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Failing to Plan? Estimating the Impact of Achieving Schooling Goals on Cohort Learning

Michelle Kaffenberger and Lant Pritchett

Abstract

The Sustainable Development Goals have targets for both expansion of schooling to achieve universal completion of primary and secondary schooling, and for learning, to reach universal basic proficiency in reading and mathematics. Yet today not a single developing country has an empirical estimate of how much reaching their schooling goal would contribute to reaching their learning goals. We build a simple, formal, parameterized model of the learning process and calibrate the parameters to replicate observed learning outcomes in developing countries. We then use this model to simulate the progress on global learning goals that would result from achieving universal completion of grade 10. Our simulations suggest that in a "typical" low income country increasing completion of grade 10 from its current level of roughly 30 percent to 100 percent increases cohort learning by only 9 points on a PISA-like scale (mean of 500, standard deviation 100), an effect size of less than one tenth of one standard deviation. More strikingly, in our simulations this massive expansion of enrollment has zero impact on the proportion of youth reaching the SDG targets for learning. The reason for this perhaps counter-intuitive finding is that our simulation model allows for children who fall behind the curriculum to stop learning while in school and assumes that those learning the least dropout first. Therefore, expanding enrollment simply shifts most children from not learning while out of school to not learning while in school. In contrast to the weak impact of expanding enrollment at existing levels of learning, even modest changes to the learning process such as reorienting the curriculum to children's learning levels can have massive effects. With an improved learning process, achieving universal grade 10 completion has ten times the impact on average scores than under the existing learning process.

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Introduction

Any adequate education involves both schooling and learning. Education goals have always gone beyond mere "time completed" goals[1]. Education goals recognize that each new generation/cohort of youth needs to reach adulthood adequately equipped with the skills, capabilities, competencies, knowledge, beliefs and dispositions to successfully fill their roles and responsibilities as parents, community members, citizens, and economic providers in a rapidly changing world. The Sustainable Development Goals adopted by the UN in 2015 include: *"By 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes."* The World Bank's World Development Report 2018 on education, its Human Capital Project[2] and the recent goal to eliminate "learning poverty" all include explicit learning goals in additional to the commitment to universal schooling. The Global Partnership for Education aims to ensure every child receives a *quality* basic education, including both schooling and learning.

But while many in the global community and individual countries have plans to reach schooling goals, most do not have explicit plans to reach learning goals and instead hope that if schooling goals are achieved learning goals will also be achieved. Existing assessments of learning show this appears extremely unlikely. For instance, the recent PISA for Development (PISA-D)[3] assessment reported results from seven lower and lower middle-income countries[4]. The percent of children aged 15 who were in grade 7 or higher and hence eligible for PISA-D ranged from only 28 percent (Cambodia) to 60 percent (Ecuador). Reaching PISA Level 2 is

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[1] The Jomtien Declaration of the Education for All conference in 1990 stated: *"Whether or not expanded educational opportunities will translate into meaningful development --for an individual or for society--depends ultimately on whether people actually learn as a result of those opportunities, i.e., whether they incorporate useful knowledge, reasoning ability, skills, and values. The focus of basic education must, therefore, be on actual learning acquisition and outcome, rather than exclusively upon enrolment, continued participation in organized programmes and completion of certification requirements."*

[2] The World Bank's Human Capital Project's new measures of human capital reflect not just years of schooling completed, but how much was learned per year.

[3] PISA is coordinated by the OECD and has typically covered high- and middle-income countries. Recently, PISA launched a new initiative called PISA for Development, which expanded the reach of PISA to low- and middle-income countries. The program included adapting the assessment to the anticipated lower learning levels of developing countries, and provided technical assistance for implementation to the participating countries. Results from the initial round of PISA-D data collection, which included seven middle-income countries (listed in Table 1), was released in 2018.

[4] We are using the PISA-D only as one illustration, not as the definitive or canonical measure of learning. Many other sources of evidence show learning deficits of different types and at different ages. The ASER and ASER-like citizen led assessments use methods that do not require reading and household based sampling to produce estimates of very basic mastery of reading and arithmetic for children across ages and grades. Pritchett and Sandefur (2017) analyze the reading assessment in the Demographic and Health Surveys (DHS) and find only about half of women who completed grade 6 (but not higher) could read a single sentence, with a wide variation across countries, from 3 percent to 100 percent. Kaffenberger and Pritchett (2017) use the reading assessment question in the FII data across 10 countries and find similarly low levels. The recent Human Capital Index amalgamates a wide variety of sources of learning data to create an estimate of learning for 164 countries which again shows many developing countries at very low levels of learning (Angrist, Djankov, Goldberg and Patrinos 2019).

considered the minimum proficiency in literacy and mathematics[5]. Of those students assessed in PISA-D (those who were aged 15 and enrolled in grade 7 or higher) only 12 percent had reached the SDG target of minimum proficiency in mathematics (Level 2) on average. Combining the percent who were eligible for the assessment with the percent who were eligible and who achieved Level 2 or above reveals that the percent of the cohort of 15 year olds demonstrating proficiency in reading per the SDG definition ranges from less than three percent (Zambia, Senegal, Cambodia) to five or six percent (Paraguay, Guatemala, Honduras) to 18 percent in Ecuador. Even though one suspects those who are in school at age 15 in the PISA-D countries are positively self-selected (e.g. likely to be higher socio-economic status, urban, adept at school) these levels are much below even the disadvantaged students in the OECD. About two-thirds of OECD students in the bottom quartile of the PISA socio-economic status index reach Level 2 or above in mathematic proficiency, six times higher than the proportion in PISA-D countries.

Table 1: The PISA-D countries had *both* low enrollment and grade attainment of children aged 15 *and* low learning levels of those enrolled

Country	Percent of all 15-year-olds in school and in at least grade 7 (therefore meeting eligibility requirements for PISA-D participation)	Percent of assessed 15-year-olds reaching Level 2 or above in Mathematics	Implied percent of all 15-year-olds at level 2 and above (assuming no non-enrolled are above level 2)
Zambia	36.0	2%	1%
Senegal	29.0	8%	2%
Cambodia	28.1	10%	3%
Paraguay	55.6	8%	5%
Guatemala	47.5	11%	5%
Honduras	41.4	15%	6%
Ecuador	60.6	29%	18%
Average of the seven	**42.6%**	**11.8%**	**5.7%**
OECD (median)		**78%**	
OECD (median), students in bottom quartile of socio-economic index (median)		**65%**	
Source: PISA-D results tables			

[5] The PISA assessment is normed to have a mean of 500 and standard deviation of 100 across a reference group of OECD children. The numerical score for reaching level 2 in reading is 407.47 and in Mathematics is 420.07. The description of the proficiency level is: *Readers at Level 2 can locate one or more pieces of information, which may need to be inferred and may need to meet several conditions. They can recognize the main idea in a text, understand relationships, or construe meaning within a limited part of the text when the information is not prominent and the reader must make low level inferences. Tasks at this level may involve comparisons or contrasts based on a single feature in the text. Typical reflecting tasks at this level require readers to make a comparison or several connections between the text and outside knowledge, by drawing on personal experience and attitudes.*

Suppose Zambia or Guatemala (or any other developing country) had a plan to achieve universal completion of grade 10, but without changing the learning profiles. How far would this expansion in schooling take them towards the SDG learning goal (as proxied by PISA Level 2 proficiency)[6]? No one knows. Table 1 suggests that even if the incremental students were to achieve the same results as the existing students the gains would range from small to modest (an improvement from 2 percent to 8 percent in Senegal, from 5 percent to 11 percent in Guatemala).

But that calculation assumes the children who are observed to have dropped out would have had the same learning trajectory under universal attainment as those who are observed to have stayed in school through age 15. In other words, it assumes the LATE of attending school for a child who is observed to have dropped out is the same as the LATE of attending school for a child who is observed to have persisted. It is well established that high performers are more likely to persist in school. Dropout has been shown to be associated with low learning (Zuilkowski et al, 2016, Das et al, forthcoming). The marginal enrollee under schooling expansion therefore is likely to learn less than the currently enrolled and extrapolation of the performance of the currently enrolled to the newly enrolled will overstate the aggregate gains.

Recent evidence further suggests that learning trajectories are often concave, flattening out in later grades. Beatty et al (2019) shows that the aggregate learning profile in Indonesia for mastery of primary school arithmetic is very flat past grade 6 and hence these skills reach their maximum at a very low level of proficiency at an early grade. They show using panel data that because the learning profile was concave and not linear a massive expansion in schooling between 2000 and 2014 had *zero* impact on improving these skills. If learning profiles are more concave (less learning per year at higher years) for lagging students then gains from schooling expansion could be even lower than otherwise anticipated.

To make any claims about the additional learning that would be produced by an expansion of schooling one needs a formal, empirically informed model to estimate a counterfactual: how much would currently non-enrolled children gain from additional schooling? Without a formal model of the learning process and clearly stated assumptions, no one can know whether the many things a government may plan to do, from expanding enrollment, to revising the curriculum, to universalizing early childhood education, will relate with the other parameters in an education system in a way that produces improvements in cohort learning goals and makes progress towards achieving learning goals.

We develop a parameterized specification of the learning process that produces learning profiles that allow us to simulate the learning gains from expansion of schooling and changes to the learning process. We fix the learning process parameters through calibration to replicate the moments of the PISA-D results. We then use the calibrated parameterized learning process to

[6] Or any other cohort learning target for any hard or soft skill. We are using the PISA results illustratively not singling PISA out as a uniquely important measure or assessment of learning.

simulate counterfactual policy scenarios, like the impact on the distribution of cohort learning from expansion of schooling with the learning process unchanged, and of changes to the learning process.

Our base case simulations produce a striking result. With our simulation model calibrated to the "typical" low learning performance country, expanding completion of grade 10 from (the observed) 30 percent to 100 percent produces *zero* progress in achieving SDG cohort learning goals. The simple intuition of this perhaps surprisingly strong result is that most students who dropped out were not learning in school even prior to dropping out. Therefore expanding enrollment simply shifted most children from not learning while *out* of school to not learning while *in* school.

In contrast, the simulation model also shows that potential gains in cohort learning goals from an improved learning process are substantial. Strikingly, just slowing down the pace of the curriculum to be consistent with the actual pace of learning leads to much larger gains than expanding enrollment. Eliminating dropout when the instructional process has been improved (even just by making actual curricular pace align with learning pace) produces more learning still.

I. A simple formal model of the learning process to simulate cohort learning outcomes

I.A. A simulation model for cohort learning outcomes

Predicted future gains in cohort learning from increases in cohort grade attainment (such as universal secondary school completion) are necessarily based on student specific assumptions about learning. We call the potential pedagogical function (PPF) what, on average, child *i* with skill level s^i would learn if they attend grade G, $LP = LP^G(s^i)$[7]. Drawing on the findings of the emerging literature on learning profiles (Kaffenberger and Pritchett, forthcoming) we allow the function LP^G to have a "trapezoidal" functional form over skill levels *s,* as in equation PPF:

$$PPF(LP(w,h,r,\pi^G),s^i) = \begin{cases} 0 \; if \; s^i < \pi^G - \frac{w}{2} \\ h_{min} + r\left(s^i - (\pi^G - \frac{w}{2})\right) \; if \; \pi^G - \frac{w}{2} < s^i < \pi^G + \frac{w}{2} \\ 0 \; if \; s^i > \pi^G + \frac{w}{2} \end{cases}$$

The equation representing the trapezoidal PPF has two distinct features.

[7] Conceptually, this is the same as the Local Average Treatment Effect (LATE) of exposing child *i* with skill level s^i to the learning process they would experience in grade G.

First, the PPF has a range of initial skill levels such that if a student is above or below those levels the learning gain is zero. If the instructional process represented by the PPF is too advanced relative to student skill level (e.g. teaching quantum field theory to second graders) or too rudimentary (e.g. teaching addition to physics graduate students) no new skills are gained. The PPF or instructional process at grade G is therefore centered on a specific skill level, π^G. The width of the PPF trapezoid is the parameter *w,* the range of initial child skills over which the instructional process can produce learning. A child too far behind ($s^i < \pi^G - \frac{w}{2}$) will learning nothing from being exposed to grade G. This width can vary. High quality teachers with the flexibility to tailor instruction can potentially provide positive learning gains to students with a wider range of abilities. Inflexible instruction not responsive to student mastery would produce learning gains over a narrower range (*w*).

Second, the trapezoidal shape with slope parameter *r* allows learning gains to be neutral (*r*=0, all students learn the same), low skill biased (*r*<0, students who enter with low skill learning more) or high skill biased (*r*>0, students who enter with high skills learn more). In our calibrated models the instructional process is high-skilled biased, with high performers learn more, *r*>0. h_{min} is the amount learned by the child with the lowest initial skill level that learns anything at all, and h_{max} is the amount learned by the child with the highest initial skill level that learns anything. Obviously for a given width, *w*, only two of the three parameters *r,* h_{max} *,* and h_{min} can be freely specified as:

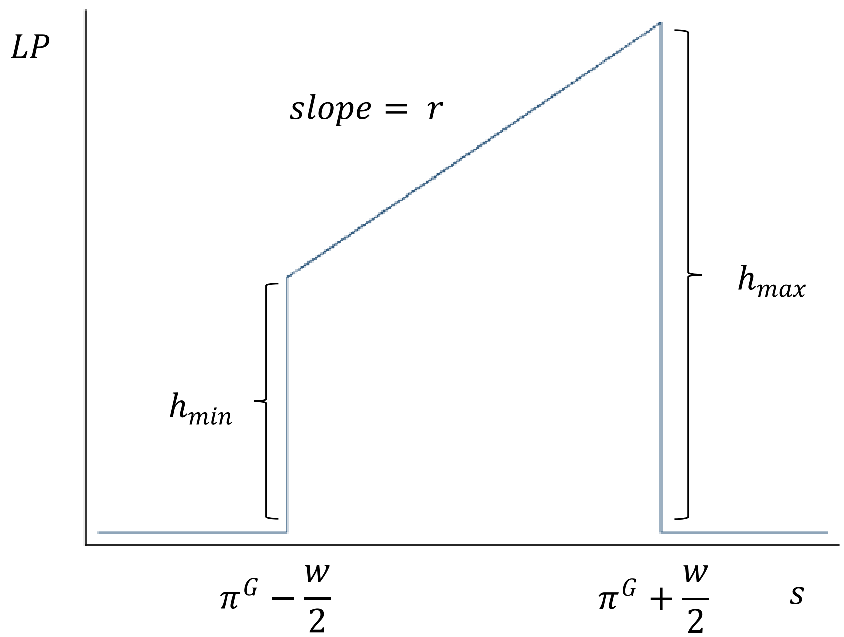
$$r = \frac{rise}{run} = \frac{h_{max} - h_{min}}{w}$$

π^1 is the student skill level that is the center of the PPF for grade 1 and is a fourth free parameter. The fifth parameter, *p*, "pace", is the magnitude of shift in the center of the PPF from grade G to grade G+1 and we assume this shift is constant across grades so that:

$$\pi^G = \pi^1 + (G - 1) * p, \forall\, G = 1, \dots 10$$

There are five free parameters for the specification of the learning gain (in a given learning domain, on a given scale) of child *i* of initial skill level s^i exposed to the typical instruction LP of grade G: *w* (width), h^{min}, *r* (that jointly determine learning for given *s*), and π^1 and *p* (that jointly determine the center π^G). Figure 1 shows this learning process on the assumption *r*>0.

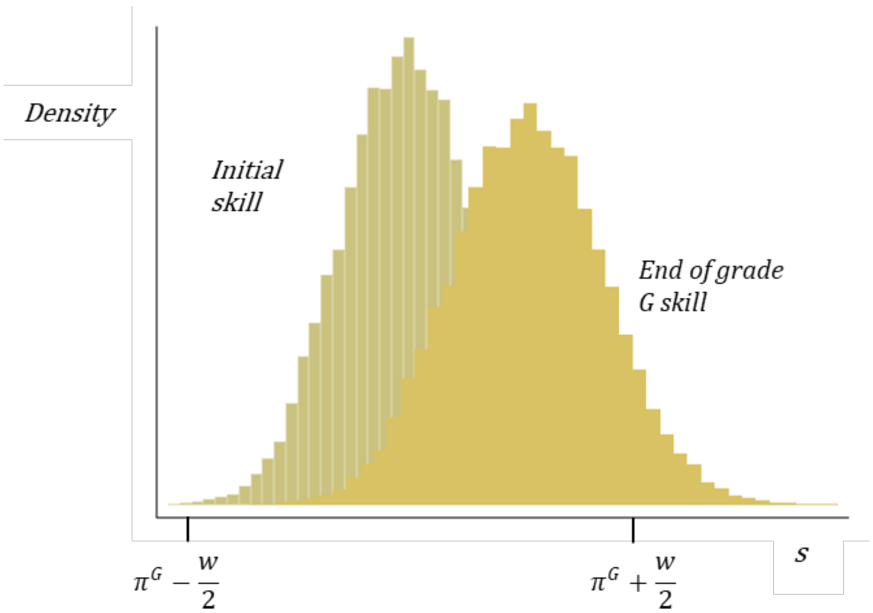
Figure 1. Modelling the learning process: *PPF(*$LP(w, h^{min}, r, \pi^G), s^i)$



To simulate the distribution of the learned skills of a cohort at end of grade G *on the assumption that all of them remain in school for all G grades* we simply iterate the learning process specified above starting from an initial distribution of student learning. Figure 2 illustrates these dynamics. Applying the learning gains at each initial skill level to the initial distribution produces a new distribution of learning from having completed grade G (the shif in the distributions in Figure 2). This is then the initial skill distribution for grade G+1 if all students remain in school. The learning process for grade G+1 is just the PPF shifted to the right according the specified pace, *p*. The new endpoints are $((\pi^G + p) - \frac{w}{2}) = (\pi^{G+1} - \frac{w}{2})$ and $((\pi^G + p) + \frac{w}{2}) = (\pi^{G+1} + \frac{w}{2})$. This is then applied to the G+1 distribution of skills to produce the post G+1 skills distribution which is initial skill for G+2, PPF shifts right by *p,* and etc.

For simplicity, we assume that the initial distribution of student skills coming into grade 1 has a Gaussian Normal distribution, with mean and standard deviation calibrated as described below.

Figure 2. Initial and end of grade student skill distribution



While this trapezoidal shape might seem overly complicated, we feel it is the minimally complicated specification. While much of the empirical literature equates "quality" of learning in classroom or school with a single average value-added measure there are two points. First, the empirically observed learning value added depends on the *interaction* of the learning process and the student skill distribution. There is no one to one mapping between, say, *h* (min or max) and observed average value added without consideration of whether the learning process is centered on the skill distribution. A very high-quality teacher could produce very little learning if they are forced to teach a curriculum too advanced for their students' actual skills. Second, the idea of a one to one mapping between "quality" (as represented by a PPF) and empirically observed learning value added assumes $r=0$, that the PPF is rectangular. There are very good reasons to believe this is not uniformly the case (Kaffenberger and Pritchett, forthcoming, KKK Rolleston reference for ETH). The "default" for this type of calculation is to assume the PPF is rectangular and of essentially infinite width, which is almost certainly false and, even so, is a special case of our model and so we could produce results under those assumptions.

I.B. Specifying which children the PPF is applied to

The parameterized PPF alone is not sufficient for simulating the distribution of learning of a cohort because we know children drop out and not all children remain in school until grade 10 (or 12 or G). The second essential input to modeling the evolution of cohort learning is determining which children enroll in grade G and hence experience the learning of the PPF^G. In general, this will be a function of the probability q that a child with skill level s drops out after grade G: $q^G = q^G(s)$.

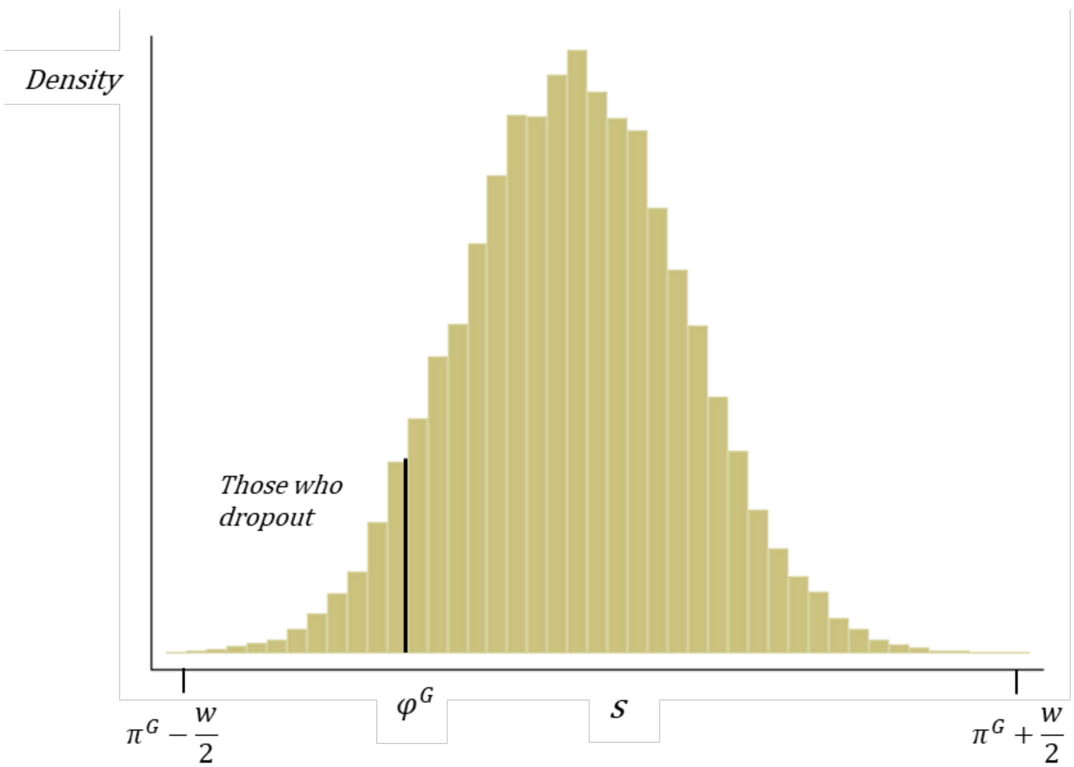
In our base case simulations, we assume that children at the bottom of the skill distribution dropout first with no random variation so that:

$$q(s) = \begin{cases} 1 & if \quad s \leq \varphi^G \\ 0 & if \quad s > \varphi^G \end{cases}$$

where φ^G is the skill level of the highest performing child who drops out after grade G. As we see below φ^G is chosen grade by grade to produce the estimated drop-out by grade.

That dropout is perfectly correlated with learning levels is a strong assumption, but illustrative, and that dropout has some correlation with learning (actual and anticipated) is both plausible and empirically supported. In Section III.D. we relax this assumption and assume dropout is instead random and has zero correlation with learning, which is the other extreme assumption.

Figure 3. Modelling dropout



II. Calibrating the model to observed learning outcomes and grade attainment profiles

To produce a simulation for any given situation (e.g. country, region, aggregate) we first search for a set of parameters that can (roughly) reproduce the observed mean and standard deviation of the existing skill distribution at the observed age or grade over:

a. The five free parameters of the learning process: h, r, w, π^1, and p.
b. The φ^G of the dropout process for each grade G.
c. The mean and standard deviation of the initial (Gaussian) skill distribution.

For these calibrations, we use the PISA and PISA-D which assess 15-year-olds who are in school and in at least grade seven to be eligible.

Table 2: OECD PISA and PISA-D 2018 math results and coverage

	Mean math score of the assessed students	Standard deviation of the assessed students	% of 15-year-olds eligible for PISA assessment (in school and in grade 7 or higher)
OECD countries	490	89	89.0%
PISA-D countries	324	74	42.6%

Source: PISA-D results tables

We first calibrate the model to reproduce the average OECD PISA mathematics mean and standard deviation. We then calibrate the PPF to reproduce the mathematics mean and standard deviation averaged across the seven PISA-D reporting countries. Because PISA tests enrolled 15-year-olds who on average are in grade 10, we simulate learning after 10 years of schooling to calibrate the base case for our model.

Because PISA results are only representative of 15-year-olds who are in school and in at least grade seven, they do not produce the learning of a cohort. In the OECD countries 89% of 15-year-olds are in the PISA sampling frame, while in the PISA-D countries grade attainment is much lower and only 42.6% of 15-year-olds are eligible for PISA. Therefore we must calibrate our PPF parameters only to the portion of the distribution who are represented by the assessment. We calibrate parameters so that the top 89% (OECD) or 43% (PISA-D) of the simulated grade 10 distribution replicates the actual assessment results.

II.A. OECD PISA parameter calibration

To replicate the mean of 490 and standard deviation of 89 among test-taking 15-year-olds, we choose the following parameters:

- *Initial skill distribution:* Students come into school with a normal distribution of skill, mean zero, standard deviation 20, N(0,20).
- *Curricular pace (p):* In order that a student who is tracking the curriculum reaches 500 (the standardized OECD mean) after 10 years starting from 0 we assume a curricular pace, *p*, of 50.
- *Initial center of PPF (π^1):* The PPF begins centered on the distribution mean, $\pi^1 = 0$.
- *Width of PPF (w):* We assume a PPF width that encompasses the full initial student distribution, so that in their first year in school all enrolled children learn some amount greater than zero: $w = 153$.
- *Height (h_{max} and h_{min}) and slope (r):* The h_{max} and h_{min} which, under the above assumptions, produces the OECD PISA mean and standard deviation are $h_{max} = 67$ and $h_{min} = 35$ and hence the trapezoidal slope is $r = 0.21$.

II.B. PISA-D parameter calibration

We want to re-calibrate the parameters to replicate the average PISA-D results with parsimony, changing as little as possible from the OECD parameters, and so we just change PPF height and curricular pace, *p*. As height and pace interact we reach the new parameters through iteration. On the assumption that learning per year is lower in the PISA-D countries we first lower h_{max} from 67 to 54, to produce (roughly) the average PISA-D results while keeping width, ratio of h_{max} to h_{min} constant (which requires adjusting *r)* and *p* constant. At this lower h_{max} the *optimal* curricular pace (that maximizes learning) slows from the OECD pace of 50 to 40 because the skills distribution, which shifts upward less per grade due to the lower *h*, cannot keep up with the OECD-calibrated pace. At the OECD pace students fall behind the curriculum, so when pace is slowed learning increases. Finally, because there is evidence that many countries have an "overambitious" curricular pace (Beatty and Pritchett 2012) we split the difference between OECD-calibrated pace and PISA-D "optimal" pace and assume a base case curricular pace of 45. At that pace, the h_{max} that comes closest to producing the average PISA-D math score is h_{max}=49 and, keeping the ratio h_{max}/h_{min} constant[8], h_{min}=26 and $r = 0.15$.

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[8] Rather than keeping the slope constant between OECD and PISA-D countries, which produced a standard deviation that was too high to replicate PISA-D results, we achieved parsimony by keeping the ratio of h_{max}/h_{min} constant and letting slope vary.

Table 3. Calibrated parameters for reproducing average OECD PISA and PISA-D scores

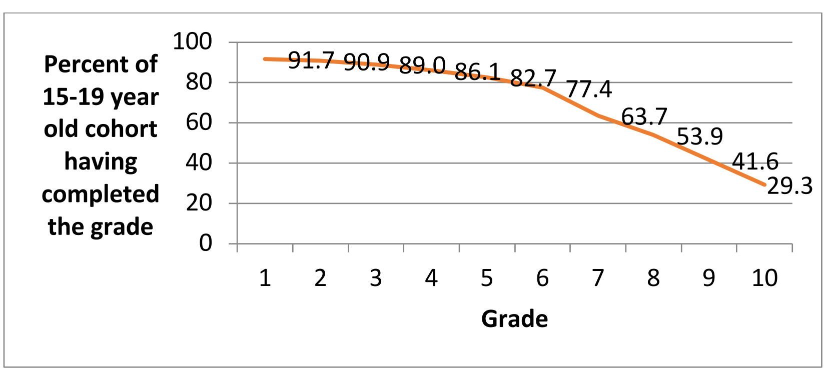
Parameter	OECD	PISA-D
W (width)	153	153
$h_{\max}$	67	49
h_{min}	35	26
Ratio $h_{\max}/ h_{min}$	1.9	1.9
r (slope)	0.21	0.15
P (pace)	50	45
$N(\pi^{1,} \sigma^{1})$	N(0,20)	N(0,20)

II.C. Grade attainment profiles for simulating dropout

In Sections II.A and II.B we calibrated parameters so that the top 89% (OECD) or 43% (PISA-D) of our grade 10 distribution (roughly) replicates the mean and variance of the actual assessment results. For the simulations for the PISA-D countries that follow, we need to also calibrate φ^G (the score below which students drop out) for each grade.

We do this with the grade attainment data from the World Bank's EdAttain database. We take the grade attainment profile of a recent cohort for the seven PISA-D countries and take the average (Figure 4). For each grade, we choose the φ^G that achieves the level of dropout specified by this grade attainment profile. For example, φ^1 is chosen so that the bottom 8.3% of the distribution do not enter grade one, and the top 91.7% of the distribution do. In the transition from grade one to grade two, φ^2 is chosen so that the bottom 0.8% of the skill distribution drops out and the remainder (90.9% of the total distribution) continue to grade two. Therefore, our drop-out rate matches the grade attainment data exactly.

Figure 4: Grade attainment profile for the seven PISA-D countries, only 42 percent of a recent cohort completed grade 9



Source: World Bank EdAttain.

III. Simulation of the cohort learning gains

Our specified PPF and dropout rule allow us to simulate *cohort learning* under observed attainment levels, which serves as our base case for low performing countries. The PPF is calibrated to produce the observed average PISA-D learning of 324 among the 43% of 15-year-olds eligible for PISA (enrolled in grade 7 or higher). The cohort learning distribution includes the learning levels of all 15-year-olds regardless of how many years of school they attended.[9] Our PPF produces a *cohort* average learning at age 15 of 213 and *cohort* standard deviation of 126. This mean is much lower and the standard deviation much larger that the PISA-D eligible population as cohort learning now includes a much longer left tail of low performers (e.g. those who dropped out or never started). The distribution of cohort learning is the base case to which simulation outcomes are compared.

We use our model to simulate three counter-factual scenarios. First, we simulate achieving universal grade 10 completion with an unchanged learning process. Second, we simulate the learning consequences of *slowing* the curricular pace. Third, we simulate improving the quality of schooling as an increase in h_{max} (holding the ratio h_{max}/h_{min} fixed?).

III.A With the base case learning process and dropout assumptions achieving universal grade 10 completion has zero impact on SDG learning goals

We simulate the change in cohort learning if all children completed ten years of school. Our calibrated PPF specifies the what the learning of those who did drop-out but now stay in school will be. The PPF provides the LATE for child *i* with learning level s^i of enrolling in grade G, sequentially from the grade at which they dropped out to grade 10.

In this scenario, grade 10 completion increases by 70 percentage points, which is, of course, a massive increase. However, this massive expansion of enrollment increases the average cohort learning by just 9.2 points on the PISA scale, from 212.7 to 221.9, an effect size of only 0.07 (=9.2/125.7).

Even more strikingly, expanding grade 10 completion by 70 percentage does not increase the percent of students achieving SDG-like goals for learning *at all*. The percent of the age 15 cohort achieving a score of 400[10] or above in our scenario of universal grade 10 attainment remains exactly constant, at a meager 7%[11]. Since we assume strongly sorted dropout, and only a small share of those who are in school at age 15 reach the SDG, all of the children who were going to reach the SDG were in school already.

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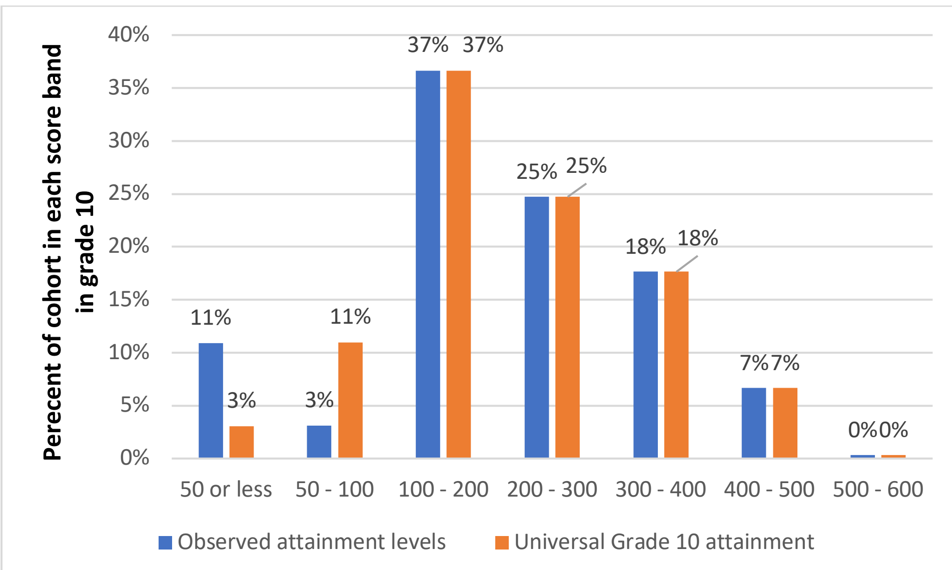
[9] This is the weighted average scores of 15 year olds who dropped out in each grade and who never went to school, where the weights are the share of the cohort with that level of attainment (from Figure 4).

[10] The monitoring report for the SDGs uses achieving level 2 in PISA which is around 400 (420 for math, 407 for reading).

[11] This is slightly higher than our 5.7 percent estimate for mathematics in Table 1 because we use 400 rather than 420.

Figure 5 shows how the grade 10 distribution of cohort learning shifted from moving from only 30 percent reaching grade 10 to universal.   The gain of 9.2 points in the cohort average comes entirely at the low end of the learning distribution. Achieving universal grade 10 attainment at existing learning shifts 8 percent of children from a score of less than 50 on the PISA scale, to a score between 50 and 100. This would not even register on the actual PISA scale as even with the PISA instrument adapted for PISA-D to measure lower levels of performance the lowest measure of math proficiency on PISA assessments, level Ic, is a score of 233.2 and for reading the lowest category starts at 189.3.

Figure 5: Universal completion of grade 10 does not change the fraction of the cohort achieving SDG-like learning goals because all of the gain is at very low levels of learning



While the result that a massive expansion in grade attainment produces so little cohort learning progress may seem implausible or even impossible, the intuition and mechanics of this striking result are straightforward. Because many children are learning less in each grade than the pace of the curriculum ($h^i < p$), they begin falling behind and their learning profile begins to flatten at a relatively early grade. Hence nearly all children who drop out would have learned little to nothing from additional years of schooling, as they were already falling behind (and in some cases not learning at all) even before dropping out.

Table 4 compares the grade attainment and fraction of students learning in the base case (columns BC:I to BC:III) and the simulation of universal grade attainment (columns S(U10):I to S(U10):III). By grade 5 the learning profiles of the lagging students have flattened out enough that 19.2 percent are not learning, *whether they are enrolled or not*: In the base case in grade 5 17.2% are out of school and not learning, and 2% are in school and not learning. Therefore, the

LATE of staying in school for the 17.2% who dropped out, given our assumption that the lowest learners dropout first, would have been zero. Therefore, in all of the grades 5 through 10, the percent of the cohort who are learning is *exactly the same* in the base case of actual grade attainment levels (Column BC:III) and under universal grade attainment (Column S(U10):III) (the **bolded** numbers in the table). Expanding enrollment without any changes to the learning process simply shifts children from not learning while out of school to not learning while in school.

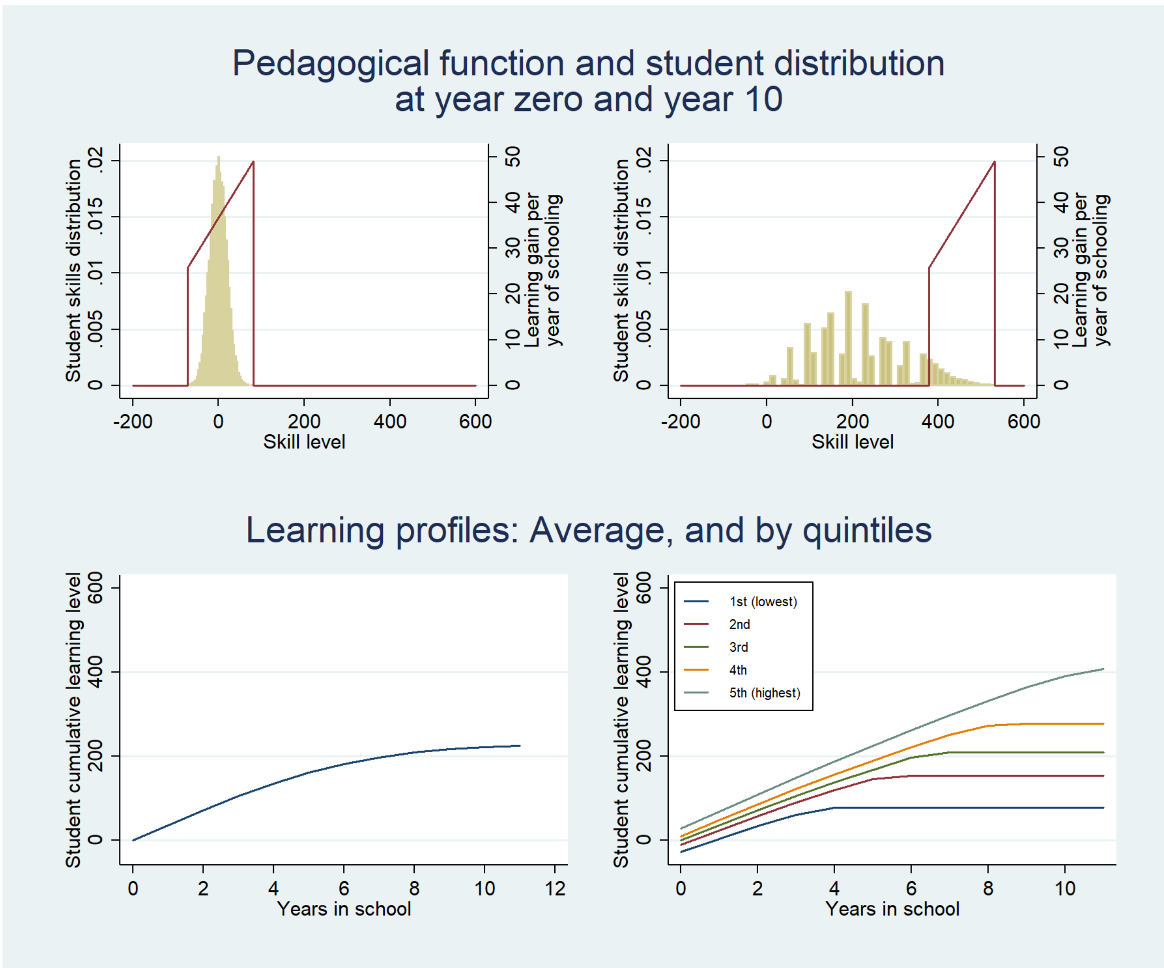
Table 4. Percent of the cohort, at each grade level, who have dropped out, attended and learned zero, and attended and learned more than zero

Grade	At observed grade attainment levels ("Base case")			Assumption of no dropout with calibrated PPF ("Simulation of universal to grade 10")		
	BC:I Not attained this grade (cumulative dropout)	BC:II Attained this grade, learned zero	BC:III Attained this grade, learned more than zero	S(U10):I Not attained this (cumulative dropout)	S(U10):II Attained this grade, learned zero	S(U10):III Attained this grade, learned more than zero
1	8.2%	0.0%	91.8%	0.0%	0.0%	100.0%
2	9.0%	0.0%	91.0%	0.0%	0.3%	99.7%
3	10.9%	0.0%	89.1%	0.0%	1.9%	98.1%
4	13.8%	0.0%	86.2%	0.0%	7.8%	92.2%
5	17.2%	2.0%	**80.8%**	0.0%	19.2%	**80.8%**
6	22.5%	12.3%	**65.2%**	0.0%	34.8%	**65.2%**
7	36.2%	14.5%	**49.3%**	0.0%	50.7%	**49.3%**
8	46.0%	18.4%	**35.6%**	0.0%	64.4%	**35.6%**
9	58.3%	17.1%	**24.6%**	0.0%	75.4%	**24.6%**
10	70.6%	12.6%	**16.8%**	0.0%	83.2%	**16.8%**

Source: Author's simulations calibrated to PISA-D learning and EdAttain attainment data.

Figure 6 illustrates the simulation of universal grade 10 attainment and shows the learning profiles that are generated by the repeated application of the learning process across ten grades. Although the PPF starts centered on the initial skill distribution (top left graph), since the pace, p, exceeds the average learning (and even more so, given positive sloping trapezoid, the learning of those who are lagging at entrance), more and more students fall out of the range of the PPF with each grade (e.g., their skill level, s^i, is lower than the leftmost edge of the PPF, $\pi^G - \frac{w}{2}$) and hence the learning profile turns flat as they are learning nothing. Hence in grade 10 only the top tail of the distribution remains within the range of the PPF and are still learning, while the rest have fallen outside the PPF range and are not learning despite attending school (upper right graph showing that very little of the skills distribution is still within the PPF trapezoid). The learning profiles of those who fall outside the range turn flat (LATE of grade *G* is zero). The learning profiles by initial quartile of skill (bottom right graph) show that by grade 5 the bottom quintile is learning nothing (as shown above the percent learning nothing is 19.2 percent) and that by grade 8 the bottom three quintiles are learning nothing.

Figure 6: By grade 10 the majority of children are outside the range of the PPF and not learning, even if they do stay in school. Learning profile of the bottom quintile of learners is flat after grade 4.



III.B. Consequences of slowing curricular pace: Slower can be better

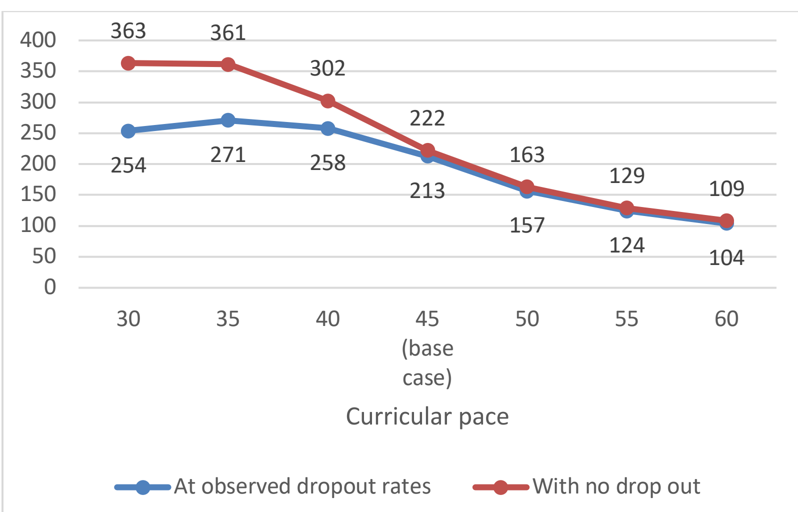
The base case has "many children left behind" (Glewwe, Kremer and Moulin 2007) not just by dropout but also by being left behind by the learning process in school. Many learn at a slower pace than the curriculum and are quickly left behind. This implies, perhaps counterintuitively, that *slowing* the curricular pace, *p,* can increase learning. If the curriculum moves too quickly from one skill to the next, before children have mastered the skill, they will not be able to learn subsequent skills. Slowing the pace of the curriculum, to ensure most children have mastered a skill before instruction moves on, could enable more children to learn for more years while in school.

In our base case the curricular pace is p=45 points, but, the *most* a child learns is h_{max}=49 points and the minimum is h_{min}=26 points. That implies that, given r>0, all children except those at the very top of the learning distribution (learning between 45 and 49) fall further and further behind and hence, learn less and less and eventually fall outside the range of learning entirely.

Slowing the curricular pace, p=45 to p=35 (without changing any other parameters or the dropout assumptions) raises average cohort learning outcomes in grade 10 by 58 points, from 213 to 271 (Figure 7). Perhaps surprisingly, a *slower* curricular pace nearly quadruples the fraction of children scoring 400 or greater from 7% to 27%.

The curricular pace can also be "too slow" and when p<35 learning begins to decline when there is dropout or level off with universal grade 10 completion (Figure 7). Conversely, a faster curricular pace from the base case makes things worse. Increasing pace to the OECD level, p=50, (as an isomorphic mimicry "best practice" adoption of an OECD curriculum might suggest) decreases average learning massively with no change in drop-out (from 213 to 157) and makes the impact of achieving universal grade 10 attainment even smaller (only six point gain from 157 to 163).

Figure 7: A slower curricular pace (from p=45 to p=35) increases the average cohort learning from 213 to 271 with no enrollment increase and from 213 to 361 with universal grade 10 completion



Source: Author's simulations based on PISA-D data.

Simulations with a slower curricular pace *and* all children completing ten years of school show massive gains: 84.6% are still learning in grade 10 (Table 5, Column S(U10,p=35):III) and average cohort learning increases to 361. Thus, eliminating dropout and slowing the curriculum results in an additional 67.8% of the cohort of children to be learning in grade 10 than in the base case, children who otherwise would have dropped out or would have been left behind by the curriculum.

Table 5. Percent of the cohort, at each grade level, who have dropped out, attended and learned zero, and attended and learned more than zero, under a slowed curricular pace of 35 points per year. With a slower curricular pace, eliminating dropout yields large gains.

	At observed grade attainment levels and slowed curricular pace			Assumption of no dropout with slowed curricular pace		
Grade	S(p=35):I Not attained this grade (cumulative dropout)	S(p=35):II Attained this grade, learned zero	S(p=35):III Attained this grade, learned more than zero	S(U10,p=35):I Not attained this (cumulative dropout)	S(U10,p=35):II Attained this grade, learned zero	S(U10,p=35):III Attained this grade, learned more than zero
1	8.2%	0.0%	91.8%	0.0%	0.0%	100.0%
2	9.0%	0.0%	91.0%	0.0%	0.1%	99.9%
3	10.9%	0.2%	88.9%	0.0%	0.4%	99.6%
4	13.8%	0.5%	85.7%	0.0%	1.0%	99.0%
5	17.2%	1.3%	81.5%	0.0%	2.3%	97.7%
6	22.5%	2.2%	75.3%	0.0%	4.0%	96.0%
7	36.2%	3.6%	60.2%	0.0%	6.4%	93.6%
8	46.0%	4.9%	49.1%	0.0%	9.2%	90.8%
9	58.3%	6.6%	35.1%	0.0%	12.6%	87.4%
10	70.6%	7.5%	21.9%	0.0%	15.4%	84.6%

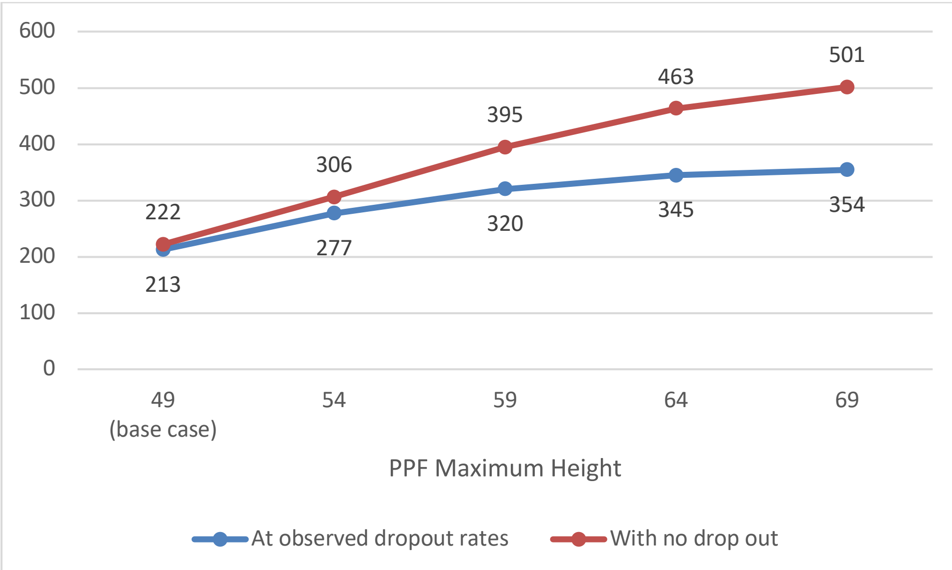
Source: Author's simulations calibrated to PISA-D learning and EdAttain attainment data.

III.C. Gains from better instruction (higher h)

Increasing the PPF height (*h*) increases cumulative learning in two ways. First, children within the range are learning more per year. Second, with a higher PPF, at any given curricular pace more children are able to keep pace with the curriculum for longer and stay within the PPF width and hence achieve positive learning.

We simulate increasing h_{max} in increments of five points, with other elements of the base case simulation the same (except those derived in part from h_{max} which, because ratio of h_{max}/h_{min} is held constant means r and h_{min} vary as a function of h_{max}). Increasing h_{max} from 49 to 54 increases the average cohort grade 10 learning by 64 points (from 213 to 277) (Figure 8).

Figure 8: Grade 10 cohort learning increases with improved instruction (increase in h_{max})



Source: Author's simulations based on PISA-D data.

Improved instruction also increases the number of children who achieve the SDG threshold. An increase in height of just 5 points results in an additional 22% of the cohort, for a total of 29%, achieving a score greater than 400 by grade 10. Increasing maximum height by another five points, to 59, increase average grade 10 learning by an additional 43 points, to 320, and 42% of children reach a score of 400 or greater by grade 10.

We next simulate this same instructional improvement with all children staying in school through grade 10. Under a scenario where instruction has improved by just 5-points per year, to a maximum PPF height of 54, eliminating drop out increases average learning by an additional 29 points, to 306 (Figure 8).

Steepening the learning profile (by raising PPF height) has an added advantage for reaching schooling *and* learning goals. Some studies suggest that many children drop out of school *because* of low learning (Zuilkowski et al, 2016, Das et al, forthcoming). Steepening the learning profile so that children learn more could entice some of these children to stay in school, helping achieve grade attainment goals through improved learning.

III.D. Assuming dropout does not depend on learning

As described above, the simulations of outcomes with and without reductions in dropout have assumed the lowest performing children drop out (calibrated to match actual grade drop-out in the base case). This strong assumption of perfect sorting gives a lower bound of the learning that would be gained from eliminating dropout. A different extreme is to assume dropout is completely unrelated to performance.

With an assumption that drop out is uncorrelated with measured learning/skill the PISA-D results are replicated with a PPF with h_{max} 55 and h_{min} 29 as the base case (compared with 49 and 26 with sorted dropout). Average cohort learning is 245, and 14% of 15-year-olds score 400 or higher. Simulating achieving universal grade 10 attainment increases learning from 245 to 324. In contrast with assuming endogenous dropout, expanding school under a scenario where dropout is uncorrelated with measured skills/learning produces more children at higher-performing PISA score levels. Eliminating dropout under assumptions of random dropout would increase the percent of all 15-year-olds scoring above 400 from 14% to 36%.

The mechanism producing these very different results is obvious, and makes an important point. With endogenous, sorted, dropout and a curricular pace that is "over-ambitious" those that are learning stay in and those that drop out would have not learned in any grade past grade 5 in any case. If dropout is random, some of those who are learning are dropping out and hence keeping those students in school until grade 10 increases their learning.

This scenario produces the naïve result that those children who are observed to have dropped out would have the same learning trajectory under universal attainment as the 30% who are observed to have stayed in school through grade 10. In other words, it assumes the LATE of attending grade *G* for a child who is observed to have dropped out is the same as the LATE of grade *G* of a child who is observed to have persisted. This then is the upper bound of what can be hoped from an "expansion alone" strategy. Even in this overly-optimistic scenario the vast majority of 15-year-olds do not reach the SDG basic proficiency even with universal attainment of grade 10.

III.E. Summary of simulations

We have six main simulations showing how changes to the learning process parameters, cohort grade attainment, and dropout assumptions change cohort learning outcomes compared to a base case which replicates PISA-D learning outcomes. Figures 9a and 9b summarize the results. Figure 9a shows the gain to the average cohort score from each scenario while Figure 9b shows the fraction of the cohort over a score of 400 in grade 10. Again, these scores are on a "PISA-like" scale where the standardized OECD mean is 500 and student standard deviation is 100 and the low-performing country (PISA-D) average of the assessed is 324 and cross-country average of standard deviation of the assessed is 74 (Table 2) and the calculated low-performing country (PISA-D) cohort average is 213 and cohort standard deviation is 124[12].

[12] And again, keeping in mind that we both follow a widely established practice of both treating these scores as cardinal numbers while acknowledging that this is not a valid practice as IRT-like scores are actually only ordinal.

The most obvious point is that in our base case specification of the learning process and dropout achieving universal completion has a very, very small effect on average cohort learning (Figure 9a), achieved entirely by raising the very bottom modestly to still very low learning levels, and hence has no impact on those above a higher threshold (Figure 9b). Slowing the curricular pace or improving instruction produce substantially higher gains, even at observed grade attainment, and when combined with schooling expansion increase average learning further.

Figure 9a. Gains over base case PISA-D learning process with endogenous dropout (in terms of PISA-scale points)

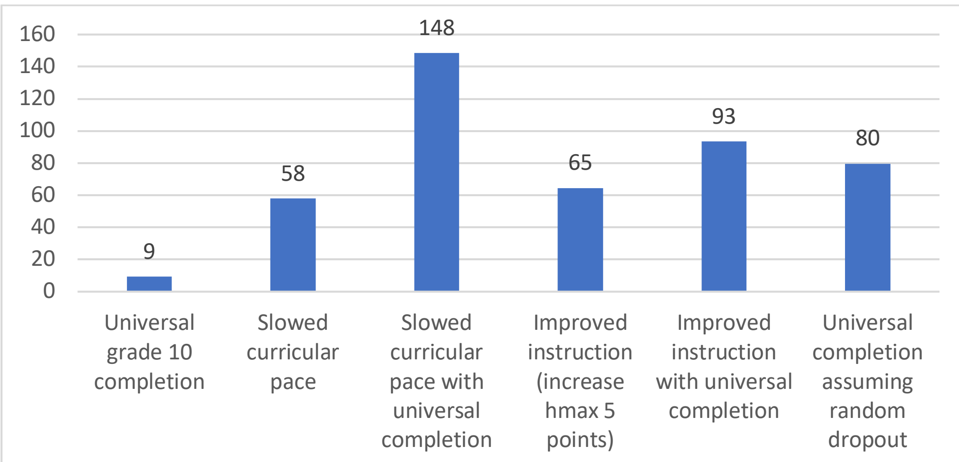
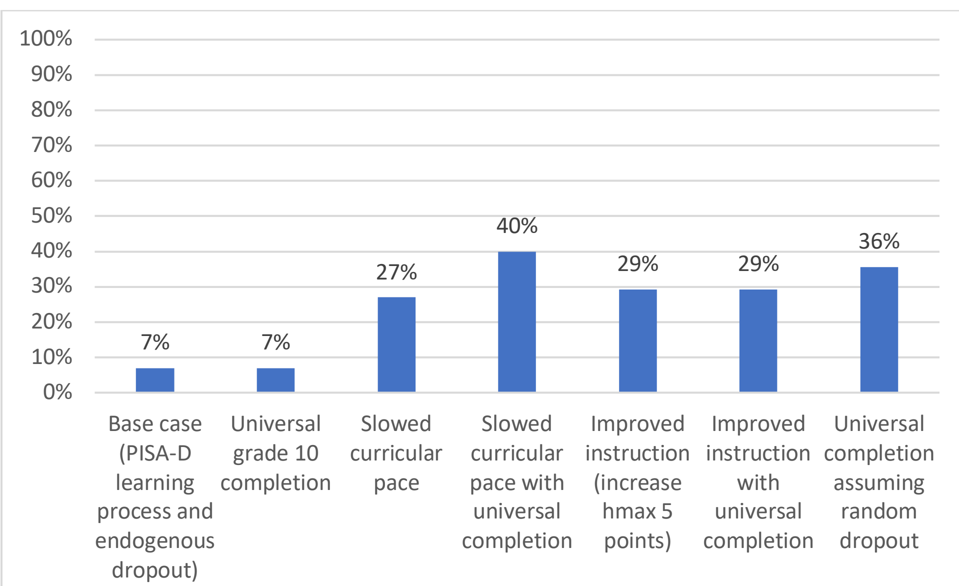


Figure 9b: Total percent of cohort over score of 400 (roughly SDG minimum proficiency) in grade 10



Conclusion

Achieving universal grade 10 completion in low- and middle-income countries will bring many more children into school—and is rightly enshrined as an SDG goal. But how much progress on the SDG for learning would this more schooling bring? Currently, no one knows, or even has a good guess. The crude extrapolation of the PISA-D results suggests very modest gains, as current learning of those enrolled is so low, and Indonesia's experience suggests massive expansion in enrollments can bring zero progress in cohort mastery (Beatty et al 2018).

We develop a simple, stylized, formal model of the learning process, calibrating it to PISA-D data to represent low-performing systems, and with that carry out various simulations that produce three main findings.

First, under our calibrated learning process and assumptions about skill sorted dropout reaching universal grade 10 completion has little impact on cohort grade 10 learning outcomes and produces *zero* progress on reaching SDG learning goals of minimum proficiency.

Second, by contrast, slowing the curricular pace would increase average cohort learning outcomes and produce progress on the SDG learning goals, even without expanding enrollment. When slower curricular pace is combined with universal grade 10 completion even larger gains are achieved.

Finally, improving instructional effectiveness produces large learning gains in average learning levels and percent of those reaching learning goals, again with even larger gains when combined with universal grade 10 completion.

Beyond these particular findings of this particular model is a broader, meta, if you will, point. The meta point is that to make any claim at all about how much additional learning would be produced by expanding enrollments one needs a formal empirically informed model about a counter-factual: How much would the currently non-enrolled children learn if they were to be enrolled? Our simulations are just one *instance* of a class of such models. We are not claiming our model is the only model, or that the particular calibrated parameters we use are the "true" parameters, or that our assumptions about the strength of sorting of drop-out are correct. But, you cannot beat something with nothing, which is currently the *status quo.*

Our meta point is that it is critically important that education planning draw explicit, formal, empirically informed, connections between grade attainment goals and cohort learning goals. Without a formal model of the learning process and clearly stated assumptions, no one can know whether the many things that a government may plan to do, such as expanding secondary school access, universalizing early childhood education, or revising a national curricula, will relate with the other parameters in an education system in a way that produces improvements in cohort learning and makes progress towards achieving learning goals. Failing to plan is planning to fail.

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