been used to analyze country-level aggregate performance (Filmer, Rogers, Angrist, & Sabarwal, 2020), which we refer to in this study as "macro-LAYS." In this paper, we adapt the LAYS concept to analyze specific intervention and policy treatment effects, which we refer to as "micro-LAYS."

This finding suggests that despite the huge challenges children and schools face in low- and middle-income countries, from poor health and nutrition of children to weakly performing teachers, the right investments can deliver huge returns, even against the benchmark of the best-performing systems. Some of the most consistently cost-effective approaches include: interventions to target teaching instruction by learning level rather than grade (e.g., "Teaching at the Right Level" interventions and tracking interventions); and improved pedagogy in the form of structured lesson plans with linked student materials, teacher professional development, and monitoring (which includes multi-faceted interventions such as Tusome in Kenya). In India, for example, targeted instruction yields up to 3 to 4 additional learning-adjusted years of schooling per \$100—a gain equivalent to the entire system-level education gap between India and Argentina.[3] In contrast, other interventions such as providing school inputs alone (that is, without necessary complementary changes) perform poorly because they tend not to boost access or learning substantively. Shifting the marginal dollar of government expenditure from low-efficiency to high-efficiency educational investments could therefore yield very substantial benefits per dollar spent.

Another striking result from our analysis is that many interventions that increase participation in schooling are often less cost-effective than interventions that improve the *productivity* of schooling—that is, the amount of actual learning gained while in school. For example, prior reviews have shown that cash transfers can increase schooling. However, those results have not been compared to those of interventions that improve learning directly. We find that cash transfers are not a cost-effective tool to improve LAYS; while they have yielded gains in schooling in systems with low-quality education, they have often done so without improving learning, all at a relatively high cost. By contrast, some policies that improve the productivity of each year of schooling, such as targeting instruction to a child's learning level or structured lesson plans, can yield on average of around 3 additional LAYS per \$100. This does not imply that cash transfers are not a useful tool to improve social welfare in general; indeed, research has shown they can be highly effective in achieving their primary aim of reducing poverty and increasing consumption. Rather, these results suggest that if the goal of governments is to achieve high-quality education, they should invest in policies that improve the productivity of schooling, instead of solely providing additional schooling.

This work contributes to three major literatures. We contribute to the literature synthesizing results from rigorous impact evaluations in education. Previous reviews of educational interventions in low- and middle-income countries include Glewwe, Hanushek, Humpage, and Ravina (2011), Kremer, Brannen, and Glennerster (2013), Krishnaratne, White, and Carpenter (2013), McEwan (2015), Snilstveit et al. (2015), Evans and Popova (2016b), Glewwe and Muralidharan (2016), and Ganimian and Murnane (2016). Our study updates the literature with the most recent and comprehensive set of evaluations and provides cost analysis for many more studies than previous work covered. Nearly all prior global reviews are over a decade old.[4] In the years since these

[3] This calibration does not imply that interventions would necessarily close the gap between country-level education systems, since many interventions are less effective at scale and political economy factors may impede effectiveness at the system-level. Rather, this comparison is meant to illustrate and calibrate the magnitude of effects.

[4] A recent policy review, a report titled "Cost-Effective Approaches to Improve Global Learning" (Akyeampong

reviews, there have been hundreds of additional impact evaluations in education, necessitating an updated review of the literature.

Moreover, gains in prior reviews are often reported in standard deviations rather than against an absolute benchmark. In countries with different levels of inequality in learning, the same absolute increase in average learning on the same test would generate very different standard deviation improvements. When we compare studies using standard deviations as our metric, we impose the assumption that the difference in learning levels between the median and 66th-percentile student in a fourth-grade math class in Kenya is equivalent to the difference in learning levels between the median and 66th-percentile student in a twelfth-grade history class in Peru. A better and more transparent approach to comparing learning gains is to measure them against how long the average student in a high-performing education system would take to make this learning gain (at the appropriate age). This yields a plausible cardinal measure for comparing different types of learning gains: a gain that would take a student in a high-quality system twice as long to achieve is one with twice the educational value.

In addition, current metrics used in the literature make it hard to judge whether the results of a program are worth the cost. If \$100 buys an additional 6 months of schooling for a child, is that a good buy if the quality of schooling is bad? Is \$100 for an increase in test scores of 0.05 standard deviation a good investment? The answers depend on the underlying quality of the additional schooling in the first case and on the underlying heterogeneity in learning outcomes in the second. To this end, our analysis takes this literature a step further by using a metric (LAYS) that enables unified comparisons of studies across access and learning in education, increases comparability of results across studies, and provides clear interpretation of the results in concrete policy terms.

The second literature we contribute to concerns the use of summary measures to inform policy analysis. Such measures have become foundational in public health, macroeconomics, and welfare analysis. In public health, such measures include Quality-Adjusted Life Years (QALY) and Disability-Adjusted Life Years (DALY), which were first introduced in the 1970s and early 1980s (Pliskin, Shepard, & Weinstein, 1980; Torrance, Thomas, & Sackett, 1972; Zeckhauser & Shepard, 1976). While DALYs rely on many assumptions, today they are used widely as the reference standard in cost-effectiveness analysis (Drummond, Sculpher, Claxton, Stoddart, & Torrance, 2015; Murray & Lopez, 1996). In economics, summary measures such as the Multi-dimensional Poverty Index (MPI) (Alkire & Foster, 2011) have enabled researchers to understand poverty as a function of multiple measures, rather than focusing exclusively on income. Our work introduces a summary measure for impact measurement in education.

By setting out the benefits of using LAYS, we hope to encourage more researchers to express their results in common metrics to facilitate comparative analysis. Moreover, by providing a unifying framework with transparent assumptions, we hope to encourage researchers to make greater use

et al., 2023) was produced by the Global Education Evidence Advisory Panel, co-convened by the World Bank, UNICEF, USAID, and FCDO, and builds directly on this paper's academic review results, in large part since it is one of the most comprehensive and up to date reviews.

of standardized learning assessments, which will in turn facilitate more meaningful comparisons across studies. To this end, introducing a common framework – even with imperfect data in the first instance – can make the best use of available data as well as set into motion a cycle of ever more comparable data and comparisons in education over time. This evolution mimics the progression of DALYs and QALYs in the health sector, which started with a framework, assumptions, and a first analysis; over time, the data inputs improved, enhancing the comparability of each underlying study as well as facilitating cross-study comparisons. Even in this first analysis using existing data, our results are broadly robust to a series of tests and alternative choices in the construction of our measure, including alternative specifications of what constitutes high-quality learning, different scaling of test scores, and tests for different distributions of performance within samples and across countries. Moreover, for a subsample of studies with identical test items, we find similar results.

Finally, we relate to a literature attempting to inform government intervention through the use of cost-effectiveness and cost-benefit analysis across a broad range of potential government interventions. Much of this literature conducts cost-effectiveness analyses, but in different ways. For example, higher education analyses typically report the cost per enrollment (Dynarski, 2000; Kane, 2004), and early childhood education studies often report a social benefit-cost ratio (Heckman, Moon, Pinto, Savelyev, & Yavitz, 2010). Hendren and Sprung-Keyser (2020) propose a unified analysis using a new measure of Marginal Value of Public Funds (MVPF) and compare benefit and cost information (expressed in monetary terms) to prioritize among 133 social policies in the United States. Their analysis reveals that investment by governments in low-income children's health and education in the United States has historically had the highest return on investment, with many such policies paying for themselves. Our study similarly demonstrates that there are investments in education interventions in low- and middle-income countries that can deliver large gains at relatively low cost, even when compared against a benchmark of education gains made by children in high-income countries.[5]

This work, like other syntheses and summary measures, has limitations. First, while this is the most comprehensive review of the education literature in low- and middle-income countries to date and covers hundreds of studies, available data are still limited, especially on costs, and many education interventions have yet to be evaluated rigorously. As data inputs improve and the range of evaluated interventions expands over time, the outputs of comparative analysis will also improve. Second, in many cases, studies report learning outcomes only in standard deviations. Our framework is general, allowing use of various learning measurements and units, including standard deviations as well as other metrics. Results are most comparable when comparing studies that use common tests and test items, which we anticipate will become increasingly common, in part motivated by the framework set out in this paper. For now, when incorporating studies that don't use common tests, we use assumptions about the distribution of learning levels in

[5]Of note, many of the studies we review examine individual policies; however, some of the most effective policies we review combine interventions, consistent with recent evidence suggesting coupling interventions has complementarities (Mbiti et al., 2019).

the study area to translate findings from standard deviations into LAYS. Third, because both impacts and costs are measured with imprecision (Evans & Popova, 2016a), it would be unwise to focus on small differences in cost-effectiveness. Rather, this analysis aims to inform broad trade-offs in cases where there are large, consistent differences. For example, we consistently see that as a cost-effective tool for improving LAYS, investments in early childhood development rank higher than cash transfers. This pattern is robust to method, data inputs, and study or country contexts. Fourth, while access to school and learning proxied by test score performance capture important components of education, they do not capture all aspects of education, such as socioemotional learning. However, the combination of these measures represents an improvement over the status quo, where typically only one measure is used. Fifth, context matters. Even for the most cost-effective interventions, policymakers should consider whether contextual conditions support local adaptation of an intervention (Bates & Glennerster, 2017).

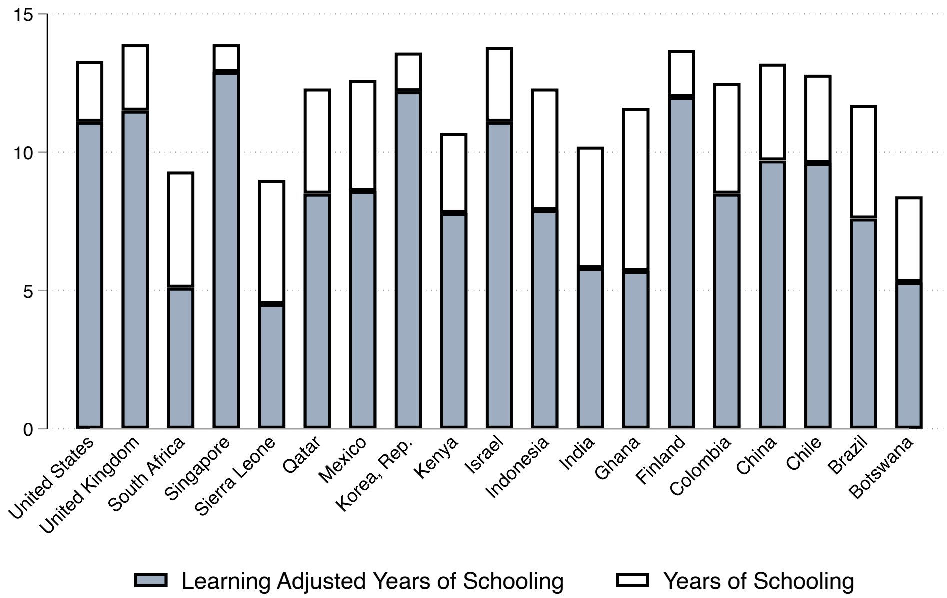
The rest of paper proceeds as follows. Section 2 outlines a framework for learning-adjusted years of schooling. Section 3 describes the set of studies and data included in the analysis of education policies and interventions. Section 4 presents the results in terms of both effectiveness and cost-effectiveness. Section 5 provides a series of robustness tests, and Section 6 concludes.

2 Learning-Adjusted Years of Schooling Framework

Learning-adjusted years of schooling for a given country—what we call macro-LAYS—are the product of years of schooling and a measure of schooling quality (Filmer et al., 2020). Specifically, they are produced by scaling the country's average schooling by its test-score performance relative to a global high-performance benchmark.[6] Figure 1 shows an example using data from the World Bank Human Capital Index. For example, Singapore's average student test scores are closer to the high-performance benchmark than any other country's scores. As a result, its 14 average years of schooling are discounted only slightly, to 13 LAYS. By contrast, South Africa has 10 years of schooling but only about 5 LAYS, because its test scores are only about half of Singapore's. In other words, macro-LAYS are produced at the country level by adjusting average schooling in a given country by the amount of learning in that country (relative to a high-performance benchmark). Expressing national education levels in terms of macro-LAYS provides a unified and user-friendly measure for a variety of education outcomes.

In this section, we show how LAYS can also be used at the micro level to compare specific education interventions and policies. The number of rigorous studies evaluating the effect of interventions on educational outcomes is growing, with around 300 impact evaluations focused on

[6]The high-performance benchmark used in the World Bank Human Capital Index is an artificial benchmark of high performance of 625 as defined by the international assessment Trends in Mathematics and Science Study (TIMSS), which was chosen because that benchmark is stable over time and is apolitical (Kraay, 2019). Other high-performance benchmarks can also be used to construct LAYS estimates. For example, we can use the top-performing country. If Singapore is the highest-performing country in a given year, we can express every country's LAYS in Singapore-equivalent years. That is, we could say that a student in South Africa achieves 10 years of schooling, but 5 years of Singapore-quality schooling.



Notes: Schooling data is based on UNESCO expected years of schooling and learning data is based on Harmonized Learning Outcomes (HLO). The figure highlights the gaps between years of schooling and LAYS due to the quality of learning adjustment that LAYS incorporate.

Source: The Human Capital Index is described in Kraay (2019) and is based on Angrist et al. (2021) learning data and UIS enrollment data.

Figure 1: Years of Schooling and Learning-Adjusted Years of Schooling (Macro-LAYS)

learning outcomes in low- and middle-income countries (World Bank, 2018). A unified education metric would enable better evidence synthesis and clearer policy recommendations. As described below, we aim to address many of the challenges that limit current comparisons—most notably, that access and learning impacts are often discussed separately, and that learning gains can be expressed only relative to local performance. We do this by expressing education outcomes from interventions and policies in terms of LAYS units that offer a single, global, and policy-salient metric. We refer to LAYS gained from an intervention or policy as micro-LAYS.

If impact evaluation studies tested students, and reported results, against internationally agreed test scores such as the Trends in International Mathematics and Science Study (TIMSS), the Programme for International Student Assessment (PISA) or the Early Grade Reading Assessment (EGRA), the translation into LAYS would be straightforward. This is what we would hope to see in future studies. However, this is currently not the norm, and therefore a number of assumptions are needed to translate existing studies into LAYS.[7] To ensure a coherent unifying approach, the

[7] Comparing education gains across age groups and learning levels is methodologically challenging. The learning jump from single-digit subtraction to long division is inherently different from the jump between recognizing letters to being able to read a sentence. But if we conclude these are fundamentally different concepts that cannot be compared, we forfeit the ability to make comparisons across impact evaluations or advise policymakers on the most cost-effective approaches to improving education.

micro-LAYS methodology invokes assumptions similar to those used in constructing country-level macro-LAYS estimates. In this section, we outline the approach to producing micro-LAYS for evaluations that report effects on schooling participation, such as attendance or years of school gained, and subsequently for evaluations that report effects on learning outcomes.

2.1 Micro-LAYS using schooling participation estimates

When studies report effects on schooling participation, micro-LAYS are the product of: (1) the access gains resulting from the intervention and (2) the schooling quality in the country where the intervention took place, measured relative to a global benchmark of high performance. We then multiply these gains by the duration over which the effects of the intervention persist. The construction of micro-LAYS derived from impacts on schooling participation, denoted by superscript p, can be expressed as follows:

$$\text{LAYS}^p = \gamma_i * L_i^h * t$$

where γ_i represents the intervention's impact on access, and L_i^h is a measure of learning for a cohort of students in country i relative to a high-performing benchmark h, such that $L_i^h = \frac{L_i}{L_h}$. Participation estimates include a combination of attendance and current enrollment harmonized to an estimate of the percentage of an additional year of schooling gained.[8] For t, the duration of impact, we use the length of the evaluation, which requires no new assumptions or projections.[9]

2.2 Micro-LAYS using learning estimates

When studies report effects on learning gains, we first express the learning gains from the intervention in terms of a quantity measure, the equivalent years of schooling gained in a given country with "business as usual" learning. For example, if students learned 0.25 standard deviations per year as a result of an intervention in South Africa, and if students typically learn 0.25 standard deviations in a given year in South Africa, then students will have learned a year's worth of South African schooling as a result of the intervention. Second, we apply a global quality-adjustment

[8] We do not include measures of final completed years of schooling, since this is often not observed over the course of a single study.

[9] In principle, various options exist for the time over which the intervention is expected to be effective. These include the length of the evaluation; the remaining school life expectancy; and per single year ($t = 1$). In our main analysis we include analysis over the time of the evaluation, which requires no new assumptions or projections. In the Appendix we include analysis on effects per year, which are similar to cost effectiveness estimates likely since cost and dosage are close proxies. For school life expectancy, consider a case where schools are built in a remote area of Afghanistan, and we observe that the intervention delivers on average an additional year of globally benchmarked high-quality schooling per child over the course of an evaluation. If we assume that students will stay in school once the school is built and that the quality of schooling remains constant, we can then adjust this estimate by the remaining school years (i.e., the number of grades in a given school system minus the grade at which the students entered the school), because we expect students to continue to benefit even after the evaluation period. However, given the current state of data available, projecting effects on learning over time is not possible since too few evaluations have evaluated persistence of learning gains. In the future this approach could become possible as long-run evaluations become more common.

factor to derive the corresponding LAYS. For example, if South African students learn half as much as the high-quality benchmark on an international test, we adjust the one year's worth of South African schooling to reflect that it is worth half a year of globally benchmarked high-quality schooling. In the third and final step, we introduce a time factor t over which effects persist, similar to the calculation for participation estimates.

Formally, we first express the intervention's learning impacts in terms of equivalent years of school gained e. We derive e by expressing learning gained relative to learning in the status quo:

$$e = \frac{\beta_i^{\text{test}}}{\delta_{i,n}^{\text{test}}}$$

where β is the learning gain produced by the intervention per year in country i; *test* denotes the test used to measure learning; and δ is the status-quo learning rate per year in country i.[10] For the status quo learning trajectory, δ, in country i we use national-level learning trajectories n.[11] While many studies typically report learning results in terms of standard deviations, this framework is more general: it can incorporate results using any learning outcome unit. When common tests are used across studies and contexts, or common test items, comparisons are most comparable.

We estimate micro-LAYS derived from impacts on learning, denoted by superscript l. To derive these estimates, we adjust equivalent years of schooling, e, gained in country i by the quality of learning L_i^h in that country relative to learning in a high-performance benchmark country h:

$$\text{LAYS}^l = \overbrace{\frac{\beta_i^{\text{test}}}{\delta_{i,n}^{\text{test}}}}^{\text{equivalent years of school}} * \overbrace{L_i^h}^{\text{learning adjustment}} * t$$

We substitute in terms for $L_i^h = \frac{L_i}{L_h}$. This is analogous to the quality adjustment used in macro-LAYS. We further specify that both the numerator and denominator of the learning-adjustment term are relevant to a given test that is representative at national level n for each country, such that:

$$\text{LAYS}^l = \overbrace{\frac{\beta_i^{\text{test}}}{\delta_{i,n}^{\text{test}}}}^{\text{equivalent years of school}} * \overbrace{\frac{L_{i,n}^{\text{test}}}{L_{h,n}^{\text{test}}}}^{\text{learning adjustment}} * t$$

For the next step we invoke two assumptions. First, we assume that learning is constant along a local trajectory. This assumption, validated along a local learning interval in Filmer et al. (2020), enables conversion of relative levels $L_i^h = \frac{L_i}{L_h}$ into relative rates $L_i^h = \frac{\delta_i}{\delta_h}$, since the relationship is constant. We explore this assumption in more detail in Appendix A as well as

[10]The conceptual notion of expressing learning gains in terms of equivalent years of schooling builds on the methodology used by Evans and Yuan (2019).

[11]National-level learning trajectories are easily interpretable, can be converted to a global metric, have greater data availability, and can be calculated using HLO scores available for 164 countries.

the possibility of incorporating non-linearities. Second, we assume that learning outcomes across tests and samples are comparable. This assumption is not novel: for example, it is implicitly invoked any time standard-deviation effect sizes are compared across studies, which is the dominant practice in the literature on education interventions. We note that this assumption is most robust when learning gains in a given study are based on similar tests to the ones used in computing the learning-adjustment factor. Over time, we expect impacts to be reported using increasingly comparable test items, in part motivated by the framework we put forward in this paper, enhancing the reliability of this assumption. We further explore robustness to this assumption in Section 5. These assumptions simplify our conversion to:

$$\text{LAYS}^l = \overbrace{\frac{\beta_i}{\delta_{i,n}}}^{\text{equivalent years of school}} * \overbrace{\frac{\delta_{i,n}}{\delta_{h,n}}}^{\text{learning adjustment}} * \ t$$

The $\delta_{i,n}$ terms cancel, and we are left with the expression:

$$\text{LAYS}^l = \frac{\beta_i}{\delta_{h,n}} * \ t$$

This expression produces an intuitive metric: the years of h-quality learning from the intervention. For example, assume that an intervention in South Africa yields 0.25σ per year of learning ($\beta_{\text{South Africa}} = 0.25$), and that in Singapore, a high-performance benchmark on international learning assessments, students learn 0.80σ over the course of a given year ($\delta_{\text{Singapore}} = 0.80$). Then we have 0.31 LAYS^l; in other words, the intervention enabled South African students to gain nearly a third of a year's worth of Singaporean-quality schooling.

We use 0.8σ as a general benchmark for high-performing learning rates, based on multiple analyses conducted in Section 5. We use a general high-performance benchmark because it is stable (unlike fluctuating benchmarks based on the performance of a leading country at a given point in time) and non-political. This approach to defining high-quality learning rates is similar to the approach used to define the high-performance benchmark learning level in the World Bank Human Capital Index (Kraay, 2019). In Section 5, we show that micro-LAYS are robust to a range of sensitivity and robustness tests.

2.3 Putting micro-LAYS estimates together

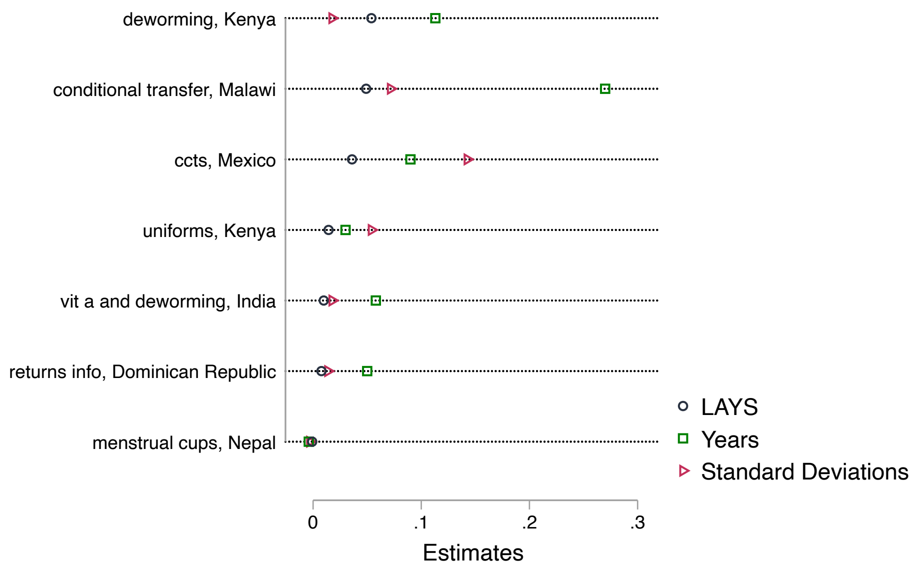
In summary, both participation- and learning-based LAYS tell us that a given intervention in a country produces a certain number of years' worth of globally benchmarked high-quality learning. Thanks to this common unit, the impacts of studies that measure these two different types of outcomes can be directly compared.

We view this framework as a starting point. By providing a unifying framework with transparent assumptions, we hope to both (a) make the best use of the available data which exists today and (b) encourage researchers to make greater use of standardized learning assessments in the future, which will in turn facilitate more meaningful comparisons across studies. To this end, introducing a common framework can make the best use of available data as well as set into motion a cycle of ever more comparable data and comparisons in education over time. This evolution follows the progression of DALYs and QALYs in the health sector, which started with a framework, assumptions, and a first analysis, and over time data inputs improved, enhancing comparability and facilitating cross-study comparisons.

As an illustration of the insights gained by using LAYS, consider the following example. Figure 2 compares LAYS with the raw and standardized estimates per year for a subsample of studies. Standardized effect sizes are the most typical measure used in the education literature to benchmark how large effects are relative to local variation, yet local variation can lead to misleading comparisons. As an example, deworming in Kenya yields 0.113 years of schooling, but only .018 standard deviation gains. Conditional cash transfers in Mexico yield 0.09 years of schooling, and 0.143 standard deviation gains. Thus, while both interventions have similar effects in terms of years of schooling, standard deviations make it appear as if CCTs are eight times more effective as an artifact of local variation.

We find that expressing outcomes in terms of LAYS yields substantive insight and new understanding of which interventions most efficiently improve education outcomes relative to standard deviation comparisons. In the same example, deworming in Kenya yields 0.054 LAYS relative to 0.036 LAYS for CCTs in Mexico. This preserves the original ranking of years of schooling gains and reflects education gains in clear, transparent, and absolute terms. Moreover, we see the added value of capturing the quality of education using LAYS. Incorporating quality, deworming in Kenya pulls a bit further ahead relative to cash transfers in Mexico, since each year of schooling in Kenya produces more learning than in Mexico. The quality adjustment is even more dramatic when comparing deworming in Kenya to CCTs in Malawi, where learning levels are far worse. CCTs in Malawi yield substantially more years of schooling (0.270) than deworming in Kenya (0.113). However, when we account for quality, we see deworming interventions yield 0.054 LAYS, while CCTs in Malawi yield 0.049 LAYS. Thus, using LAYS, we see that deworming interventions enhance education outcomes slightly more than CCTs (and at substantially lower cost). Had we used standard deviations or just years of schooling, our understanding of which education interventions are more effective would be flipped. By adjusting for quality and reducing the influence of local variation, using LAYS allows us to say something about how effective an education intervention is using an absolute, cross-country standard as well as a unified education measure.

One challenge in assembling micro-LAYS estimates is how to handle a study that reports impacts on both participation and learning. If we sum the estimates, we will double-count in cases where gains in learning resulted directly from gains in participation or where gains in learning led to gains in participation (e.g., because students had a greater incentive to attend schools that delivered more learning). As an alternative to adding the two estimates, we could choose to use only estimates from either participation or learning. However, under this approach we would be assuming that one is the central output, and that the other outcome dimension is largely captured within that central output. Instead, for the purposes of this paper, we use the LAYS impact that is greater—whether that was obtained through schooling or learning increases—for each evaluation. This approach places *a priori* equal weight on schooling and learning, introduces no new assumptions, and avoids double-counting.[12]



Notes: a subsample of interventions retrieved from J-PAL studies that focus on school access. Estimates are reported per year. Standardized effects are calculated as $\frac{\mu_i}{s.e._i\sqrt{N_i}}$*, where* μ_i *is the raw estimate,* $s.e._i$ *is the standard error, and* N_i *is the number of observations in the raw estimate's regression for each intervention* i*. This figure highlights the insights gained by using LAYS as opposed to just SDs or additional years of education when comparing the effects of different interventions. Incorporating the quality adjustment allows more informative comparisons of impacts across contexts and interventions.*

Figure 2: Comparing LAYS, Standardized Deviations, and Years of Schooling

[12]Out of the 217 studies in our sample, 35 have both learning and access outcomes, 33 have access only, and 149 have learning only. Out of the subset of papers for which we have both types of outcomes, on average LAYS calculated from learning exceed LAYS calculated from participation in 60% of cases. As more interventions are evaluated using both access and learning outcomes, our understanding of how the two outcomes move together will further improve.

3 Data and Analysis Framework

We compare impact estimates from over 200 evaluations of education interventions in 52 countries using a unified measure. In our comparison, we highlight findings from a subset of studies that have comparable cost data[13] and that therefore allow us to compare cost-effectiveness of interventions. We examine how many LAYS each policy or intervention delivers; how cost-effective those gains are; and how much of the gap between learning-adjusted years of schooling and actual years of schooling that intervention could close if it were scaled up.[14]

We aggregate studies across multiple evaluation databases.[15] We then add studies from the World Bank Strategic Impact Evaluation Fund (SIEF) as well as from a new large-scale data collection effort conducted in partnership with the Global Education Evidence Advisory Panel. This new set of studies draws from multiple rounds of reports as well as a systematic review of education interventions from low- and middle-income countries.[16] In total, we have 363 observations of impact estimates generated by nearly 230 studies, nearly a hundred of which include cost data. Our review nearly doubles the number of cost-effectiveness estimates over earlier analyses, enabling us to draw substantial new insight over prior literature reviews on the state of the education literature in low- and middle-income countries.

Our inclusion criteria are that studies should be based on a credible causal inference strategy, using either randomized controlled trials or quasi-experimental methods, such as differences-in-differences, instrumental variables, regression discontinuity, fixed effects, or propensity score matching. To aggregate across outcomes, we code outcomes such that positive impacts always represent an improvement; for example, a reduction in absenteeism is coded as an increase in attendance. We interpret increases in enrolment rates as increases in the percent of an additional year of schooling gained. Most learning outcomes are reported as standard deviations, but when they are not we normalize them. In the future, we aim to continue adding more studies and build as comprehensive a database of education interventions as possible.

In total, after applying our inclusion criteria, we analyze data from over 200 impact estimates across 52 low- and middle-income countries. The set of studies with cost data that we can include in our cost-effectiveness analysis comprises around 40% of the total sample of studies. The median

[13] Given that there are substantial difficulties when comparing cost data across contexts and interventions, we believe the field will benefit from efforts to standardize how these costs are reported, for example by consistently using $PPP.

[14] For this last analysis, we assume that the effectiveness of the intervention remained constant. This assumption of scalability is not trivial, given that effectiveness at system scale is often substantially lower than effectiveness in even a large pilot study; we therefore carry out this calculation as a calibration exercise rather than a simulation exercise.

[15] These databases include: Evans and Yuan (2019); Ganimian and Murnane (2016); Glewwe et al. (2011); Kremer et al. (2013); Krishnaratne et al. (2013)

[16] The systematic review started with over 13,200 studies. After reviewing abstracts and titles, this list was narrowed to 725 studies, which were then analyzed and further reduced to 325 research papers. Out of these studies, 46 included data on cost. After separating data points by treatment arm, we keep 53 new observations that we integrate into our aggregation of prior study databases and the SIEF database. LAYS analysis of the systematic review and prior evidence reviews have informed multiple Global Education Evidence Advisory Panel (GEEAP) policy reports (Akyeampong et al., 2023).

study in terms of sample size has 2,300 observations, and close to a tenth of our sample includes over 10,000 observations, which we consider large-scale interventions.[17,18] All analyses are carried out at the level of each study's treatment arm.

In our analyses, we calculate the learning adjustment rate (L_i^h) using Harmonized Learning Outcomes (HLO), which are global measures of learning introduced by Angrist et al. (2021) and used in the World Bank Human Capital Index. Angrist et al. (2021) generate comparable learning measures across 164 countries by linking psychometrically-designed international assessments to regional assessments to construct globally comparable learning outcomes at national levels.[19] We choose HLO data over alternative test score data for various reasons. First, these data enable us to use the same learning scale for interventions from 164 countries across the world, a wide range of countries from which we also draw impact evaluation education estimates. Second, these data are used in the World Bank Human Capital Index (HCI), which enables us to produce micro-LAYS that map directly to the macro-LAYS in the HCI.[20]

4 Results

4.1 Aggregate categories of policies and interventions

We first compare results for classes of policies and interventions, rather than focusing on individual studies. To this end, we summarize results by category, such as Early Childhood Development (ECD) or instruction targeted to the child's level of learning rather than grade level. Intervention categories are based on original study designations, with a few adjustments. These adjustments help classify interventions more precisely based on the primary theory of change underlying them. First, we recategorize technology interventions into either "computer assisted learning" or "additional inputs alone" based on whether they involved adaptive software or were largely a hardware-based intervention. We include a separate category for categories that leverage the use of mobile phones specifically to deliver tutoring, which was often targeted to students' learning levels. Second,

[17] While we are able to include a sizeable share of large-scale studies, more large-scale intervention and evaluation is needed.

[18] We provide correlational evidence on the relationship between scale and effectiveness in Table B4. A simple correlation between scale and effectiveness measured in LAYS suggests a negative relationship–effectiveness dilutes with scale. However, we find that the statistical significance of this relationship disappears after including further controls such as country fixed effects or intervention category fixed effects in the regressions. These results suggest some level of effect persistence at scale. This analysis is merely suggestive and far from conclusive.

[19] Of note, HLO scores are calculated within schooling levels (e.g. primary vs secondary). This is both since understanding learning scores is of interest for each schooling level, and since this helps address potential selection issues, with fewer students in secondary school potentially leading to higher test scores due to selection effects rather than true learning gains, rendering comparisons across schooling levels challenging.

[20] The international tests of student learning that are included in the HLO data are often scaled to a mean of 500 and standard deviation of 100. For micro-LAYS, we also derive a learning scale whose lower limit plausibly represents zero learning. We use data from early grade reading assessments (EGRA), where underlying test items have a plausible zero: no reading comprehension. In Appendix Figure B7 we show that the HLO score that corresponds to a floor of zero reading comprehension is 300. In accordance with this, in our analysis we scale the HLO data with a linear transformation of 300. In Section 5, we further explore the sensitivity of results to the score scale.

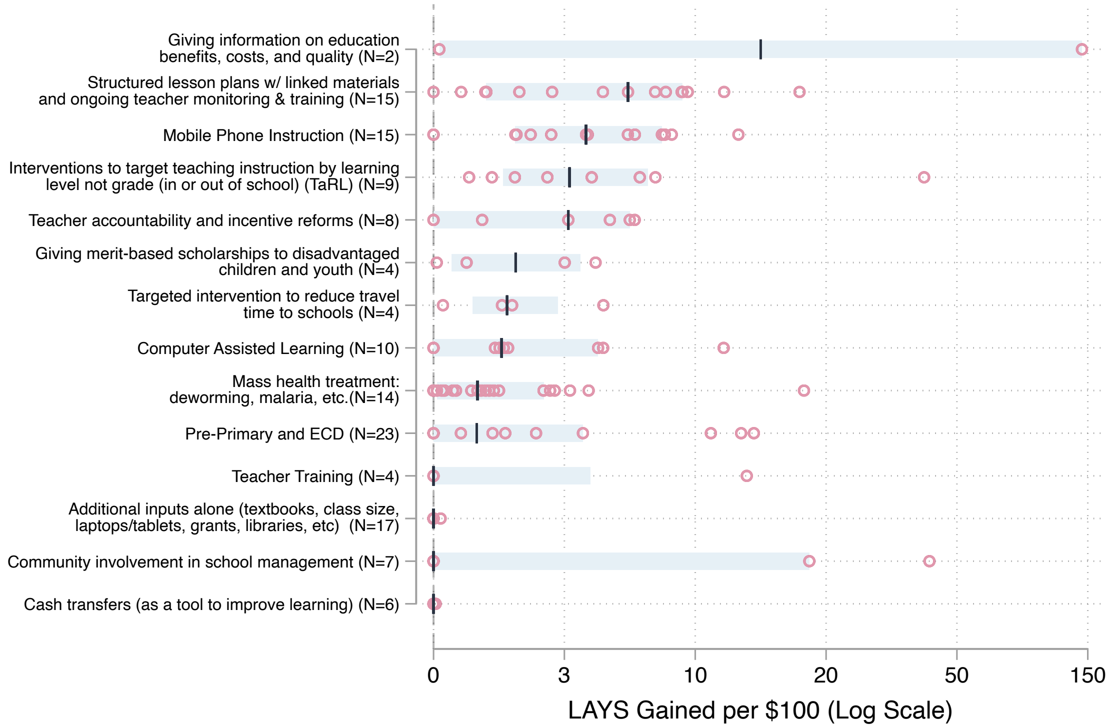
we classify interventions for ECD that involved building or opening of schools or classrooms as "targeted intervention to reduce travel time to schools" alongside other school construction programs. Third, we define teacher training interventions narrowly. Many interventions include training of teachers; for this analysis, when a program provides materials to help teachers target instruction to the level of the child and also provides training to those teachers, we classify that as a "targeted instruction" intervention. "Teacher training" captures only general-skills teacher training programs without other major elements. Fourth, for interventions with multiple components, we selected the central component and used that as a category. Later in the paper, we examine individual studies where we characterize studies more precisely.

Comparative information on effectiveness will be most useful to policymakers when it incorporates information about cost. Therefore, we start by analyzing cost-effectiveness of policies and interventions with a subset of studies where cost information is available. Figure 3 shows the LAYS gained per $100. To calculate this, we divide the per-student gains by the per-student costs. Typical spending in education systems ranges from $208 per student in Sub-Saharan Africa to $7,908 in East Asia in primary school in terms of 2013 PPP USD (Bashir, Lockheed, Ninan, & Tan, 2018). Therefore, cost-effectiveness expressed in terms of LAYS gained per $100 is a metric consistent with many status-quo spending benchmarks, even at the lower tail of system spending.

The top performers, ranked by median effect size, are: targeted information campaigns on benefits, costs and quality; improved pedagogy in the form of structured lesson plans with linked materials and monitoring (which includes combination interventions such as Tusome in Kenya), mobile phone instruction such as targeted tutoring, interventions to target teaching instruction by learning level rather than grade (such as "Teaching at the Right Level" interventions and tracking interventions), teacher accountability and incentives (such as camera monitoring of teacher attendance or merit based pay), scholarships for disadvantaged groups, targeted interventions to reduce travel time to school (for example, constructing schools in remote underserved areas), computer assisted learning (such as adaptive learning software), health products (such as anti-malarial or deworming pills), and early childhood development (ECD) broadly defined. The last four categories in Figure 3-—cash transfers, community involvement in school management (such as training for community members), additional inputs alone (such as textbooks, technology hardware, uniforms, school grants, or reducing class size without complementary reforms), and general skills teacher training—have a zero median effect on LAYS.[21]

We also observe that some categories have low variance—–as in the case of class-size reductions and additional inputs, which are tightly concentrated around zero—–while other categories have high variance. Structured lesson plans produce large gains with relatively low variation, whereas community involvement has a lower average effect but high variation. This indicates that when

[21] These findings fed into, and are consistent with, the Global Evidence for Education Advisory Panel report (2023). Small differences include that here we combine ECD and interventions focusing on pre-primary education into a single category. We do the same for deworming and other mass health treatment interventions. We also group interventions on accountability and finding pathways to hiring educators into a joint group focus on teacher accountability and incentive reforms.



Notes: The figure offers a ranking of the cost-effectiveness of different categories of education interventions. Each category shows the learning-adjusted years of school (LAYS) per $100 USD gained from a given intervention or policy. Each marker represents a cost-effectiveness estimate. The boxplot is ordered from largest to smallest median effects and the shaded boxplot describes the 25th and 75th percentile. The y-axis is reported on a natural log scale. Studies with a negative effect size are set to a value of zero for this figure given they are by definition not cost effective.

Figure 3: Learning-Adjusted Years of School (LAYS) Gained per $100 by Category

considering interventions, we should consider not only the average effect but also the variance. This further points to the importance of contextual relevance: some interventions have similar effects across contexts, while others work extremely well in one context, or under some conditions, but not in others.

Moreover, context is essential to consider across all categories regardless of variation. For example, early childhood development might be most effective in contexts with strong primary education systems where these early investments translate into preparedness for primary school, thus enabling dynamic complementarities (Johnson & Jackson, 2019); providing information on the returns to education may be highly cost-effective in one country but ineffective in a context where those returns are well known; and similarly, a deworming program is unlikely to be cost-effective in a place with low levels of intestinal worms.

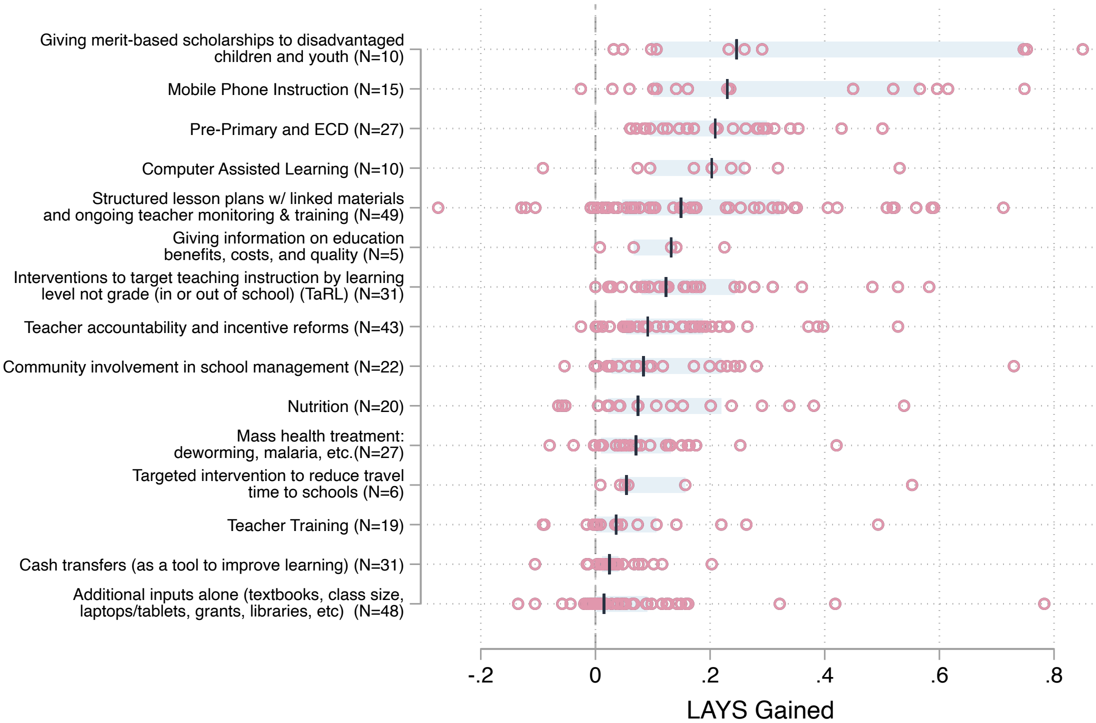
Some of the categories analyzed have moderate effects in absolute terms, but are extremely cheap, making them very cost-effective; an example is providing information on the returns to schooling.[22] Other interventions are highly effective in absolute terms, but are expensive, and are thus moderately cost-effective; these include school construction to reduce travel times to school as well as scholarship schemes. Figure 4 illustrates this difference by ranking the interventions on the median LAYS gained per category. This figure enables us to assess LAYS gains in absolute terms, rather than per $100, and decompose whether an intervention is cost-effective due to being effective, cheap, or both. For example, health products are moderately effective in improving outcomes, with up to 0.2 LAYS gains per child, but are cheap. Thus, in Figure 3 we see these modest absolute gains translate into up to 3 LAYS gained per $100 per child, indicating that these health interventions can be highly cost-effective. Other interventions are highly effective but expensive. Giving merit-based scholarships can yield up to 1 LAYS, but since this policy is relatively expensive, it shifts from being the most effective category to the upper end (but not the highest end) of cost-effectiveness. Finally, Figure 4 also includes a new category: nutrition interventions (such as school feeding), which did not enter the cost-effectiveness analysis in Figure 3 due to a lack of cost data. We observe that school feeding has a positive effect on LAYS, although with high variance, and in future analyses we aim to incorporate more cost data for this category.

We further find that studies with cost-effectiveness data are broadly representative of those with only effectiveness estimates. In Figure B1 we show our full set of studies, highlighting the subset of impact evaluations that include cost-effectiveness data. The most important takeaway from this figure is that, by and large, the subset of interventions with cost-effectiveness data are not systematically biased towards high or low impacts.

Overall, it is important to consider these results in the context of how governments typically spend their budgets. They make substantial investments in textbooks, technology hardware, uniforms, school grants, class-size reductions, and general-skills teacher training. When not well integrated with other interventions, these categories of interventions consistently produce almost no effect. By contrast, investments such as targeting instruction to students' learning levels can yield gains of up to 3 additional LAYS per $100 per child. To this end, shifting the marginal dollar of government investment from status-quo spending to more efficient educational investment could substantially improve education outcomes.

Our unified analysis reveals some important new insights. One is that many interventions that increase participation in schooling are less cost-effective than interventions that improve the productivity of schooling–that is, the amount of actual learning that students gain while in school. For example, prior reviews have shown that cash transfers can increase schooling. However, those results have not been compared to those of interventions that improve learning directly. We find that cash transfers are not a cost-effective tool to improve LAYS; while they yield gains in schooling in systems with low-quality education, they have done so without improving learning across the studies in our sample, all at relatively high cost. This does not imply that cash transfers are not a useful tool to improve social welfare in general; indeed, research has shown they can be highly

[22] For a detailed analysis on interventions that provide information on the returns to schooling, see Evans and Mendez Acosta (2024).



Notes: This figure includes a ranking of LAYS gained across categories of education interventions. Each category shows LAYS gained from a given intervention or policy across over 200 interventions in 52 countries. The boxplot describes the 25th and 75th percentile. The boxplot is ordered form largest to smallest median effects. Note the "nutrition" category has no cost-effectiveness data and does not appear in Figure 3.

Figure 4: Learning-Adjusted Years of School (LAYS) Gained by Intervention Category

effective in achieving their primary aim of reducing poverty and increasing consumption (Fiszbein et al., 2009; Haushofer & Shapiro, 2016). Rather, these results suggest that if the goal of governments is to improve learning, cash transfers might not be the most efficient tool for this specific purpose. By contrast, some policies can yield on average around 3 additional LAYS per $100. We highlight two categories in particular that are both consistently effective and cost-effective, with relatively low variation and a large number of observations: interventions to target teaching instruction by learning level rather than grade (e.g., "Teaching at the Right Level" interventions and tracking interventions);[23] and improved pedagogy in the form of structured lesson plans with linked student materials,teacher professional development, and monitoring. These categories of interventions have also been tested under multiple delivery models and are being scaled by multiple governments, demonstrating their relevance beyond the context of a controlled study. More broadly, our analysis reveals the importance of focusing on policies and interventions that improve the productivity of schooling, rather than solely providing additional schooling.

[23] Angrist and Meager (2023) provide a meta-analysis for a subset of interventions in this literature accounting both for intention-to-treat and treatment-on-the-treated effects showing effects are also generalizable across settings.

4.2 Specific cost-effectiveness studies

4.2.1 Effectiveness and cost-effectiveness

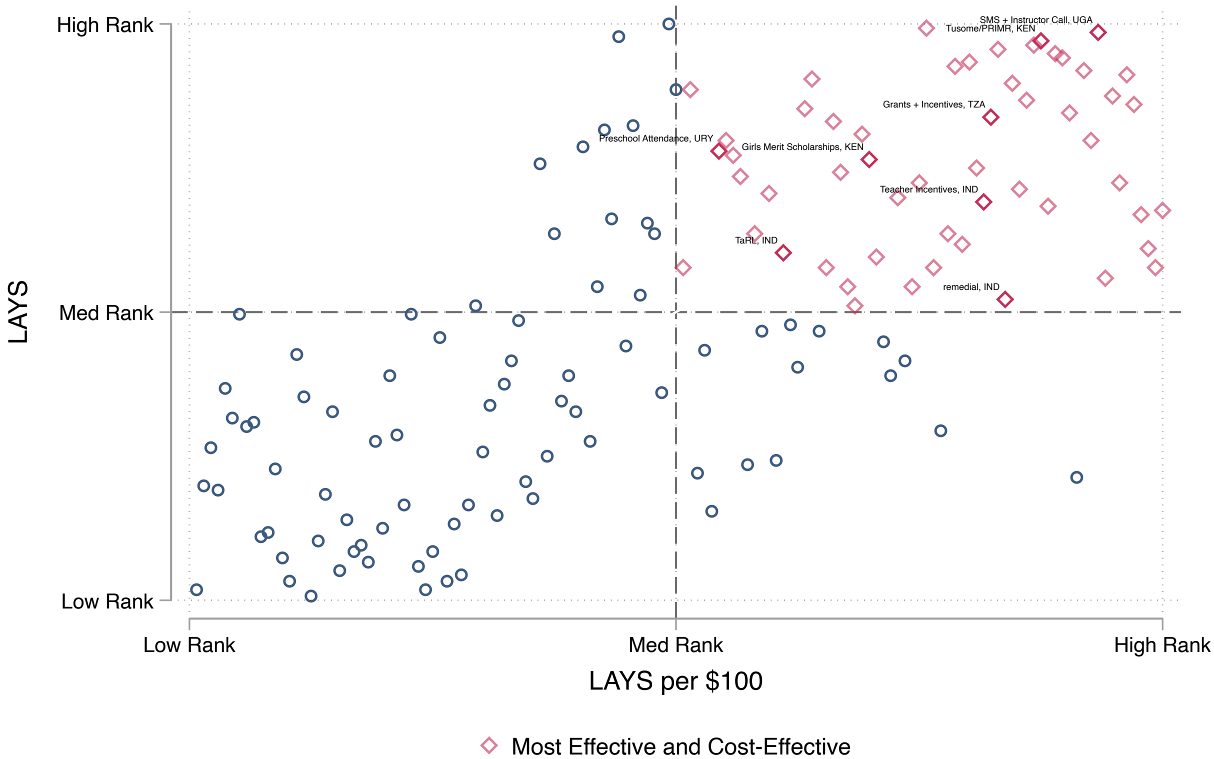
Next, we examine specific interventions to explore the degree to which aggregate patterns might parallel more granular ones or reveal underlying heterogeneity. Figure B2 shows results for absolute LAYS gained by intervention and country for the studies that include cost-effectiveness data. Some of the top performers are: a combined intervention with improved pedagogy, para-teachers and targeted instruction in The Gambia (4.04 LAYS); the Campaign for Female Education (CAMFED) program in Tanzania – a holistic program including scholarships and mentorship for girls, school materials, and training for teachers and parents (1.12 LAYS); phone call tutorials incorporating targeted instruction in Uganda (1.11); Tusome (the Kiswahili word for "Let's Read") in Kenya—a program that provides structured pedagogy via textbooks, teacher coaching, and teacher training (1.04 LAYS); a comprehensive teacher training, structured curriculum, and coaching intervention in Argentina (0.81 LAYS); and an early literacy program in Uganda (0.80 LAYS).

These findings point to a few overall lessons. In this sample of studies, the most effective programs are: multidimensional programs (a combined intervention in The Gambia, Camfed in Tanzania, and Tusome in Kenya); pedagogical instruction that is pitched to students' levels of learning, not based on a rote syllabus or an over-ambitious curriculum;[24] programs that facilitate early childhood development; and programs that are carefully targeted to a local need, such as scholarships for girls.

Figure B3 shows cost-effectiveness estimates for these interventions, expressed in LAYS per \$100. When we take cost into account, several new interventions join the list of top performers–for example, provision of information on the returns to schooling in Madagascar, school links to village councils in Indonesia, tracking and grouping students by their learning level in Kenya, creating community-based preschools in Mozambique, and deworming in Kenya. By contrast, other interventions such as public-private partnerships, scholarship programs, targeted school construction and access, and computer technology-assisted adaptive instruction drop down the list because of their higher cost. However, these programs are still cost-effective in absolute terms.

There are two broader key takeaways from these figures. First, note that relatively few interventions have any positive impact at all. Indeed, over half of interventions reviewed had non-significant effects and are omitted from these figures. Thus, any intervention identified as effective is already near the 50th percentile. Second, the cost-effectiveness of some interventions is an order of magnitude greater than the median. These highly cost-effective interventions include providing information on the returns to schooling in Madagascar, creating school links to village councils in Indonesia, and grouping students by ability level in Kenya. These interventions stand out for being both effective and extremely cheap.

[24] Related approaches to teaching at the right level include reforming the curriculum so that it focuses on foundational skills and aligns better with students' actual pace of learning. Such reforms have been evaluated in Tanzania with promising effectiveness (Rodriguez-Segura & Mbiti, 2022).



Notes: "High rank" means more effective or cost-effective, respectively. We create the high and low rank categories by splitting the sample across the median LAYS and LAYS per $100, respectively.

Figure 5: Effective and Cost-Effective Interventions

The upper-right quadrant of Figure 5 highlights a set of example interventions that are both effective and cost-effective. Some of the programs that do well on both measures include: targeted scholarships (for girls); instruction targeted to student levels through pedagogical interventions, grouping students, and technology; structured pedagogy interventions; and early childhood development programs. We include a more complete list of interventions that fall in this quadrant in Table B1 in the Appendix.

Overall, this exploration of specific interventions reveals consistent patterns with the aggregate categories in Figures 3 and 4. Rather than delivering precise estimates or identifying specific interventions to invest in, this analysis is most useful for the aggregate patterns that it reinforces, such as the relative efficiency of interventions like targeting instruction to children's level or structured pedagogy over input-only reforms. Results for aggregate categories of policies are often most useful to inform prioritization by governments, with specific interventions being determined based on contextual relevance. In Appendix Figures B5 and B6 we explore effects standardized per year ($t = 1$) which show broadly consistent results with our cost-effectiveness analysis.[25]

[25] The pairwise correlations between our measure of LAYS and LAYS per $100 USD, and their per-year counterparts

4.2.2 Calibrating gains from specific interventions and policies to system-level gaps

To explore how specific interventions and policies map onto systemwide gaps, we show how many LAYS a given intervention could contribute towards closing system-level educations in a given country, assuming, as mentioned before, that the nationally scaled-up version of the program was as effective as the evaluated version. Of course, this is rarely the case, and this exercise is meant as a calibration rather than as a simulation. An alternative approach would be to apply a "discount rate" to intervention effectiveness as an intervention goes to scale. In essence, in this exercise we map micro-LAYS onto macro-LAYS. Figure B4 in the Appendix takes cost-effectiveness into account, showing the system-level gap that a given intervention could close at a cost of $100 per child. This analysis reveals that policies which improve the productivity of each year of schooling, such as targeting instruction to a child's learning level, can yield up to 3 additional LAYS per $100 in India – a gain equivalent to the entire system-level education gap between India and Argentina. This calibration illustrates that shifting the marginal dollar of government expenditure from low-efficiency to high-efficiency educational investments could help countries make much more out of the years of education they offer.

5 Robustness

In this section, we present sensitivity analyses of our assumptions and parameter choices. We focus on four main areas: the high-quality learning benchmark, scaling of the learning assessments, standard deviations across tests and samples, and finally a comparison of results using identical tests across different contexts, drawing on new data from a cross-country intervention implemented in four countries (Angrist et al., 2023). Results show that LAYS conversions preserve ranks in line with the 'ideal' scenario which uses identical tests.

5.1 High-quality learning benchmark

We use 0.8σ as a benchmark for high-performing learning rates. As noted above, this value is an artificial high-performance benchmark chosen because it is stable (unlike benchmarks based on actual performance of leading countries) and non-political. This approach to defining high-quality learning rates is similar to the approach to defining the high-performance benchmark learning level in the World Bank Human Capital Index (Kraay, 2019). We explore three approaches to validating this high-performance benchmark: (a) average annual learning trajectories in high-performance cases; (b) policy-relevant learning changes; and (c) rules of thumb and a range of effect sizes in reviews of multiple studies.

The first approach draws on high-performance learning trajectories. Although there is surprisingly little year-on-year raw data on learning, one notable example where there is longitudinal

are 0.91 and 0.92, respectively (see Panels A and B, Table B3). Further, our measures of LAYS per year and LAYS per $100 USD are similar. After having accounted for sample sizes, we find a statistically significant and positive correlation between both measures, likely since dosage and cost are close proxies (Panel C, Table B3).

data is from the Young Lives survey. That survey follows students in India, Vietnam, Peru, and Ethiopia over 15 years and uses learning assessments based on Item-Response Theory (IRT). Using this data and a combination of value-added estimates, instrumental variables, and regression discontinuity methods, Singh (2020) finds that the causal effect of an additional year of primary school in Vietnam is 0.76σ, the largest value among the four countries. This is likely a lower bound for "high performance" on a global scale, since Vietnam—while an excellent performer for its income class—ranks in the second decile of average Harmonized Learning Outcomes (which, as noted above, covers 164 countries from 2000-2017). We can compare these results to an alternative high-benchmark year-on-year comparison: changes analyzed in the United States by Bloom, Hill, Black, and Lipsey (2008), building on methods used by Kane (2004). The largest year-on-year learning gains are between grade 1 and 2, and range from 0.97σ in reading to 1.03σ in math. Finally, we can derive approximate year-on-year changes for global high performers using rescaled HLO benchmarks which yields year-on-year gains of 0.96σ.[26]

The second approach examines large, system-level gains. Here, we explore what would constitute a large learning gain in systemic terms as a way to benchmark what high-performing learning progress would look like. One example is to consider cross-country learning gaps in terms of HLO scores used for the World Bank Human Capital Index. A gain of 0.8σ would enable the United Kingdom or Vietnam to catch up to Singaporean learning levels: because the cross-country standard deviation is equivalent to 70 HLO points, a 0.8σ gain for the United Kingdom (517) or Vietnam (519) translates into nearly closing the gap with Singapore (581). In another example, consider that the black-white achievement gap in the United States in math ranges from 0.99σ to 1.04σ in grades 4 and 8 (Bloom et al., 2008). A gain large enough to nearly close either of these gaps would be highly meaningful in policy terms.

The final approach uses rules of thumb. Cohen (1988) proposed the following standardized effect-size benchmarks: at least 0.20 for "small" effects, 0.50 as "medium" effects, and 0.80 for "large" effects. This framework has been broadly applied across interventions and contexts for decades. However, there is debate about the relevance of these indicators to education interventions, given that almost all interventions in high-, middle-, and low-income countries have much smaller impacts. For high-income countries, the 90th-percentile effect size is 0.47 (Kraft, 2020); for low- and middle-income countries, it is 0.38 (Evans & Yuan, 2022). Both of those fall below the traditional Cohen benchmark for even medium effects.

In summary, these various approaches—particularly those focused on high-performance learning trajectories and meaningful systemic improvements—yield high-performance benchmark learning rates ranging from around 0.8σ to 1.0σ. In this paper, we use an artificial benchmark of 0.8σ for learning gains, which is a conservative high-performance benchmark consistent with this range.

[26] We assume a rescaled high performance score of 325 at the primary level. This score is assumed to be obtained over four years, since most primary international assessments occur in grade 4; average high-performance learning per year is thus 81.25 points. We then assume a within-country standard deviation of 85 points, based on the values for the five highest-performing countries using 2006 PISA microdata. Taking the ratio of these two values yields a year-on-year gain of 0.96σ.

5.2 Test-score scaling

Next, we explore sensitivities to score scales, comparing our results based on scores rescaled via a linear transformation of 300 points to the original HLO score scale. This enables us to use a scale that starts at zero. In Appendix Figure B7, we corroborate this *de facto* floor with data from EGRA, which shows that an HLO score of 300 corresponds roughly to zero percent reading comprehension.

Appendix Figure B8 compares the L_i^h value using the two score scales. While the scale that we use largely does not affect relative ranks, it does affect the degree of the absolute learning adjustment. Using the original scale (vertical axis), the distance between Mexico and Ghana is 0.2; by contrast, under the rescaled version (horizontal axis), the distance is closer to 0.5.

Rescaling mainly reduces the micro-LAYS values that are based on participation impacts—for example, conditional cash transfers in Malawi. This is because under the original scale, the maximum learning adjustment discounted a year of school in Malawi by about half, since the *de facto* floor of the HLO scale was 300, which produced a learning-adjustment factor, L_i^h, of 0.48 relative to the high-performance benchmark of 625. Under the rescaling, the minimum learning factor converges to zero, and the learning adjustment factors drop substantially, reducing participation-based LAYS estimates. As an example, the learning adjustment in Kenya shifts from an original L_i^h of 0.73 to 0.48, while countries on the lowest tail of distribution, such as Malawi, shift from a learning-adjustment of 0.57 to 0.18. The rescaling does not affect the computation of learning-based micro-LAYS, since those values are derived relative to an artificial high-performance benchmark of 0.8σ. However, as an added sensitivity test, we can use the old scale to derive a new corresponding high-performance benchmark of 1.6σ. Overall, our findings are not affected by using these alternative definitions of LAYS. We show in Table B2 that the correlation between rescaled measures as well as their rankings all have correlations above 0.98.

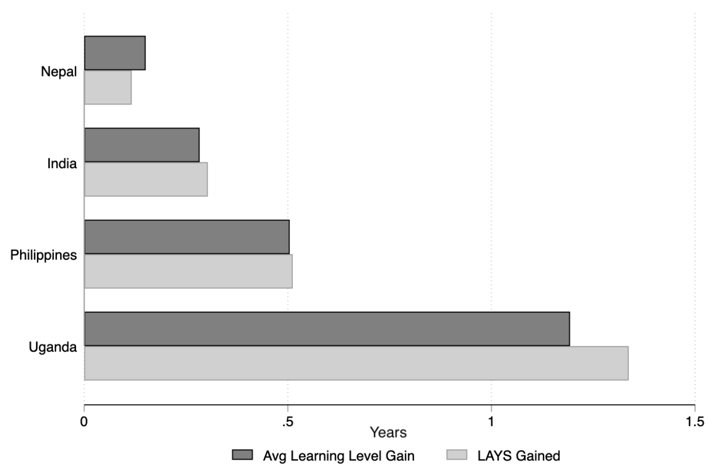
In the main results presented in this paper we use micro-LAYS based on rescaled scores. Since the lowest-performing countries are already far behind, rescaling scores is unlikely to yield major new insights and will not change ranks. Overall, rescaling is our preferred approach given it reflects null levels of reading comprehension, which correspond to the *de facto* floor of HLO scores. This allows us to focus on the range of scores where we see meaningful learning occur.

5.3 Standard deviations across tests and samples

We test sensitivity of our results to differences in standard deviations across tests and samples. Standardized effect sizes are used to account for differences across measurement scales and express those effects in relative terms. This should prove useful when comparing effect sizes in education across various assessments and scales. However, standard deviations will not account for whether a given test is either “too hard” or “too easy”, causing floor or ceiling effects. We test for this possibility empirically by comparing standard deviations from tests on nationally representative samples, chosen to ensure that the same underlying population is represented. We focus on primary-level tests for countries that have participated in multiple tests and that have interventions featured in this paper. Appendix Figure B9 compares standard deviations for Tanzania, Malawi, and Indonesia using various assessments: HLO scores derived from EGRA, Progress in International Reading Literacy Study (PIRLS), raw EGRA or Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) tests. We find only small differences of a few points, and as a result, the estimated learning rates per year across assessments are quite similar, as shown in Appendix Figure B10. As a robustness check, Appendix Figure B10 also shows learning rates per year using raw data from the assessments before they are converted to HLO scores.

5.4 Comparing LAYS with identical underlying test items

An 'ideal' comparison would involve comparing an intervention's effectiveness across contexts using identical underlying test items. While such common assessment is rare in the education sector, a recent study by Angrist et al. (2023) involved a large-scale randomized trial across several countries using the same tests in each context. These assessments were adapted from the ASER numeracy test, which has been widely used in the literature (Banerjee et al., 2017). The common assessment captures core competencies including addition, subtraction, multiplication, and division. Figure 6 compares the average level gained across four countries– India, Nepal, the Philippines, and Uganda–that implemented a phone call tutorial intervention targeting instruction to students' learning levels. First, we estimate the average level gained, coded 1 for each additional proficiency learned. The figure also shows the impact of each intervention measured using LAYS units. We see that the ranking of impacts is preserved. This analysis highlights the value of using comparable tests to measure the impact of interventions across contexts, as well as the substantial degree of robustness of the LAYS metric to the ideal scenario of comparisons using common test items.



Notes: Average level refers to mean proficiencies gained (e.g. addition to division). The data come from a large-scale randomized trial using identical tests across contexts from Angrist et al. (2023). The figure highlights the value of using common metrics to measure the impact of interventions across contexts and the robustness of LAYS as a measure.

Figure 6: LAYS vs. Common Test Item Learning Level Gains

6 Conclusion

In this paper, we analyze which investments most efficiently improve education outcomes. Expanding on previous reviews, we analyze over 200 interventions and policies across 52 countries using a unified education measure: learning-adjusted years of schooling. A central insight from this analysis is that many interventions that increase participation in schooling are less cost-effective than interventions that improve the productivity of schooling—–that is, the amount of actual learning gained. Policies that improve the productivity of each year of schooling, such as targeting instruction to a child's learning level or improving pedagogy through structured lessons plans and coaching, can yield large gains in LAYS, narrowing the gap between high- and low-preforming education systems globally. These results should be interpreted with context in mind: challenges should be identified locally and global evidence should then be used to identify possible cost-effective solutions, which should then be carefully adapted to the local context.

We provide the most comprehensive synthesis of rigorous evaluations to date in education in LMICs focused on cost-effectiveness. Results provide guidance on which policies and interventions are the most efficient investment in education, given the state of evidence and data available today. This paper further strengthens the foundation for the use of LAYS as a common metric for the economic evaluation of education interventions. Similar unified metrics have played important roles in public health, macroeconomics, and economic welfare analysis, but to date no reference standard exists for education cost-effectiveness analysis, and approaches to comparative analysis have been *ad hoc*. Using micro-LAYS to express impact sizes achieves three goals: (a) it places attainment and learning outcomes on a unified scale, allowing interventions to be compared directly; (b) it expresses educational outcomes in terms of an easy-to-interpret measure that improves incentives for policymakers to promote both quantity and quality of schooling; and (c) it identifies levers for countries to close gaps between their current performance and the high-quality schooling that they aspire to. Recent research suggests that policymakers may not reap political benefits from learning gains alone (Habyarimana, Opalo, & Schipper, 2020), yet an additional year of schooling can lead to very different levels of learning (Singh, 2020; World Bank, 2018). Using LAYS as a metric of progress allows a focus on additional years and learning together. At the same time, the LAYS framework also helps make a clear case for future impact evaluations to use common approaches to measuring learning. This shift would greatly improve the likelihood that policymakers can make informed decisions about which interventions to prioritize and scale up.

The LAYS metric has recently been incorporated into large-scale policy efforts to improve education. It is a component of the World Bank's recently launched Human Capital Index (World Bank, 2019), and is being used by the Global Education Evidence Advisory Panel, World Bank, UNICEF, USAID, and United Kingdom's Foreign, Commonwealth & Development Office (FCDO) to prioritize cost-effective education investments. These efforts demonstrate the value of the analysis in this paper to provide a useful tool and synthesis for policymakers, researchers, and decisionmakers who are seeking to address persistent gaps in access and learning worldwide.

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Appendices

Appendix A Constant average learning trajectories

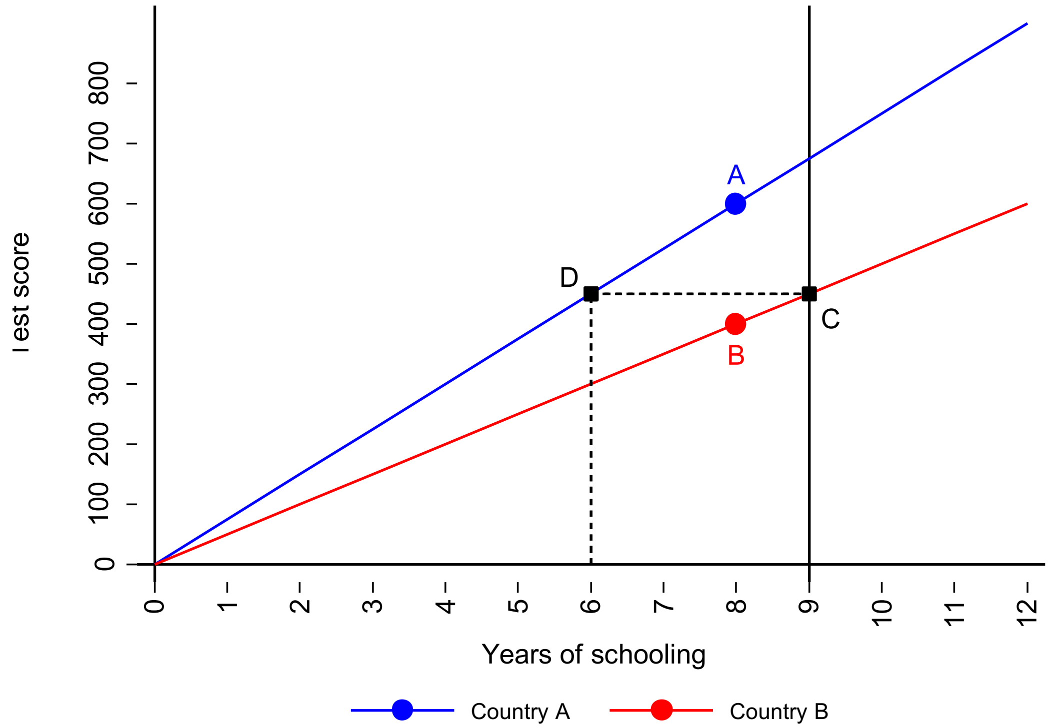
The assumptions invoked in the construction of macro-LAYS are explored in depth in Filmer et al. (2020). Here, we highlight one assumption: constant average learning trajectories, or the idea that students learn the same amount with each additional year of schooling.[27] Figure A1 shows the utility of this assumption using a hypothetical example. Assume that we observe Grade 8 test scores of 600 for Country A and 400 for Country B and that individuals in Country B average 9 years of schooling. LAYS allow us to "convert" the 9 years of schooling in Country B into the number of years of schooling in Country A that would have produced the same level of learning. Moving along the average learning profile from Grade 8 allows us to infer what Country B's average score would be if its students were tested in Grade 9. This calculation is represented by the move from point B to point C, or from a test score of 400 to 450. The next step is to go from point C to point D, to find the number of years of schooling that it would take in Country A to produce that level of learning (450) given the average learning profile in Country A. In this example, it takes 6 years, so the resulting LAYS measure in Country B is 6. Both steps of the calculations rely on the linearity assumption, because we do not have data on the actual learning trajectories but rather on learning at one point in time for each country.

How realistic is this assumption? Filmer et al. (2020) explore this question with a series of empirical tests on whether learning trajectories are constant on a locally defined interval. Figure A2 showcases one example using data from India's Annual Status of Education Report (ASER), which administers the test consisting of the same questions to students from ages 5 to 16, covering Grades 1 to 12 (ASER Centre, 2018). The ASER data enable us to assess the rate of learning with a stable, comparable metric across grades and over time. To allow us to map out the specific trajectory for learning in school, we restrict our sample to school-going children.[28] In the case of a mathematical skill, division, Figure A2 shows that students learn along an "S-shaped" learning trajectory, but with a locally linear interval from Grades 5 to 10. Other, more complex skills than division are likely to have a linear learning trajectory across an even wider interval because they cannot be mastered so quickly.

The other empirical tests in Filmer et al. (2020) also yield results consistent with the linearity assumption (at least over a significant local interval). This includes using quarter of birth instruments from PISA data to estimate the causal effect of a year of school and predicting learning trajectories, which, assuming linear learning trends, align with PISA learning outcomes in later years, validating the linear learning trend assumption. Filmer et al. (2020) explore a series of additional robustness tests. Our assumptions for micro LAYS are consistent with macro LAYS.

[27] This framework focuses on learning within schools. Clearly, not all learning happens within schools. However, learning outside schools is beyond the scope of this exercise. For a fuller discussion see Filmer et al. (2020).

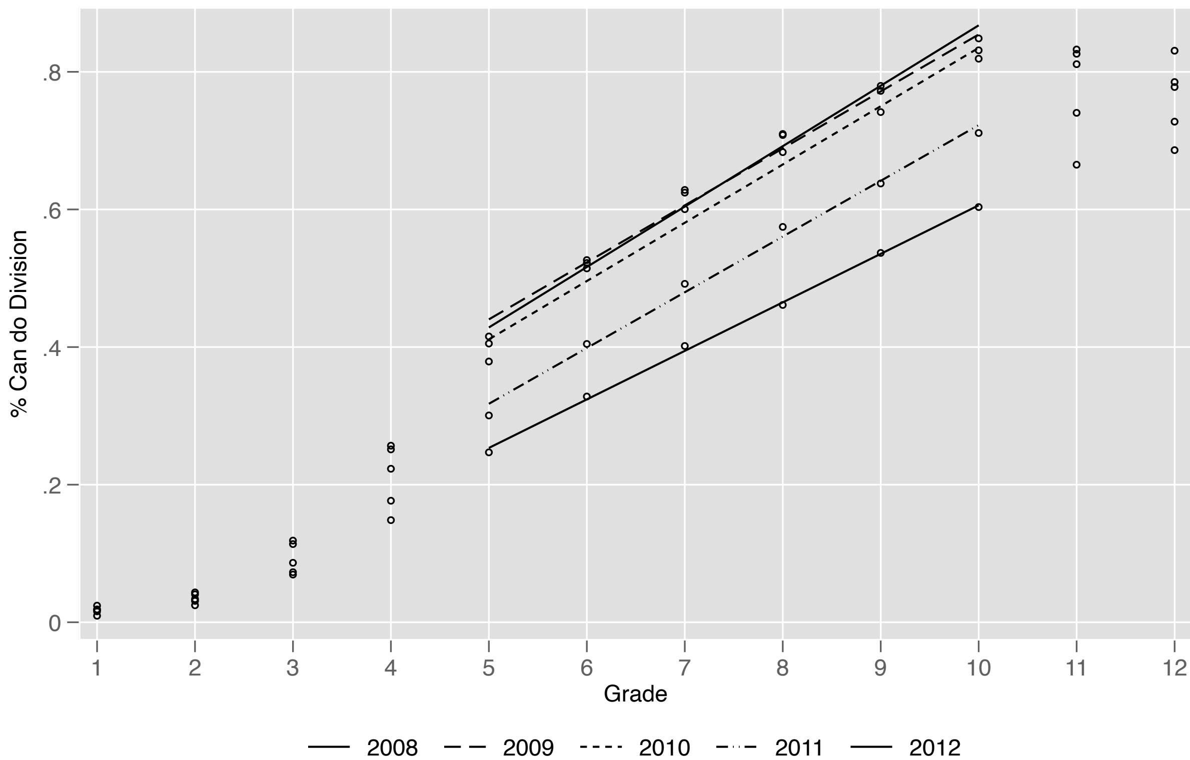
[28] This comparison is conducted across different cohorts of students at different grades.



Notes: We map hypothetical learning trajectories in countries A and B to demonstrate the utility of the assumption of constant learning trajectories. The ratio between the observed scores for a high performing country (A) and a low-performing country (B) is 2/3. We use this as the ratio between the slopes of the hypothetical linear learning trajectories. The slope of the learning trajectory of B is 2/3 the slope of the learning trajectory of A. We could think of this ratio as the "exchange rate" between learning across country A and B. In this context, a student in 9th grade in country B (point C) would have the educational attainment of a 6th grade student in country A (point D).

Figure A1: Constant Learning Trajectories

The linearity assumption can be generalized further. The most general version of the assumption is that learning trajectories can be traced across grades using the data available. If two data points exist, linearity enables tracing of the curve between grade level equivalents, whereas if learning trajectories are non-linear two data points would not be enough to trace the learning curve. However, if more datapoints are available, learning trajectories could be non-linear. In practice, since data on learning remains limited and rarely exists across more than two points in time, linearity is a convenient assumption. But as measurement of learning outcomes becomes ever more common across more grade levels, this framework could be expanded to non-linear learning trajectories.

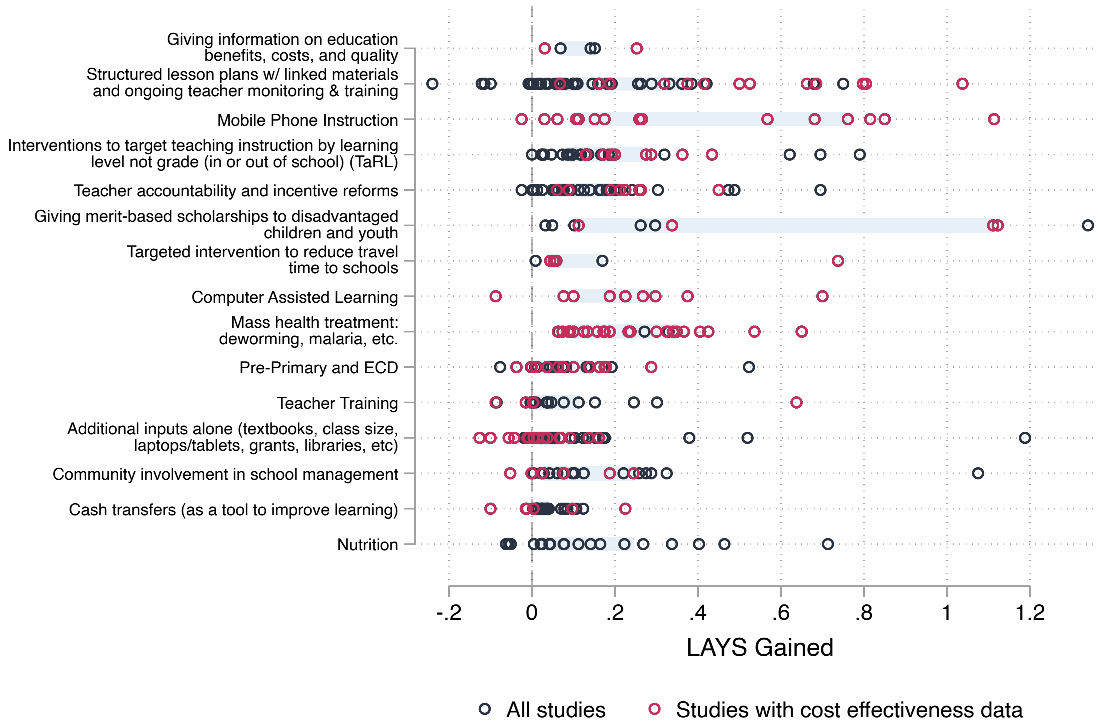


Notes: We derive learning trajectories using empirical data from a national survey conducted in households in India for students aged 5 to 16 in grades 1 through 12. We include only students at the household who are in school.

Source: ASER India data from 2008 to 2012 as analyzed by Filmer et al. (2020).

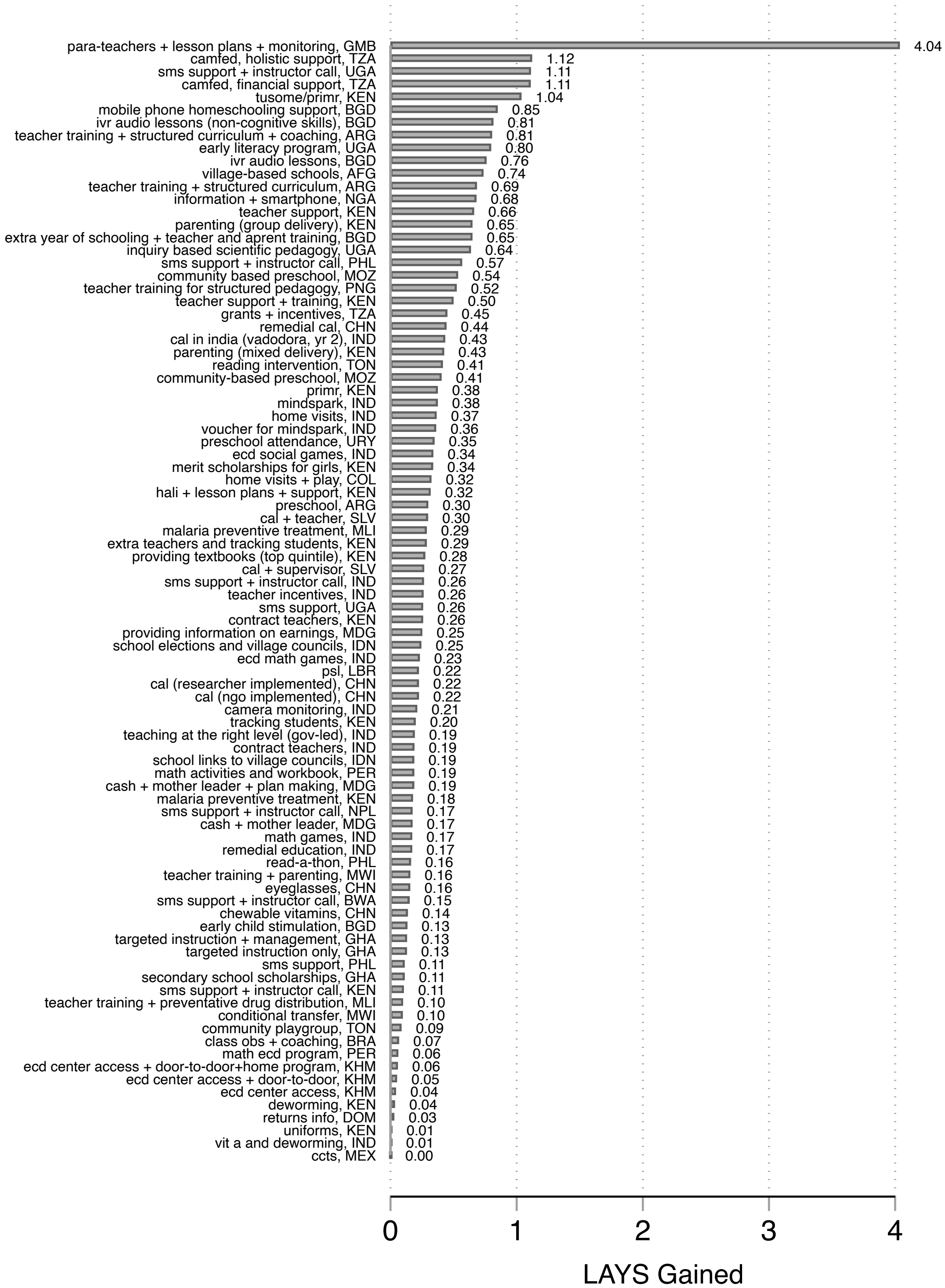
Figure A2: Learning Trajectories in India

Appendix B Additional Figures and Tables



Notes: Each category of education intervention shows the learning-adjusted years of school (LAYS) gained from a given intervention or policy across over 200 interventions in 52 countries. The boxplot describes the 25th and 75th percentile. The boxplot is ordered in the same order as Figure 3 to provide a direct analogy, with the exception of the "nutrition" category which has no cost-effectiveness data and does not appear in Figure 3.

Figure B1: Learning-Adjusted Years of School (LAYS) Gained by Intervention Category



Notes: We rank interventions by their LAYS. We do not include interventions with non-significant impacts, which by definition are not cost-effective.

Figure B2: Learning-Adjusted Years of Schooling (LAYS) by Intervention

Table B1: Interventions with Above Median Rank in Cost Effectiveness and Effectiveness

Intervention	LAYS per $100 USD	LAYS
providing information on earnings, MDG	140.988	0.252
school links to village councils, IDN	43.275	0.188
tracking students, KEN	41.487	0.200
school elections and village councils, IDN	16.675	0.245
community based preschool, MOZ	15.966	0.536
teacher training + structured curriculum, ARG	15.400	0.685
inquiry based scientific pedagogy, UGA	9.957	0.637
malaria preventive treatment, KEN	9.495	0.179
sms support + instructor call, UGA	9.281	1.114
primr, KEN	8.214	0.375
remedial cal, CHN	8.183	0.700
teacher support + training, KEN	5.978	0.500
early literacy program, UGA	5.705	0.798
teacher training + structured curriculum + coaching, ARG	5.663	0.805
sms support, UGA	5.175	0.259
tusome/primr, KEN	4.900	1.038
mobile phone homeschooling support, BGD	4.859	0.850
sms support + instructor call, PHL	4.729	0.567
providing textbooks (top quintile), KEN	4.450	0.275
teacher support, KEN	4.440	0.663
remedial education, IND	3.838	0.172
ivr audio lessons (non-cognitive skills), BGD	3.659	0.815
grants + incentives, TZA	3.652	0.450
teacher incentives, IND	3.481	0.262
hali + lesson plans + support, KEN	3.422	0.319
ivr audio lessons, BGD	3.418	0.761
camera monitoring, IND	2.850	0.213
village-based schools, AFG	2.662	0.738
cal (ngo implemented), CHN	2.656	0.225
remedial cal, CHN	2.517	0.188
camfed, holistic support, TZA	2.450	1.122
extra teachers and tracking students, KEN	2.350	0.287
cash + mother leader, MDG	2.272	0.175
sms support + instructor call, IND	2.208	0.265
contract teachers, IND	1.802	0.190
merit scholarships for girls, KEN	1.725	0.338
community-based preschool, MOZ	1.525	0.405
read-a-thon, PHL	1.475	0.162
sms support + instructor call, NPL	1.458	0.175
preschool, ARG	1.438	0.300
cal in india (vadodora, yr 2), IND	1.388	0.434
cash + mother leader + plan making, MDG	1.319	0.188
information + smartphone, NGA	1.101	0.681
teacher training for structured pedagogy, PNG	0.927	0.525
teaching at the right level (gov-led), IND	0.863	0.192
cal + supervisor, SLV	0.768	0.268
cal (researcher implemented), CHN	0.710	0.225
cal + teacher, SLV	0.656	0.298
ecd social games, IND	0.650	0.340
mindspark, IND	0.599	0.375
preschool attendance, URY	0.585	0.349
parenting (group delivery), KEN	0.531	0.650
math activities and workbook, PER	0.498	0.188
extra year of schooling + teacher and aprent training, BGD	0.489	0.650

Notes: This table reports the interventions that fall in the top-right quadrant of Figure 5. These are interventions that are highly effective and cost-effective.

Table B2: Pairwise Correlations Between LAYS and Unscaled LAYS

Panel A: LAYS			
LAYS	1.000		
LAYS Unscaled (Learning conversion rates)	1.000	1.000	
LAYS Unscaled (1.6σ Performance Benchmark)	0.978	0.978	1.000

Panel B: Ranks			
LAYS	1.000		
LAYS Unscaled (Learning conversion rates)	1.000	1.000	
LAYS Unscaled (1.6σ Performance Benchmark)	0.988	0.988	1.000

Notes: Panel A shows the pairwise correlations between LAYS under alternative definitions: our baseline definition, and two definitions where we use different learning benchmarks. Panel B shows the pairwise correlations between the rankings generated by our baseline definition of LAYS and the two alternative definitions. Our baseline definition is robust to these alternative definitions given the extremely high correlations between them.

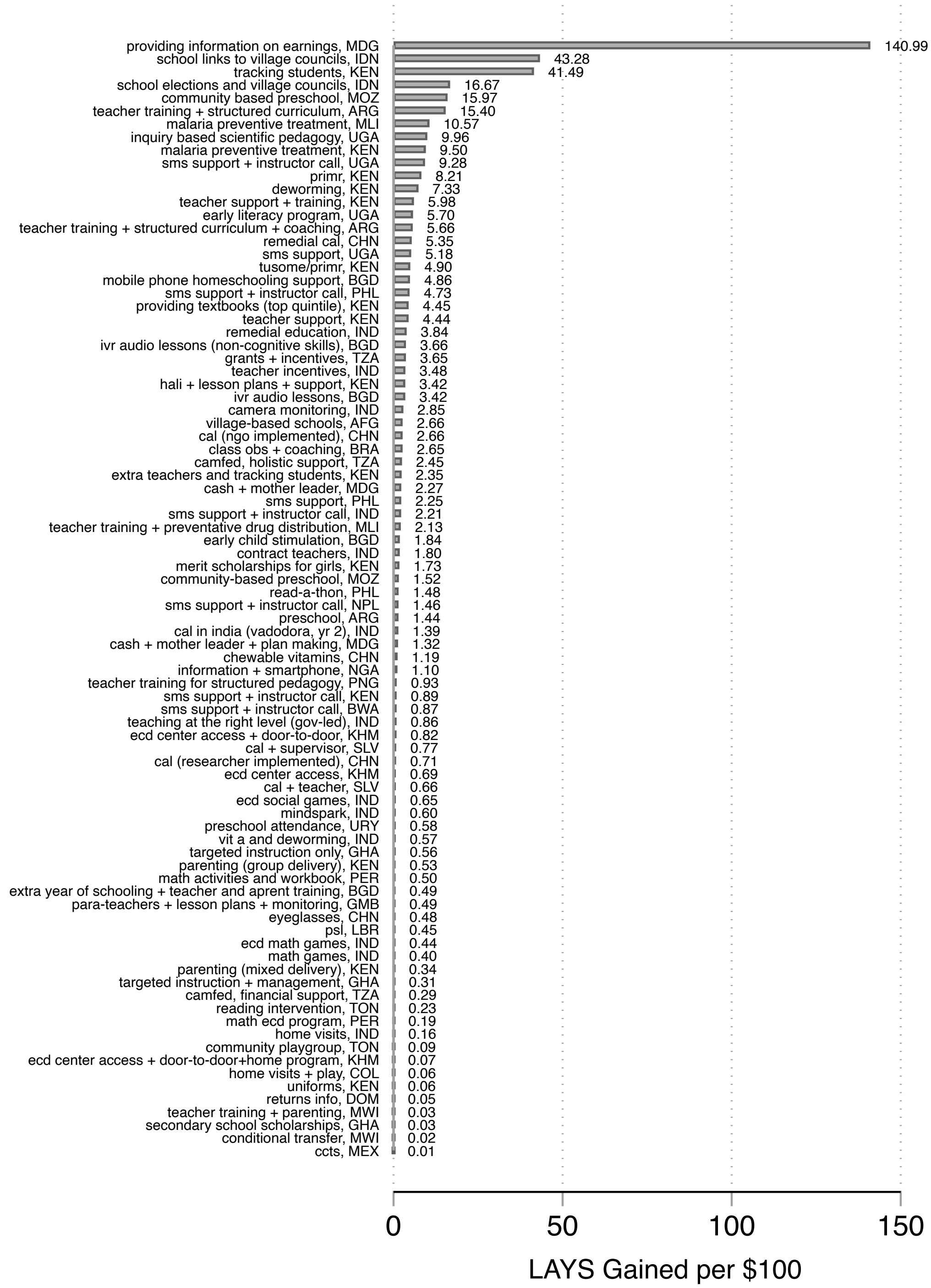
Table B3: Correlations Between LAYS for an Intervention's Duration and LAYS per Year

Panel A: LAYS		
LAYS	1.000	
LAYS ($t = 1$)	0.912	1.000

Panel B: LAYS per $100 USD		
LAYS per $100 USD	1.000	
LAYS per $100 USD ($t = 1$)	0.922	1.000

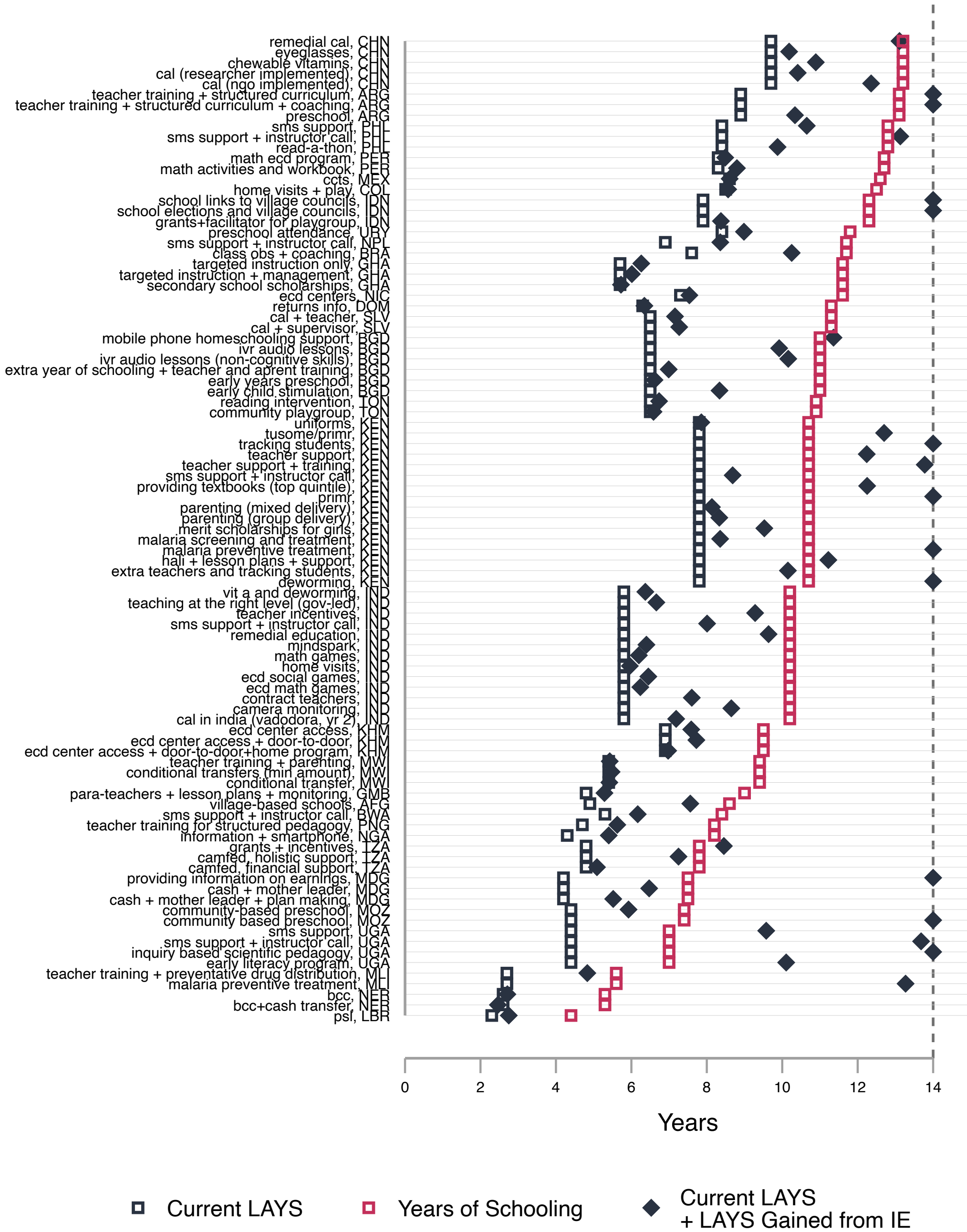
Panel C: LAYS per Year and LAYS per $100 USD		
LAYS ($t = 1$)	1.000	
LAYS per $100 USD	0.376	1.000

Notes: The table shows the pairwise correlations between LAYS under alternative definitions: Panel A shows the correlation between LAYS and LAYS per year. Panel B shows the correlation between LAYS per $100 USD and LAYS per $100 USD per year. Panel C shows the conditional correlation between LAYS per year and LAYS per $100 USD after having controlled for sample size. This positive correlation is suggestive that time and cost are proxies. All correlations are significant at 99% confidence.



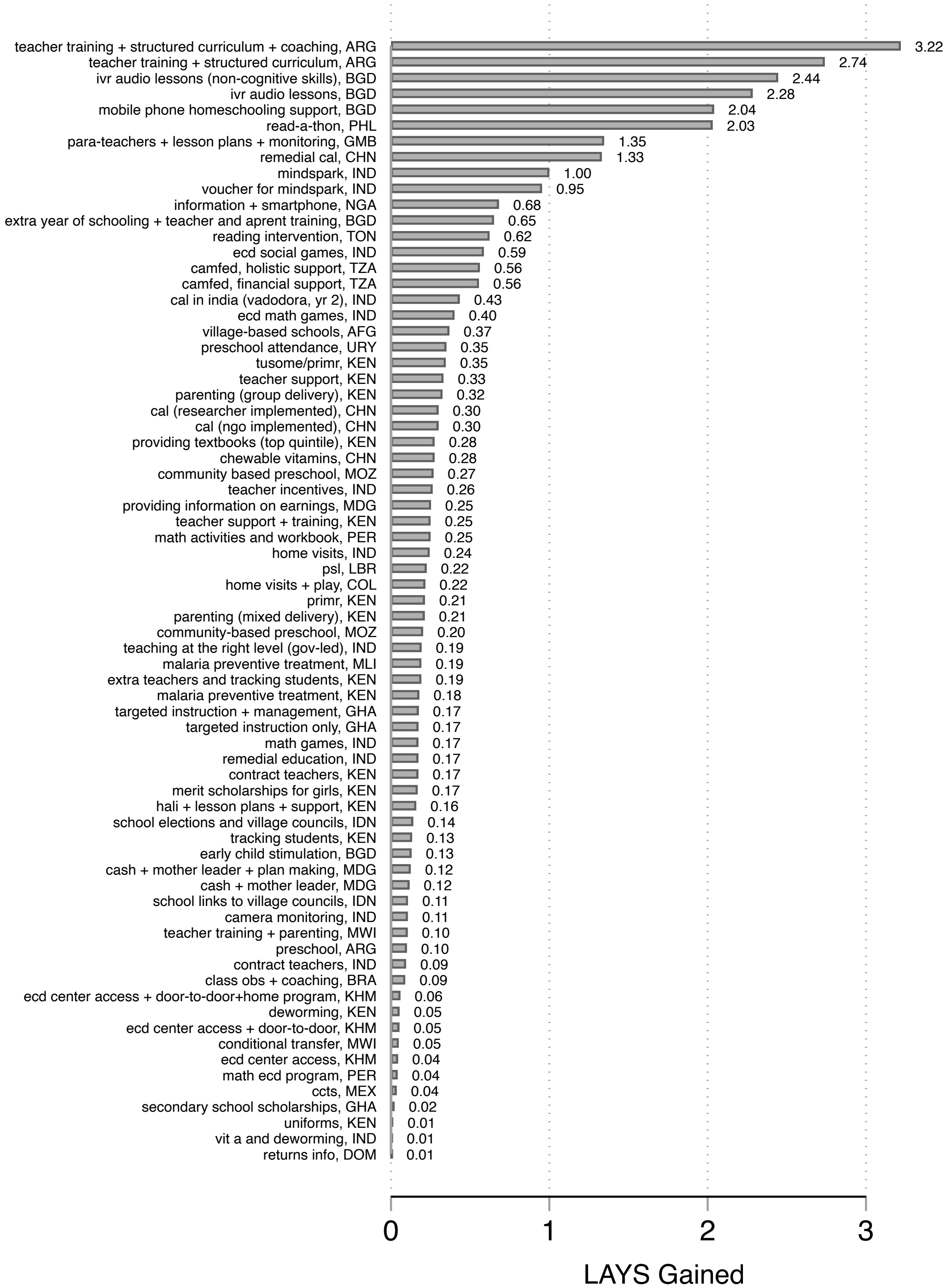
Notes: We rank interventions by the LAYS per $100 they generate. We omit interventions with a non-significant effect.

Figure B3: Learning-Adjusted Years of Schooling (LAYS) Gained per $100, by Intervention



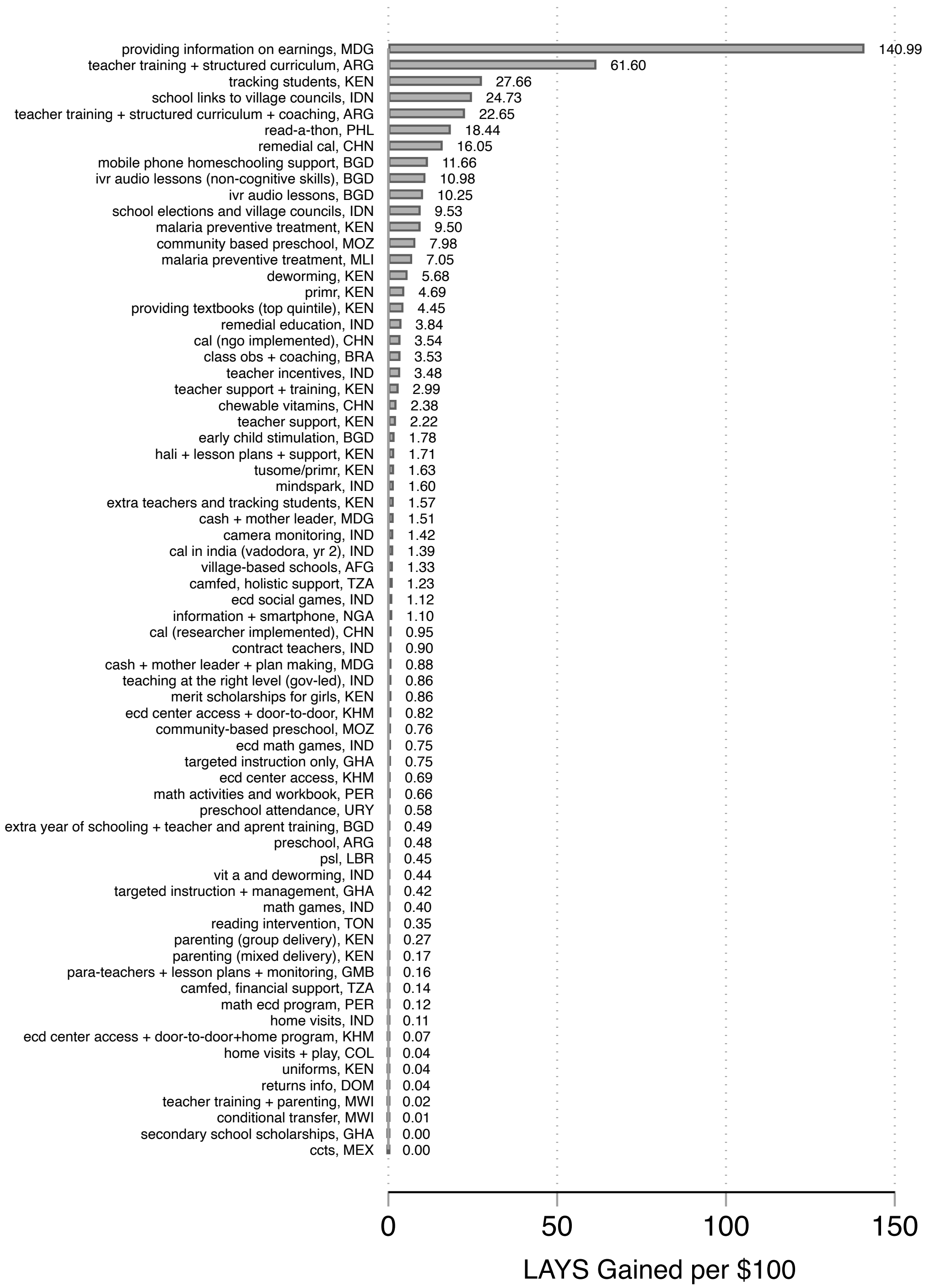
Notes: This calibration assumes no loss of effectiveness once an intervention operates at national scale, which often is not the case. Alternative calibrations could apply a discount factor to account for weaker effects at scale. For the purposes of this exercise, which are designed only as a calibration of effect sizes, we provide a single estimate. We include years of schooling and learning-adjusted years of schooling (LAYS) from publicly available data used in the World Bank's Human Capital Index for each country. The LAYS gained from the impact evaluation (IE) indicates how much a given intervention or policy helps a country close its country-specific LAYS gap as well as bridge the global LAYS gap. The dashed red line at 14 years of schooling indicates the "distance to the frontier" as defined by the HCI as 14 years of high-quality schooling. Where the LAYS gained from the IE result in a LAYS estimate that exceeds the global benchmark of 14 of high quality schooling, we set the LAYS gained from IE estimate to the value needed to close the global LAYS gap fully.

Figure B4: LAYS Gained per \$100 per Intervention, Calibrated to Country-Level LAYS Gaps



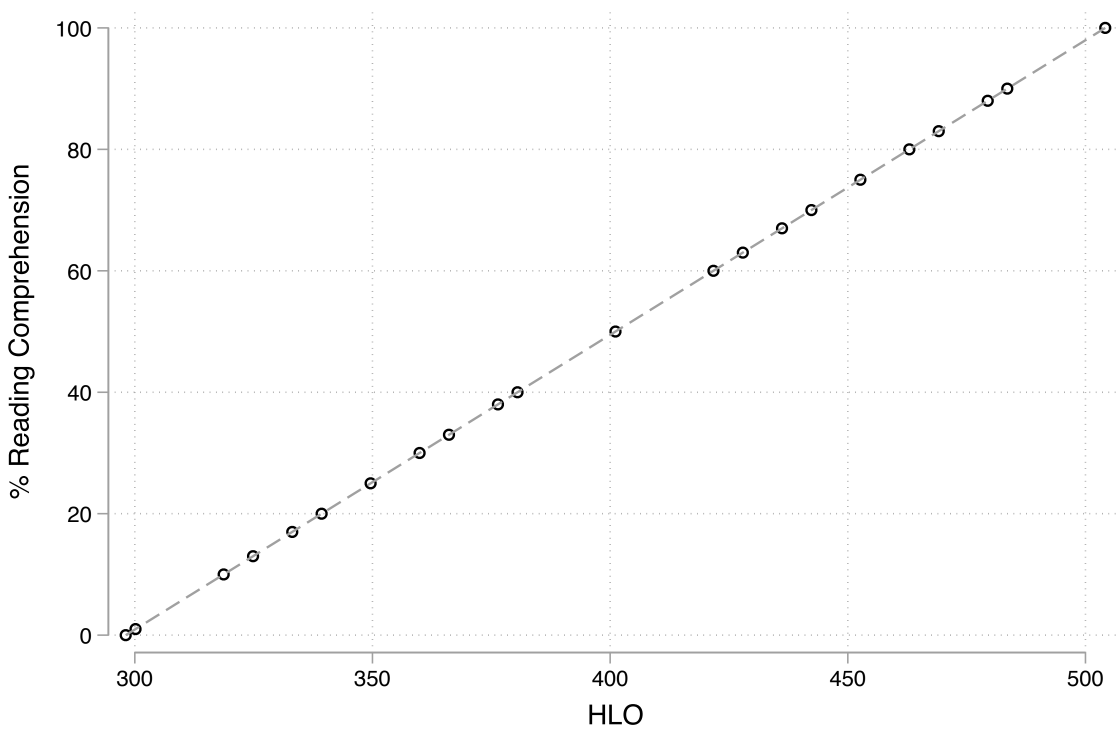
Notes: We estimate per year estimates of the LAYS of each intervention and rank them. Our main takeaways are robust to this rescaling.

Figure B5: Expressing LAYS gained per year (t = 1)



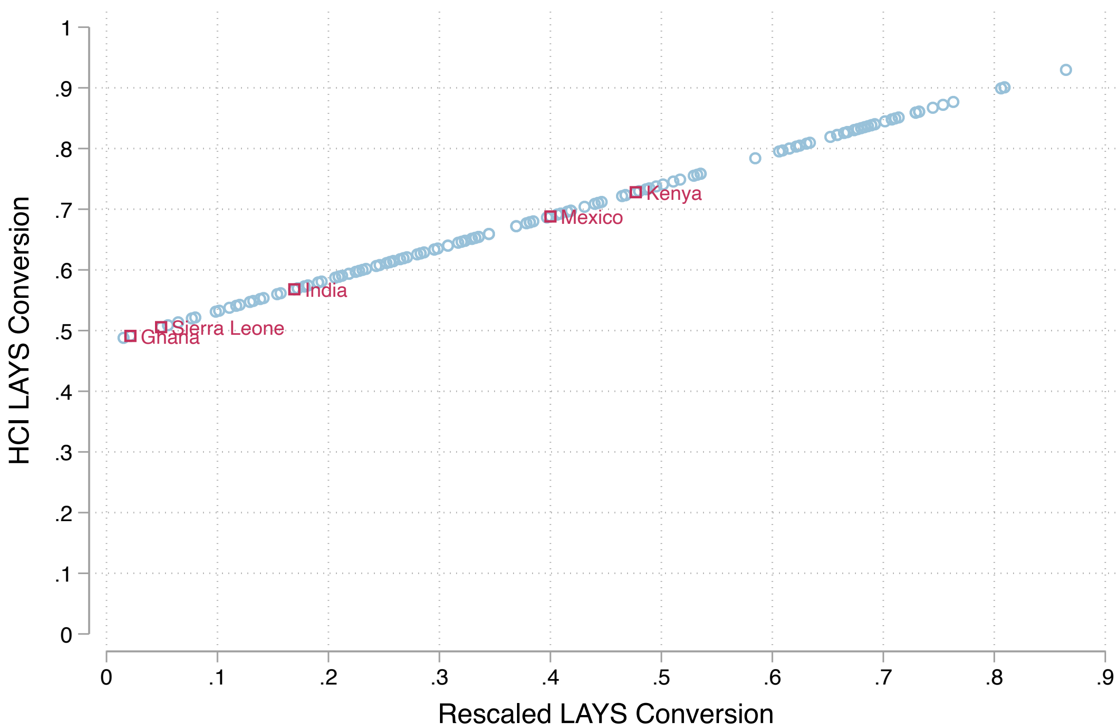
Notes: We estimate per year estimates of the LAYS per $100 of each intervention and rank them. Our main takeaways are robust to this rescaling.

Figure B6: Expressing LAYS gained per $100 USD year (t = 1)



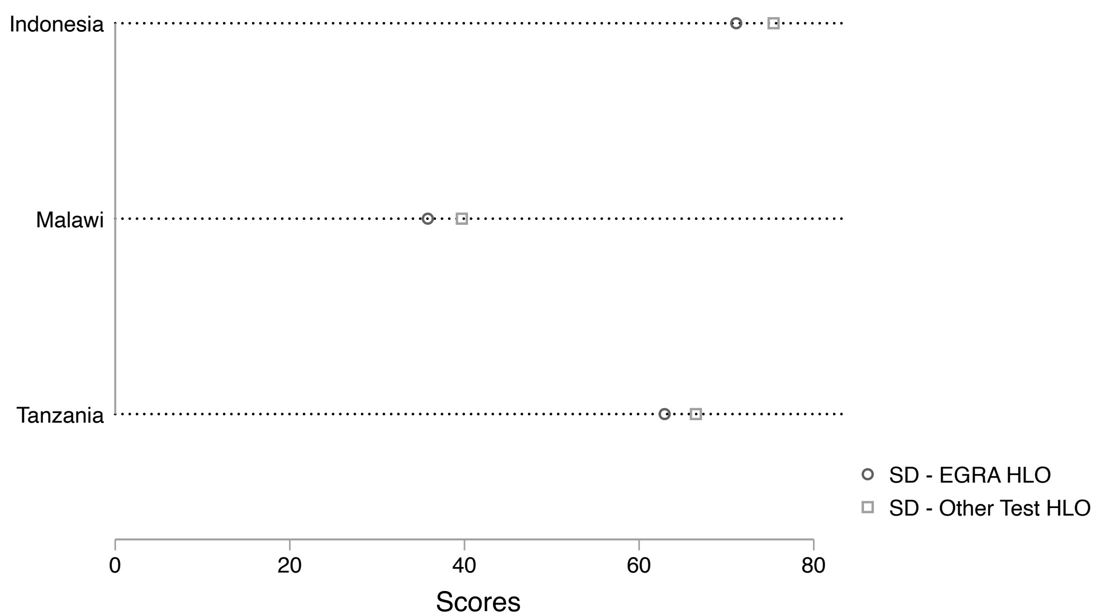
Notes: We analyze EGRA data across 39 countries and match raw score on reading comprehension modules with the Harmonized Learning Outcome (HLO) scores used for the World Bank Human Capital Index. An HLO score of 300 roughly corresponds to a floor level of reading comprehension of 0%.

Figure B7: EGRA raw reading comprehension relative to HLO score



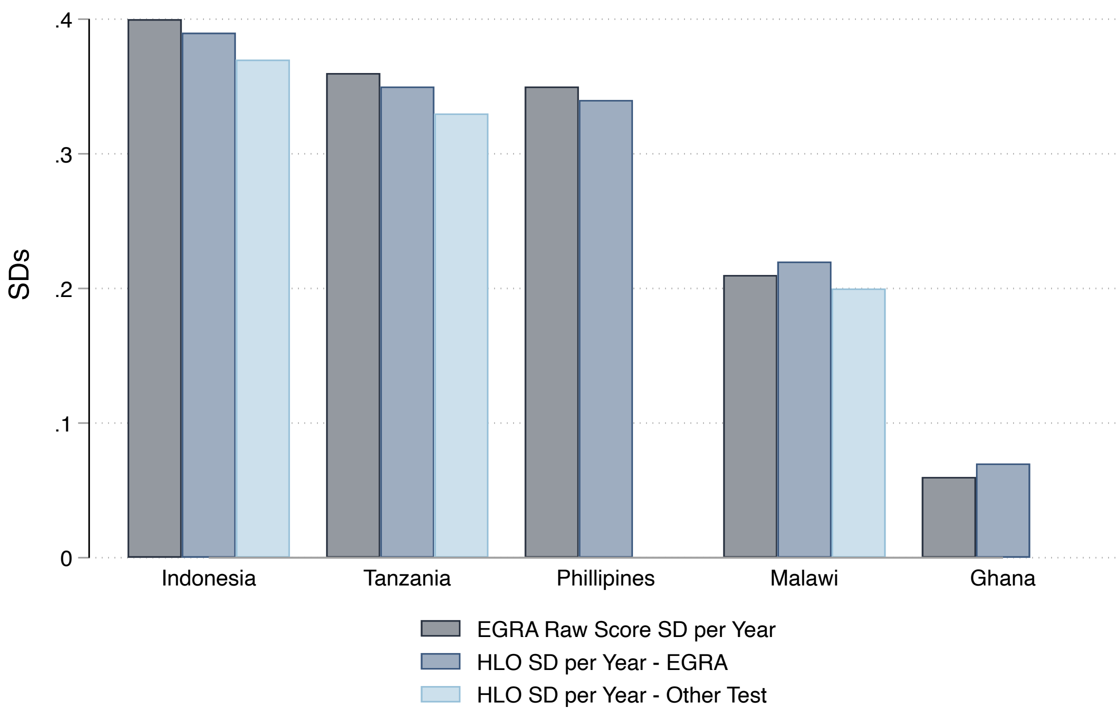
Notes: We rescale LAYS conversion rates. Initial conversion rates are based on scores which often floor around 300 due to underling test scores scales. Since the LAYS conversion rate is calculated out of 625, this produces a floor conversion rate of .48 (vertical axis). However, when learning levels are very low this conversion will under-adjust learning. We rescale LAYS exchange rates to range from 0 to 1 (horizontal axis) to higlight that the ranking of interventions is preserved regardless of the scale we use.

Figure B8: Learning Adjustment Rates



Notes: We compare test scores using EGRA and other scores for select countries. For Indonesia, the "other test" is PIRLS 2011; for Tanzania and Malawi it is SACMEQ 2007. This highlights robustness of our learning rates to the tests used to calculate them.

Figure B9: SD Comparisons, by Source Test



Notes: For Indonesia, the "other test" is PIRLS 2011; for Tanzania and Malawi it is SACMEQ 2007. We assume all scores were obtained in Grade 4 as a placeholder for primary school scores. This figure highlights the robustness of our learning rates to using raw EGRA scores or HLO scores.

Figure B10: Learning Per Year (in SD), by Source Test

Table B4: Correlational Results on Intervention Impact at Increasing Scale

	(1) LAYS	(2) LAYS	(3) LAYS
Log Scale	-0.016**	-0.013	-0.011
	(0.007)	(0.010)	(0.009)
Observations	292	292	292
Country FEs	No	Yes	Yes
Study Category FEs	No	No	Yes
R^2	0.016	0.290	0.395

Notes: This table shows correlational evidence on the relationship between an intervention's impact measured in LAYS and its scale. To proxy for scale we use the number of observations in each intervention. We restrict our sample to interventions with impacts smaller than 1 LAYS and use the natural logarithm of scale to address concerns about outliers on our analysis. Column 1 shows a statistically significant and negative correlation between these measures, suggesting that impact dilutes with scale. However, this relationship is no longer statistically significant once we control for country fixed effects and intervention category fixed effects (columns 2 & 3). These findings suggest that impact might have surprising persistence at scale, although this analysis is merely suggestive and is not conclusive.

Appendix C Mapping of Point Estimates

Table C1: Point Estimate Mapping Figure B2

Study	Study ID	LAYS	Point Estimate
para-teachers + lesson plans + monitoring, GMB	127	4.037	3.230
camfed, holistic support, TZA	209	1.122	0.898
sms support + instructor call, UGA	062	1.114	0.891
camfed, financial support, TZA	209	1.111	0.889
tusome/primr, KEN	199	1.038	0.830
mobile phone homeschooling support, BGD	003	0.850	0.680
ivr audio lessons (non-cognitive skills), BGD	004	0.815	0.652
teacher training + structured curriculum + coaching, ARG	001	0.805	0.644
early literacy program, UGA	043	0.798	0.638
ivr audio lessons, BGD	004	0.761	0.609
village-based schools, AFG	100	0.738	0.590
remedial cal, CHN	012	0.700	0.560
teacher training + structured curriculum, ARG	001	0.685	0.548
information + smartphone, NGA	035	0.681	0.545
teacher support, KEN	028	0.663	0.530
extra year of schooling + teacher and aprent training, BGD	002	0.650	0.520
parenting (group delivery), KEN	029	0.650	0.520
inquiry based scientific pedagogy, UGA	045	0.637	0.510
sms support + instructor call, PHL	061	0.567	0.454
community based preschool, MOZ	034	0.536	0.429
teacher training for structured pedagogy, PNG	036	0.525	0.420
teacher support + training, KEN	028	0.500	0.400
grants + incentives, TZA	040	0.450	0.360
cal in india (vadodora, yr 2), IND	068	0.434	0.347
parenting (mixed delivery), KEN	029	0.425	0.340
reading intervention, TON	041	0.415	0.332
community-based preschool, MOZ	179	0.405	0.324
mindspark, IND	022	0.375	0.300
primr, KEN	026	0.375	0.300
home visits, IND	023	0.366	0.293
voucher for mindspark, IND	192	0.363	0.290
preschool attendance, URY	087	0.349	0.788
ecd social games, IND	118	0.340	0.272
merit scholarships for girls, KEN	169	0.338	0.270
home visits + play, COL	016	0.325	0.260
hali + lesson plans + support, KEN	027	0.319	0.255
preschool, ARG	084	0.300	0.240
cal + teacher, SLV	017	0.298	0.238
extra teachers and tracking students, KEN	124	0.287	0.230
providing textbooks (top quintile), KEN	145	0.275	0.220
cal + supervisor, SLV	017	0.268	0.214
sms support + instructor call, IND	058	0.265	0.212

teacher incentives, IND	019	0.262	0.210
sms support, UGA	062	0.259	0.207
contract teachers, KEN	125	0.259	0.207
providing information on earnings, MDG	193	0.252	0.202
school elections and village councils, IDN	202	0.245	0.196
ecd math games, IND	118	0.233	0.186
psl, LBR	206	0.225	0.180
cal (ngo implemented), CHN	013	0.225	0.180
cal (researcher implemented), CHN	011	0.225	0.180
camera monitoring, IND	122	0.213	0.170
tracking students, KEN	124	0.200	0.160
teaching at the right level (gov-led), IND	070	0.192	0.154
contract teachers, IND	020	0.190	0.152
cash + mother leader + plan making, MDG	030	0.188	0.150
school links to village councils, IDN	202	0.188	0.150
remedial cal, CHN	009	0.188	0.150
math activities and workbook, PER	037	0.188	0.150
malaria preventive treatment, KEN	024	0.179	0.143
sms support + instructor call, NPL	060	0.175	0.140
cash + mother leader, MDG	030	0.175	0.140
eyeglasses, CHN	014	0.175	0.140
math games, IND	021	0.173	0.138
remedial education, IND	068	0.172	0.138
read-a-thon, PHL	047	0.162	0.130
teacher training + parenting, MWI	032	0.157	0.126
sms support + instructor call, BWA	005	0.151	0.121
eyeglasses, CHN	010	0.138	0.110
chewable vitamins, CHN	008	0.138	0.110
early child stimulation, BGD	104	0.134	0.107
targeted instruction + management, GHA	080	0.131	0.105
targeted instruction only, GHA	080	0.130	0.104
sms support, PHL	061	0.112	0.090
secondary school scholarships, GHA	121	0.112	0.090
sms support + instructor call, KEN	059	0.106	0.085
teacher training + preventative drug distribution, MLI	033	0.100	0.080
conditional transfer, MWI	066	0.097	0.535
community playgroup, TON	041	0.087	0.070
class obs + coaching, BRA	098	0.068	0.054
math ecd program, PER	139	0.062	0.050
ecd center access + door-to-door+home program, KHM	083	0.059	0.126
ecd center access + door-to-door, KHM	083	0.052	0.112
ecd center access, KHM	083	0.044	0.094
deworming, KEN	184	0.036	0.075
returns info, DOM	163	0.031	0.200
uniforms, KEN	125	0.014	0.030
vit a and deworming, IND	093	0.010	0.058
ccts, MEX	107	0.004	0.010

Notes: We include specific estimates for each study treatment arm with positive and significant effects mapping to Figure B2. We omit interventions with a non-significant effect. Study ID maps references to the full list of citations provided in Appendix D.

Table C2: Point Estimate Mapping Figure B3

Study	Study ID	LAYS per $100 USD	Point Estimate per $100 USD
providing information on earnings, MDG	193	140.988	112.790
school links to village councils, IDN	202	43.275	34.620
tracking students, KEN	124	41.487	33.190
school elections and village councils, IDN	202	16.675	13.340
community based preschool, MOZ	034	15.966	12.773
teacher training + structured curriculum, ARG	001	15.400	12.320
inquiry based scientific pedagogy, UGA	045	9.957	7.965
malaria preventive treatment, KEN	024	9.495	7.596
sms support + instructor call, UGA	062	9.281	7.425
primr, KEN	026	8.214	6.571
remedial cal, CHN	012	8.183	6.546
deworming, KEN	184	7.327	15.364
teacher support + training, KEN	028	5.978	4.782
early literacy program, UGA	043	5.705	4.564
teacher training + structured curriculum + coaching, ARG	001	5.663	4.531
sms support, UGA	062	5.175	4.140
tusome/primr, KEN	199	4.900	3.920
mobile phone homeschooling support, BGD	003	4.859	3.887
sms support + instructor call, PHL	061	4.729	3.783
providing textbooks (top quintile), KEN	145	4.450	3.560
teacher support, KEN	028	4.440	3.552
remedial education, IND	068	3.838	3.070
ivr audio lessons (non-cognitive skills), BGD	004	3.659	2.927
grants + incentives, TZA	040	3.652	2.922
teacher incentives, IND	019	3.481	2.785
hali + lesson plans + support, KEN	027	3.422	2.737
ivr audio lessons, BGD	004	3.418	2.734
camera monitoring, IND	122	2.850	2.280
village-based schools, AFG	100	2.662	2.130
cal (ngo implemented), CHN	013	2.656	2.125
class obs + coaching, BRA	098	2.650	2.120
remedial cal, CHN	009	2.517	2.013
camfed, holistic support, TZA	209	2.450	1.960
extra teachers and tracking students, KEN	124	2.350	1.880
cash + mother leader, MDG	030	2.272	1.818
sms support, PHL	061	2.250	1.800
sms support + instructor call, IND	058	2.208	1.767
teacher training + preventative drug distribution, MLI	033	2.132	1.706
early child stimulation, BGD	104	1.837	1.470
contract teachers, IND	020	1.802	1.442
merit scholarships for girls, KEN	169	1.725	1.380
community-based preschool, MOZ	179	1.525	1.220
read-a-thon, PHL	047	1.475	1.180
sms support + instructor call, NPL	060	1.458	1.167

preschool, ARG	084	1.438	1.150
cal in india (vadodora, yr 2), IND	068	1.388	1.110
cash + mother leader + plan making, MDG	030	1.319	1.055
chewable vitamins, CHN	008	1.189	0.952
information + smartphone, NGA	035	1.101	0.881
teacher training for structured pedagogy, PNG	036	0.927	0.742
sms support + instructor call, KEN	059	0.885	0.708
sms support + instructor call, BWA	005	0.869	0.695
teaching at the right level (gov-led), IND	070	0.863	0.690
ecd center access + door-to-door, KHM	083	0.823	1.760
cal + supervisor, SLV	017	0.768	0.614
eyeglasses, CHN	010	0.731	0.584
cal (researcher implemented), CHN	011	0.710	0.568
ecd center access, KHM	083	0.688	1.470
cal + teacher, SLV	017	0.656	0.525
ecd social games, IND	118	0.650	0.520
mindspark, IND	022	0.599	0.479
preschool attendance, URY	087	0.585	1.320
vit a and deworming, IND	093	0.570	3.367
targeted instruction only, GHA	080	0.562	0.450
parenting (group delivery), KEN	029	0.531	0.425
math activities and workbook, PER	037	0.498	0.398
extra year of schooling + teacher and aprent training, BGD	002	0.489	0.392
para-teachers + lesson plans + monitoring, GMB	127	0.486	0.389
psl, LBR	206	0.450	0.360
ecd math games, IND	118	0.438	0.350
math games, IND	021	0.399	0.319
parenting (mixed delivery), KEN	029	0.335	0.268
targeted instruction + management, GHA	080	0.312	0.250
camfed, financial support, TZA	209	0.287	0.230
reading intervention, TON	041	0.235	0.188
eyeglasses, CHN	014	0.232	0.186
math ecd program, PER	139	0.188	0.150
home visits, IND	023	0.159	0.127
community playgroup, TON	041	0.087	0.070
ecd center access + door-to-door+home program, KHM	083	0.075	0.160
home visits + play, COL	016	0.065	0.052
uniforms, KEN	125	0.055	0.116
returns info, DOM	163	0.046	0.297
teacher training + parenting, MWI	032	0.027	0.021
secondary school scholarships, GHA	121	0.025	0.020
conditional transfer, MWI	066	0.016	0.090
ccts, MEX	107	0.005	0.013

Notes: We include specific estimates for each study treatment arm with positive and significant effects mapping to Figure B3. We omit interventions with a non-significant effect. Study ID maps references to the full list of citations provided in Appendix D.

Appendix D Full List of Citations

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