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Test Scores and Educational Opportunities: Panel Evidence from Five Developing Countries

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Abstract

Whether better test scores can increase college attendance among poor students in low- and middle-income countries remains an open question. Using data from five long-running panels in Ethiopia, India, Pakistan, Peru and Vietnam, we show that (a) at age 22 there are substantial gaps in years of schooling by socioeconomic status but, (b) conditioning on test scores at the end of primary school eliminates only between 15--50% of these gaps. An exclusive focus on test score improvements in primary schools or earlier will not equalize access to post-secondary education for the poor in these five countries.

Test Scores and Educational Opportunities: Panel Evidence from Five Developing Countries

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1. Introduction

In the United States, college attendance has emerged as a clear marker of advantageous life outcomes—and test scores at the end of school are a key predictor of college attendance. In the National Longitudinal Survey of Youth (NLSY) 1979, for instance, a single measure of cognitive skills, the Armed Forces Qualification Test (AFQT) score at age 14, explains 70-100% of the Black-White wage difference for men and women (Neal and Johnson 1996) as well as the college attendance gap (Cameron and Heckman 2001, Carneiro and Heckman 2002). Consequently, what explains test score gaps and to what extent these gaps can be remediated through age-specific interventions has become a key focus of research and policy in recent years (Heckman and Mosso 2014).

There is a strong prima facie case to be made for a similar emphasis on test scores in low- and middle-income countries (LMIC). Like in the U.S., private returns to years of schooling are now much higher for those who have completed their post-secondary education.[1] Also like in the U.S., students from less advantaged family backgrounds are more likely to drop out of schooling *and* perform worse on cognitive assessments (World Bank 2018b). Further, multiple studies in LMIC point to very low test scores and 'flat' learning profiles (Pritchett, 2013). If returns to test scores exhibit diminishing returns, this suggests that that marginal gain from improving test scores for poorer and more disadvantaged populations should yield even higher dividends than in the U.S.[2] Yet, policy makers *within* LMIC remain concerned that even children who have demonstrated high achievement in school face significant constraints in pursuing further studies; they argue that providing a viable path for high-achieving low-income students to pursue higher education should be the first priority.[3]

These two policy proposals -- of improving learning during the compulsory schooling years and/or enabling high achieving students to study further by relaxing barriers to schooling at the secondary and college levels of education -- need not be mutually exclusive. At its heart, the efficacy of either policy proposal depends on a decomposition of the effect of socioeconomic status (SES) on college attendance into an indirect effect through test scores and a direct effect that conditions on test scores. This seemingly straightforward decomposition relating test scores, SES and schooling attainment would allow us to make progress on many of these policy dilemmas: A large indirect effect would

[1] For instance, Mincerian returns to secondary education in Latin America and South Asia are lower than in high-income economies, while returns to tertiary education are substantially higher (Montenegro and Patrinos 2014). Although these naïve computations of returns do not account for the option value of further study induced through schooling completion at each level, what is striking is the rising wage premium to tertiary education over the last two decades.

[2] Rapid increases in average years of education have not been accompanied by an improvement in test scores, which remain 1 to 1.5sd below those in the U.S. or other OECD countries (Sandefur 2018, Patel and Sandefur 2019). International organizations such as The World Bank and the United Nations argue that low test scores constitute a 'learning crisis', leading to the adoption of learning goals in international agreements. The Sustainable Development Goal #4 relates to education and argues for the first time that students should have access to free primary and secondary schooling that leads to `relevant and effective learning outcomes.'

[3] One example of such policy focus has been the debate around affirmative action in higher education for disadvantaged groups in India, which has been much more salient in the policy and public discourse than improvements at primary education (see Bagde et al 2016 for an evaluation of such a policy). A similar focus on higher education in Africa is advocated by Shimeles (2016). Duflo, Dupas and Kremer (2017) look at the impacts of providing scholarships to high-achieving low-income students in Ghana. These are scholarships given to children who have been selected into higher secondary schools but cannot afford the fees. The study shows significant labor and non-labor market returns for scholarship recipients.

favour increasing test scores relative to expanding access to higher education. What holds this research back is not its conceptual complexity, but a lack of high-quality longitudinal data that links test scores at earlier ages to completed schooling later in life: cohort studies with long horizons (such as the NLSY), or comprehensive administrative registers such as in the Nordic countries, remain scarce in LMIC.

This is the gap we address in this paper. Specifically, we use data from longitudinal studies in five countries (Ethiopia, India, Pakistan, Peru and Vietnam), each of which has high-quality information on household background and test scores to examine the link between SES, test scores and college attendance. These are the *first* longitudinal studies that allow us to link test scores at the end of primary school to schooling at age 22 in LMIC, and the datasets are of uniformly high quality with low attrition, tests conducted by survey teams themselves, and careful consideration of test construction that allows us to link scores across years to study gains over the schooling years.

Using these data, we examine (a) the relationship between test-scores at age 12 (roughly the completion of primary school) and completed years of schooling at age 22 as well as (b) the gain (or loss) of test scores through the primary schooling years, which we call 'learning'. Our aim is to unify what we know about how learning differs by SES in multiple LMIC and how learning at younger ages translates (or not) into further schooling using the best data currently available for this purpose in these settings.[4]

Our emphasis throughout will be on gaps in completed years of schooling between individuals from the bottom and top terciles of SES within each country. There are large differences in multiple dimensions across our SES categories: among households in the top tercile, the more-educated parent reports, on average, 7-10 more years of schooling than in the households in the bottom tercile; these households are 1.6-2sd higher on an index of assets based on consumer durables with real per-capita expenditures that are between 35-125% greater. These differences are large in every country, a pattern that is important to interpret the cross-country differences in our data.

In terms of education outcomes, the test scores of students from the top SES tercile are 0.5-1.4sd higher at age 12 years, when most children are still in school, compared to students from the bottom tercile in each country. At age 22, these high-SES students have completed 2.5 to 4 more years of schooling, and are better able to access higher levels of education, where returns to education are the highest: Reflecting a sharp rise in college attendance, 48.9% of rich students have attended some college, compared to 16.3% among the poor.

We document three patterns in the data relating test scores to later gaps in educational attainment. First, for both high- and low-SES students, in all countries, higher achievement at age 12 is correlated

[4] Since these are long-running panel datasets, there have been previous investigations of SES gaps in enrolment and achievement at different ages (see e.g. Sanchez and Singh 2018). This is, however, the first time that most individuals have been observed at an adequate age to capture their final schooling.

with more years of schooling completed. Conditional on parental education and household wealth, a 1sd increase in test scores at age 12 is associated, with a 1-2 years increase in the years of schooling completed by 22. The consistency of this association across countries with widely differing levels of achievement (our sample includes Vietnam, which tests at the top of PISA assessments and Peru, which test at the bottom) suggests that a focus on test score improvements is equally promising across vastly different education systems.[5]

Second, at all levels of achievement at age 12, the expected years of schooling conditional on test scores is meaningfully higher for students in the top SES tercile. This is evident both in non-parametric investigations following Cattaneo et al (2019) and in linear specifications. Third, Oaxaca-Blinder decompositions show that if test scores were equalized for high- and low-SES children at age 12, the gap in eventual schooling would reduce from ~15% (Pakistan) to ~35-50% (other countries). However, in four of the five countries (except Ethiopia), gaps in household wealth and parental education appear to be at least as, and frequently more, important as test score gaps for predicting later education, especially at post-secondary levels. Evidence from these countries, therefore, seems closer to the evidence for recent cohorts in the U.S. and in Scandinavia (Belley and Lochner 2007, Landerso and Heckman 2017) than with the seminal work on the NLSY 1979 cohort.

Given that test scores do seem to matter for completed years of schooling in all of the countries, even if not to the extent in Carneiro and Heckman (2002), we then examine when these gaps emerge during childhood. In all five countries, as in the U.S., we show that SES gaps in test scores are already large by the time the children are 8 years old. Using a particular design of these tests that allow us to place test scores across years on the same scale (so that they are "vertically-equated") we show that the absolute magnitude of the SES gap does not change appreciably in these countries between the ages of 8 and 15. The exception is Pakistan where test score gaps increase between 12 and 17, entirely due to a larger number of dropouts who are disproportionately concentrated in the low-SES group.

This paper makes three contributions to our understanding of test scores and schooling in LMICs. Our most important contribution is to provide the first assessment from multiple LMICs of the link between test scores at age 12 and completed years of schooling. Our finding that test scores at age 12 correlates with completed years of schooling at age 22 provides some confidence that the focus of a now-substantial literature on identifying effective interventions to boost test scores early on in schooling is not misplaced. However, the magnitude of this correlation is relatively low: a 1sd increase in test scores at 12, which would be a much larger treatment effect than has been demonstrated at scale from well-identified studies in primary schooling (see Glewwe and Muralidharan 2016, and McEwan 2015), is associated with 1-2 years of extra schooling. Unless our correlations are severely

[5] Students in Ethiopia and India, which do not participate in PISA or TIMSS, perform much more poorly even than students in Peru (Singh, forthcoming).

biased towards zero, even the larger treatment effects documented in literature on test scores at scale (usually around 0.2-0.3sd) will have at best a modest impact on the later life outcomes of children.

Our second contribution is to quantify the potential role of test scores in mediating the link between parental and child education, which has served as the basis for multiple studies of relative and absolute mobility in LMIC (see Chetty et al 2014, and World Bank 2018a). In all countries, like in the existing literature, we find that children's eventual education remains significantly correlated with their parents' education and household wealth. Conditioning on test scores at 12 years of age reduces the coefficient on parental education by half in most countries, and to statistical insignificance in Ethiopia, suggesting that the lack of relative mobility does in fact capture some aspects of schooling quality. In all five countries, closing the SES gap in test scores at 12 accounts statistically for 15-50% of the eventual gap in completed years of schooling between the top and bottom SES terciles. This suggests that even though better test scores do allow children to progress further in school, they will not permit the poor to catch up with the rich.

Our final contribution is to a literature on the evolution of test score gaps. We present, to our knowledge, the first such assessments in LMIC. The pattern we find — that mean test score gaps across SES emerge early but then are steady over the period that children remain in school — is similar to that documented in the U.S. for Black and White students which show, across various datasets, that SES gaps grow substantially until Grade 3 but then are steady until middle school (Hanushek and Rivkin 2006, Clotfelter, Ladd and Vigdor 2009). However, we urge caution in interpreting these results: constant mean gaps are consistent with fresh divergence in test scores during the schooling years if test score gains are negatively correlated with initial values—a pattern that we indeed confirm in all five countries.

2 Data

The data in this paper come from two separate longitudinal studies — the Learning and Education Achievement in Punjab Schools Project (LEAPS) study in Pakistan and the Young Lives study in Ethiopia, India (Andhra Pradesh and Telangana states), Peru and Vietnam. These projects are the longest-running cohort studies focusing on children in LMIC. Importantly for our purposes, they contain measures of cognitive skills and socioeconomic background in childhood and a sufficient follow-up until early adulthood when final schooling levels are observed. Both studies measure cognitive skills in a way that can be linked on a comparable metric over time.

The Young Lives study has surveyed two birth cohorts of children – born in 1994/95 ("older cohort") and 2000/1 ("younger cohort") – over five survey rounds (in 2001, 2006, 2009, 2013 and 2016). The LEAPS sample used in this paper comprises a cohort of Grade 3 students in 2003 in rural Punjab (Pakistan) who were also interviewed at home in 2011 and 2017. In all five countries, the sample covers a wide range of variation with similar educational trends as in nationally representative datasets (see Singh, forthcoming and LEAPS Report). Attrition rates in both datasets are low: in Young Lives, total attrition from all causes including mortality and non-response is 4.9% in the younger cohort and 12% in the older cohort over the 15-year period, averaged across countries[6]; in LEAPS, by 2017, we have information for 94.8% of the children observed between 2003 and 2006 in the household sample used in this paper[7]. The sample numbers and the characteristics of individuals in the top and bottom terciles are presented in Appendix Table A.1. We next explain the measurement of key variables used in this paper.

Educational attainment

In both LEAPS and Young Lives, the survey asked respondents directly whether the sample individual was still enrolled in formal education (and the grade that they are enrolled in) and, if now outside of formal education, then the highest grade they had completed. We use this to construct the years of formal schooling received until that point, which is our main measure of human capital attainment. In LEAPS, this information in early adulthood is collected in the 2017 round, which is about 14 years after they were in Grade 3. In Young Lives, this was collected in 2016. In all surveys, the mean age of respondents was between 21-22 years when this information was collected. The recency of survey rounds also means that our estimates are likely to be much more relevant for understanding the relevant patterns for current cohorts than older datasets: this is important because all of these countries, like other LMIC, have seen substantial increases in educational attainment over the past two decades (Sanchez and Singh, 2018).

Socio-economic background

Our measure of socioeconomic background aggregates the material wealth of households and the educational level of the parents. We measure wealth using ownership of household consumer durables and access to services. In both surveys, we use data from the first year in childhood from which we would be using test score data (2006 in Young Lives, 2003 in LEAPS). We aggregate material well-being into a single index using the first component from a Principal Components Analysis, a method that is widely used to provide reasonable proxies for inequalities in living standards, particularly in LMIC (Filmer and Pritchett 2001, McKenzie 2005).[8] For the second dimension, we use the years of schooling of the most educated parent in the household. We aggregate these two dimensions into a single SES measure again using the first PCA component. Our results are not very sensitive to our choice of SES measure. We find similar patterns when using

[6] See Sanchez and Escobal (forthcoming) for a detailed analysis of attrition in the Young Lives sample over this 15-year period.
[7] LEAPS tested children at the school-level, starting with grade 3 in 2003. At the same time, it surveyed their households. Every year, in addition to tracking the initial sample, new children in grade 4 for 2004, 5 for 2006, and 6 for 2006 were added to the sample. Some of the new children belonged to the sample of LEAPS households and are included in this paper. In 2017 all children observed were tracked regardless of the year they entered the panel.
[8] This approach also forms the basis for the World Bank's International Database on Educational Attainment and Enrolment around the world which presents the most comprehensive global picture of SES gaps on this metric (http://iresearch.worldbank.org/edattain/)

measures of per-capita consumption and present all core results using an alternative consumption-based definition of SES in Appendix B.[9]

Test scores

Both Young Lives and LEAPS tested student achievement directly using purpose-designed tests. The Young Lives study has measured cognitive achievement in math and language consistently since the second round of the survey in 2006. These tests were individually administered to children. They include a mixture of written items and those asked by the interviewer directly and thus can also accommodate non-literate students. In this paper, we focus on two tests — mathematics and receptive vocabulary — which were administered to the older cohort at 12 and therefore are central to investigating the relationship between test scores in childhood and later education. Receptive vocabulary was tested using versions of the Peabody Picture Vocabulary Test III adapted into local languages. Children in LEAPS were tested in Urdu, Mathematics and English, first in Grade 3 in 2003 in schools. In 2011, children whose households were surveyed in the previous rounds were also tested in their households.

Measuring the evolution of learning gaps over time is challenging because students need to be administered items that can be scored on the same metric to enable meaningful comparisons over time. This is particularly difficult over a long time-horizon since an identical test administered to a student at 8 and 18 years of age may not, given time constraints, adequately capture "new" learning for both groups. Third, and of particular importance to LMIC, any such surveys need to track not just all children in school but also all of those who have dropped out or are attending irregularly.

The LEAPS and Young Lives datasets, perhaps uniquely in LMIC, allow us to make progress on all of these dimensions. Both studies follow individuals over a substantial period in primary schooling and test them in home visits, thus limiting the non-random attrition arising from non-enrolment or non-attendance. They also administered tests that contain a substantial fraction of test questions that are repeated across survey rounds/ages. These 'anchoring items' allow for test scores to be linked (vertically equated) on a common metric using Item Response Theory models (see Das and Zajonc 2010 for an overview).

In LEAPS, it is possible to construct linked test scores in all of the three subjects tested – Maths, Urdu and English – for the cohort used in the analysis in Section 3. In Young Lives, unfortunately, very limited tests were administered to the older cohort in the first survey round. Hence, when we discuss the evolution of test score gaps over the schooling years, we focus our attention on the younger cohort where mathematics tests can be linked up from 8-15 years on the same metric (as can the older cohort from 12-19 years). We will label both cohort and age groups when presenting test score gaps.

[9] We prefer our measure of SES for classifying high and low-SES households both due to its links with other efforts to look at SES inequalities but also because consumption in LMICs is much more seasonally-variable and more prone to measurement error.

3 Results

3.1 SES inequalities in completed education

We first discuss the extent to which differences in completed years of schooling at 22 years of age correlates with SES and test scores measured towards the end of elementary education in the five countries. Test scores in this part of the analysis refer to an average of the IRT scores for Math, English and Urdu in LEAPS. In Young Lives, they aggregate the Math IRT scores and normalized scores for the PPVT test of receptive vocabulary.

Figure 1 divides the sample in each country by terciles of test score and of SES, both measured at 12, and plot the mean years of schooling at 22 years for each of the nine groups. This is similar to the analysis in Carneiro and Heckman (2002) and Belley and Lochner (2007).

Several patterns are noteworthy. To begin with, even children in the bottom SES tercile in these cohorts now complete 8-10 years of schooling in all countries. This is consistent with a fairly remarkable expansion in schooling attainment over the last two decades. However, *within* each test score tercile, the years of schooling increase with SES. Children from a low SES background will have 2-3 years fewer years of completed schooling compared to those from the top SES tercile even when they are among the high achievers. Although SES is clearly associated with more schooling, there is still a role for test scores. Reading across the bars, a move from the bottom to the top tercile of test scores for low SES children corresponds to an increase in average years of schooling by 2.5-4 years in Ethiopia, India, Pakistan and Vietnam. The exception is Peru where such a move translates into only one additional year of schooling. Overall, this initial exploration suggests that each of these five countries look quite different from the pattern suggested in Carneiro and Heckman (2002) with SES continuing to play a role even conditional on prior test scores.

Completing high school and college entry are typically conditional on passing standardized exams, potentially making some parts of the test score distribution more consequential than others. Figure 2 therefore examines the relationship between test scores and final schooling non-parametrically, separately for the top and bottom tercile of SES in each country. We use the approach of Cattaneo et al (2019) to plot the quintiles of test score in each SES group and fit a quadratic polynomial in each bin with a smoothness restriction requiring it to be twice-differentiable at boundary points.

Figure 2 shows, first, the divergence in test scores that has already taken place by age 12 and the extent to which there is common support between the top and bottom SES terciles varies by country. In India, Pakistan and Vietnam, there is substantial overlap at the top end of achievement i.e. these countries all have a substantial number of high-achieving children from low-income backgrounds. Peru, however, offers a stark contrast with very little common support in achievement between high-and low-SES students: like in the U.S. (Chetty et al, forthcoming), there are very few high achieving low-income students. Second, at each level of achievement where there is common support between the achievement of high- and low-SES students, final years of schooling are significantly higher for high-SES students. A remarkable fact is that in the countries with substantial overlap in support (India, Pakistan and Vietnam), the highest test score children from a low SES background complete about as many years of schooling as the *lowest* test score children from a high SES background.

Third, there is some evidence of SES gaps differing across the test score distribution, but this varies by country. However, plotting Figure 2 along with the relevant 95% confidence intervals in appendix Fig A.1, it is clear that we lack sufficient statistical power to reject linearity within each SES group.[10] Thus, in the rest of this section, we will restrict ourselves to linear specifications.

Panel A in Table 1 presents linear regressions that relate final years of schooling to the subcomponents of SES (parental education and wealth index) and test scores. In each country, an increase in test scores by 1sd is correlated with an increase of about 1-2 years of education. These are substantive magnitudes. However, in all countries, even conditional on test scores, the wealth index remains a significant predictor of final schooling and going to college.

We use these coefficients, alongside the mean differences in the characteristics of bottom and top SES terciles, to present Oaxaca-Blinder decompositions in Panel B which quantify the extent to which equating various characteristics may close SES gaps in final schooling.[11] Equating levels of test scores at 12 closes 35-50% of the overall gap in Ethiopia, India, Peru and Vietnam and a smaller 15% of the gap in Pakistan. Considering wealth and parental education as core components of SES, it appears that in all countries SES is at least as important, and frequently more so, in predicting later gaps in educational attainment.

We emphasize that these patterns are even starker if we instead use a binary indicator for completing 12 or more years of formal education as the outcome variable. In fact, this might be a more relevant measure of disadvantage if there are non-linear returns to education. Appendix Figures A.2 and A.3 and Table A.2 show that the gap in completing secondary education ranges from 25-38 percentage points between the top and bottom terciles of SES. A 1sd increase in test scores is associate with an increase in the probability of college attendance by 4-18 percentage points. Closing the test score gaps at 12 helps close these later gaps by a similar proportion as completed years of schooling with a similar importance accorded to SES.

[10] This reflects the sample size available to us within each group. A further caveat is that estimated non-linearities are particularly unreliable at the extremes of the distribution, especially for high-SES students with very low absolute scores as the sample is very sparse at that point and problems of measurement error most severe.

[11] This is only one particular way of doing these decompositions, essentially fixing the coefficients associated with each input from the "pooled" model. Alternatives could, for instance, choose to take coefficients from either the "rich" or the "poor" groups in each country as a benchmark or indeed allow for a full three-fold decomposition (see Fortin et al, 2015). We adopt this particular decomposition because of the simplicity of exposition given that we intend these to be descriptive rather than imply any causal connection.

3.2 The emergence of SES gaps in education

Given that test score gaps account for a quarter to half of the gap in years of schooling, we can then ask at what age these gaps arise, and whether they widen over the schooling years. Panel A of Table 2 presents, for context, enrolment gaps at different ages across SES groups. Nearly all children are in school at 12 but the share of drop-outs (and associated SES gaps) grows by 15-17. In all Young Lives countries, we see improvements in enrolment between two cohorts in a seven-year period.

Panel B, Table 2, presents SES gaps in vertically-equated test scores for the LEAPS cohort in Pakistan and the 2000/1 cohort in Young Lives at different ages.[12] SES gaps are already large and evident at age 8 in all of the Young Lives countries, although much more modest in Pakistan. By age 12, in all five countries, these gaps appear to have neither widened nor narrowed. Indeed, students in both low- and high-SES groups to increase their test scores by a roughly similar amount of 1sd over four years.

Third, in the Young Lives countries, it appears that the SES gaps remain largely unchanged even at 15 years of age. In contrast, Pakistan sees stable test score gaps between 8-12 years although they then double by 17 with increasing SES gaps in enrolment. That the gap between high and low SES students is large by ~8 years of age and does not change in the four years afterwards is similar to patterns documented by Hanushek and Rivkin (2006) and Clotfelter, Ladd and Vigdor (2009).

Table 2 could, in principle, have been generated using repeated cross-sections. We use the panel dimension of the data explicitly in Figure 3 and relate, using non-parametric local linear fits, the relationship between test scores at 8 (on the X-axis) and at 12 (on the Y-axis) for rich and poor students. The distance between the two curves indicates the expected difference in test scores at 12 for students in the two groups who had scored exactly the same at 8. In all countries, and across the full range of the test score distribution, students in high SES groups have a higher predicted achievement at 12 than low SES students.

This result is important for two reasons. First, it cautions against interpreting the constant absolute gaps in Table 2 as indicating that only early years matter for the development of SES gaps in achievement. Such an interpretation implies perfect persistence of achievement, which is widely rejected across settings, even after correcting for measurement error (Andrabi et al 2011). If test score decay is proportional to initial achievement, a constant absolute gap between groups indicates that rates of learning in the high-SES group are higher. That is, children who start off at higher levels of test scores always have smaller net gains in achievement over their years in primary schooling compared to children who start off at lower levels. The implication of this result is that focusing exclusively on closing early gaps in learning is unlikely to be a successful strategy to reduce the extent of differences at the end of schooling.

[12] The test scores used here refer to the composite of the math, Urdu and English test scores in LEAPS and the math scores in Young Lives. All scores are vertically equated using IRT.

Second, it also highlights that our results are less sensitive to issues of scaling than in many settings which assume interval scaling for test scores. Such issues have been shown to make significant difference to inter-group comparisons in the U.S. (see Bond and Lang 2013, Nielsen 2015 for discussion). Since the curve for high-SES students is always higher than for low-SES students, in all countries, Fig. 3 suggests that our conclusion of divergence is robust to any rank-preserving transformation of the baseline score. Further, since it relies only on local smoothing, it also highlights that this result is not dependent on particular functional form assumptions.

3.3 Limitations

While these are the most-suitable datasets available for studying the link between test scores and future outcomes as well as the evolution of test score gaps in developing countries, we remain constrained by the data along multiple dimensions.

First, we cannot make causal claims. Instead, our work is similar to a substantial literature based on cohort studies such as the NLSY or the ECLS-K and is a precursor to potential studies that exploit exogenous variation in SES and/or test scores to examine later life outcomes (see for instance Cesarini et al 2016). Our attempt here is maintain maximal fealty to the data and document broad patterns, which have so far eluded the research on this topic. We can do better: In principle, the causal effect of raising test scores could be studied by long-term follow-ups of RCTs that have demonstrated an improvement in test scores. However, this is likely to be difficult. Taking our results at face value, in order to detect the (small) impacts on college attendance or years of schooling would require large sample sizes; a simple power calculation suggests that, even if a clustered RCT at the school-level raises achievement by 0.3 SD, it would likely require roughly 260 schools in the experiment with ~13,000 students in the sample for the experiment to be sufficiently powered to detect the effect on the years of schooling.[13] Few experiments in LMIC combine both effect sizes and sample sizes in this range or conduct follow-up surveys over a decade later.

Second, we are not powered to detect non-linearities in the relationship between test scores and later schooling (Figure A.1). Nor are we powered to detect heterogeneity across sub-groups in the relationship between years of schooling and test scores at age 12. This reinforces the need to invest in much larger panel studies in LMIC with long follow-ups. In the absence of reliable linked administrative datasets, these remain likely the only sources for meaningful investigation in many areas of substantial interest.

Our final limitation comes from potential measurement error in test scores. To the extent that measurement error does not differentially affect low- and high-SES groups, the results in Figures 2

[13] We assume that each school has a sample of 50 students, that the causal effect of 0.3 SD test score improvement is to raise the years of schooling by 0.5 years, that the intraclass correlation in years of schooling within a school is 0.15, that the mean and standard deviation of years of schooling in the control group is 11 years and 3.5 years respectively.

and 3 continue to suggest the substantive importance of SES in determining both later achievement and, our primary interest, the final educational attainment of individuals. However, despite well-designed tests which aggregate across dimensions, it is possible that coefficients on test scores are attenuated by measurement error.

4 Discussion

The acquisition of human capital is increasingly seen as a key policy lever for reducing poverty and decreasing inequality. However, although schooling attainment has risen rapidly in LMIC, relative mobility remains low. The question is what should be done. We make three points based on our results.

First, while our results do provide some support for using test score improvements in primary education as a channel for improving access to higher education, they also highlight the limitations of this approach. Even a 0.5sd improvement (which is larger than sustained gains seen in any large-scale policy experiments) will raise the probability of going to college by only ~5-7 percentage points: While this is substantive, it is still a mere fraction of the average gap of 28-38 percentage points between students from the top and bottom terciles of SES.

Second, at all levels of test scores high-SES students have more years of schooling and are more likely to progress to higher education. If schooling and ability are complements, as in the classic models of selection and investment (Becker 2009), our results are consistent with substantial misallocation in access to education. Bluntly put, many potential geniuses do not get the schooling they need to fulfil their potential if they are from poorer backgrounds. This is damaging both for efficiency and for equity reasons. Although we cannot speak to the precise channel of these non-test score channels through which SES affects access to higher education, it is likely that credit constraints matter a great deal more in LMICs than in the US (Cameron and Heckman, 2001), a view consistent with evidence using subjective expectations data from Mexico (Kaufmann 2014, Attanasio and Kaufmann 2014). Other constraints, such as information (Jensen 2010) and access to networks, may also limit children from poorer households more. Targeted access programs for poor students which ease these constraints, for example by providing credit, information and application assistance, might be more effective in reducing socio-economic gaps in higher education access than remedying test score gaps alone.

Finally, our results should not be interpreted as a call to de-emphasize the importance of skill acquisition in primary school. We may value cognitive skills for many reasons not captured in the final years of schooling: they plausibly have independent returns in LMIC labour markets, substantial intrinsic value in boosting the capabilities of students (Sen 2001) and are more predictive of economic growth than years of schooling alone (Hanushek and Woessman 2008, Hendricks and Schoellman 2019). Moreover, even with an exclusive focus on years of schooling, a substantial share of children in LMIC fail to acquire even basic skills, such as ability to read paragraph or simple arithmetic computation, at the end of compulsory schooling (World Bank 2018b). For these students, easing financial and other (non-test-score) structural constraints to college attendance is still unlikely to be productive. What our results highlight is that many children from more-deprived backgrounds could be brought into higher education, without any loss of efficiency, if these constraints were relaxed. Addressing socioeconomic disparities in eventual schooling years will require more than just the current focus on improving foundational skills in primary and middle schools: We need to create a viable pathway for high achieving low-income students to attend college.

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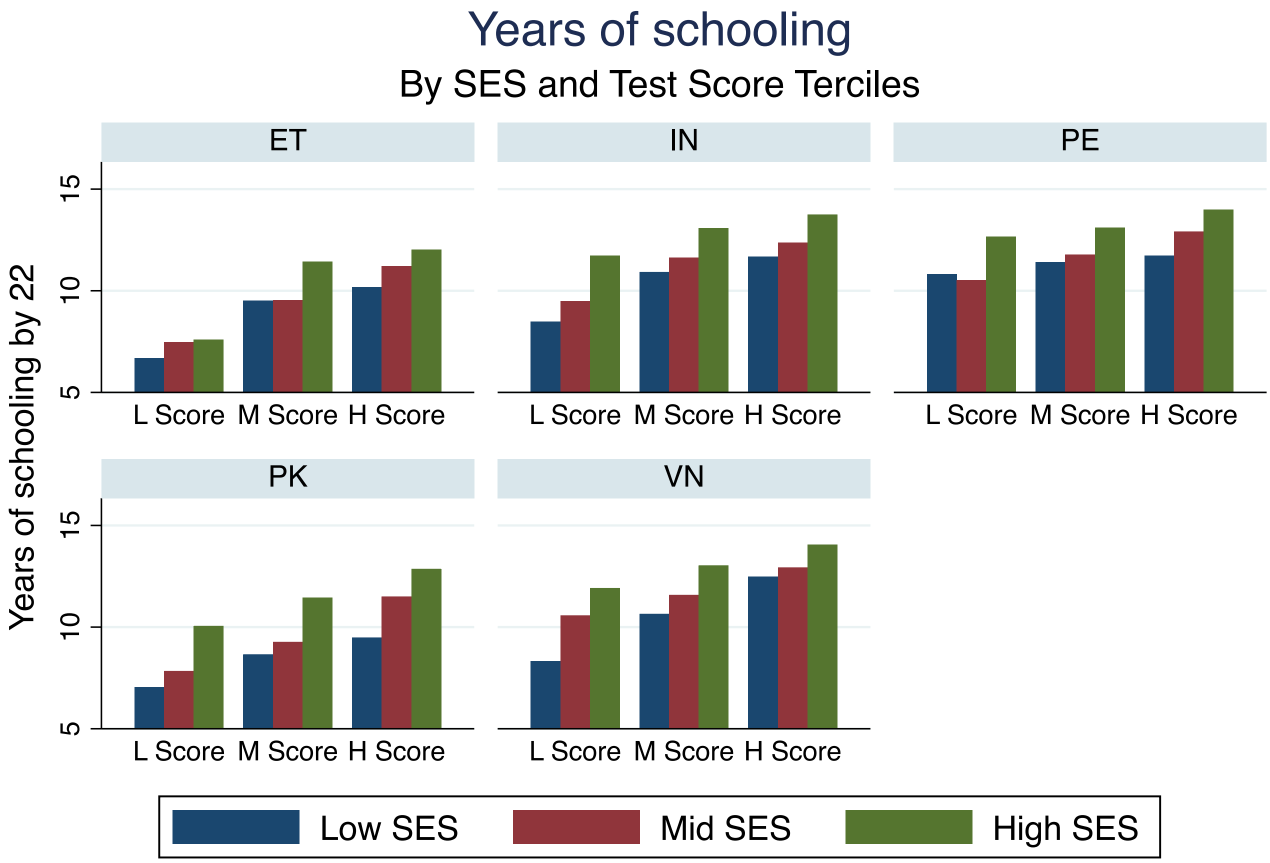
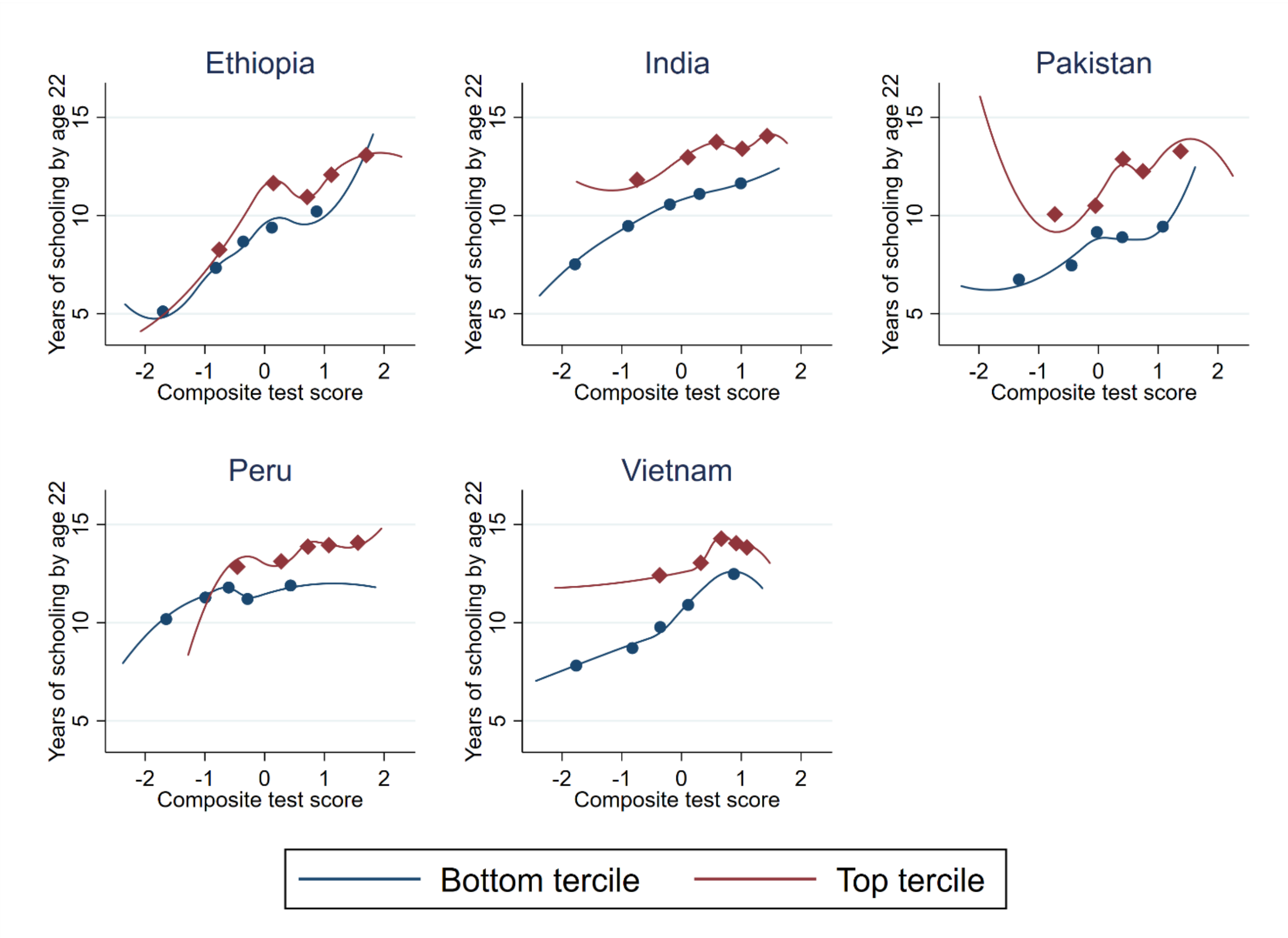
Figures

Figure 1: Difference in years of completed schooling, by SES and test score terciles



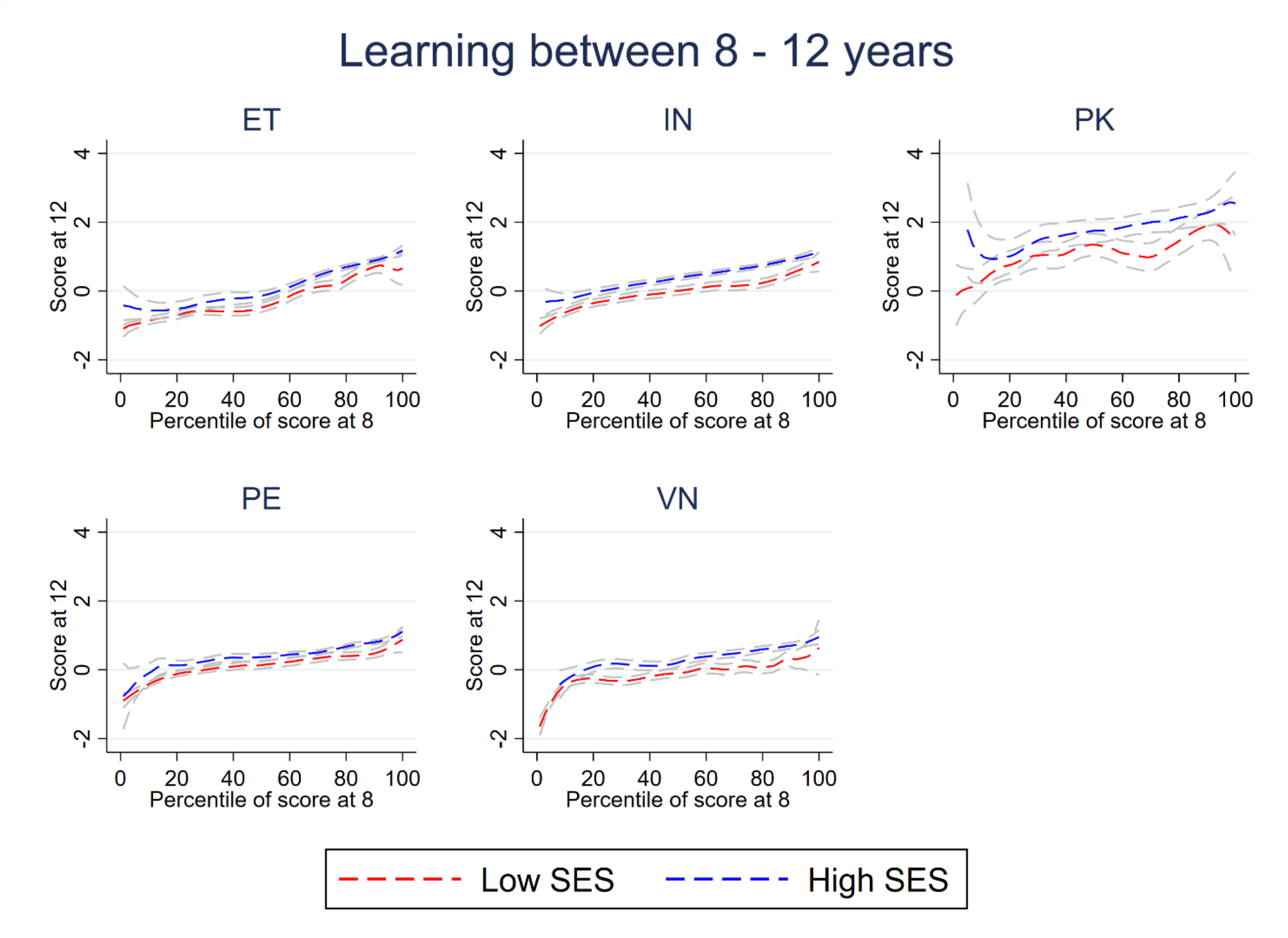
Note: Test score terciles are based on achievement tests administered at around 12 years of age. SES is defined as a composite of parental education and household material conditions at age 12. Please see Section 2 for details.

Figure 2: Predicted final schooling by achievement in primary school and SES



Note: This figure presents non-parametric graphs following the procedure in Cattaneo et al (2019) separately for the bottom- and top-tercile of SES in each country. Markers in each fitted line present the mean years of schooling in each bin in the (within-group) quintiles for each group i.e. a non-parametric binscatter. The fitted line corresponds to a quadratic polynomial estimated within each bin with a smoothness restriction requiring it to be twice-differentiable at boundary points. For Pakistan, the test scores aggregate scores in Math, Urdu and English; for the other countries, taken from the Young Lives data, the test scores refer to scores in mathematics and the PPVT test of receptive vocabulary.

Figure 3: Divergence in learning between 8-12 years across high- and low-SES students



Note: This figure presents local linear regression lines predicting test scores at 12 years, conditional on test scores at 8 (in percentiles of the full sample at 8), separately for high and low-SES students in each country. For Pakistan, the test scores aggregate scores in Math, Urdu and English; for the other countries, taken from the Young Lives data, the test scores refer to mathematics test scores. 95% confidence intervals are also shown. In all countries, students in the high-SES group have a higher predicted test score at 12, conditional on achievement at 8, across the full range of achievement at 8.

Table 1 - Correlates of years of schooling by for top and bottom SES terciles

Panel A - Correlates of years of schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	ET	IN	PK	PE	VN	ET	IN	PK	PE	VN
Wealth index PCA	0.47**	0.38**	0.85***	0.44**	0.31*	0.32*	0.59***	0.83***	0.86***	0.64***
	(0.21)	(0.16)	(0.18)	(0.19)	(0.16)	(0.18)	(0.13)	(0.18)	(0.20)	(0.15)
Maximum parental education	0.09**	0.12***	0.20***	0.04	0.19***	0.09**	0.09**	0.18***	0.03	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Test scores (12y/G6), all subjects	1.77***	1.33***	1.05***	0.98***	1.34***	1.84***	1.50***	1.12***	1.10***	1.36***
	(0.17)	(0.17)	(0.15)	(0.25)	(0.24)	(0.16)	(0.13)	(0.16)	(0.23)	(0.23)
Constant	8.96***	10.83***	8.95***	11.95***	10.08***	9.00***	10.96***	9.01***	12.01***	10.15***
	(0.35)	(0.34)	(0.26)	(0.44)	(0.40)	(0.18)	(0.18)	(0.25)	(0.35)	(0.33)
R-squared	0.37	0.38	0.30	0.34	0.43	0.46	0.45	0.32	0.42	0.49

Panel B - Oaxaca-Blinder Decompositions

Difference	**3.06*** **	**3.24*** **	**3.53*** **	**2.57*** **	**3.84*** **	**3.06*** **	**3.24*** **	**3.53*** **	**2.57*** **	**3.84*** **
	(0.53)	**(0.38)**	**(0.31)**	**(0.36)**	**(0.42)**	**(0.52)**	**(0.41)**	**(0.31)**	**(0.44)**	**(0.50)**
Wealth index PCA	0.75**	0.71**	1.40***	0.88**	0.58*	0.51	1.11***	1.37***	1.74	1.22
	(0.35)	(0.29)	(0.30)	(0.38)	(0.30)	(0.75)	(0.43)	(0.30)	(1.30)	(0.76)
Maximum parental education	0.66**	1.18***	1.63***	0.33	1.38***	0.62**	0.91**	1.53***	0.27	1.29***
	(0.26)	(0.35)	(0.36)	(0.33)	(0.31)	(0.30)	(0.41)	(0.37)	(0.38)	(0.33)
Test scores (12y/G6), all subjects	1.70***	1.11***	0.53***	1.35***	1.49***	1.76***	1.26***	0.56***	1.52***	1.52***
	(0.34)	(0.22)	(0.13)	(0.36)	(0.36)	(0.37)	(0.27)	(0.14)	(0.45)	(0.47)
Cluster FE						Yes	Yes	Yes	Yes	Yes
Observations	536	600	481	402	593	536	600	481	402	593

Note: Robust standard errors, clustered at the site level. For Pakistan, the test scores aggregate scores in Math, Urdu and English; for the other countries, taken from the Young Lives data, the test scores refer to mathematics test scores.

Table 2 - SES Gaps in Enrolment and Test Scores

Panel A - SES Gaps in Enrolment

	Ethiopia			India			Pakistan			Peru			Vietnam		
Cohort	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff
YC 5Y	0.04	0.04	0.00	0.51	0.33	-0.18				0.00	0.02	0.02	0.01	0.01	0.00
YC 8Y	0.67	0.90	0.23	0.98	1.00	0.02				0.97	0.99	0.02	0.95	0.99	0.04
YC 12Y	0.88	0.99	0.11	0.94	1.00	0.06				0.98	0.99	0.01	0.93	1.00	0.07
YC 15Y	0.85	0.97	0.12	0.79	0.98	0.19				0.92	0.99	0.07	0.64	0.93	0.29
OC 8Y	0.50	0.86	0.36	0.96	0.98	0.02	1.00	1.00	0.00	0.97	1.00	0.03	0.96	1.00	0.04
OC 12Y	0.93	0.98	0.05	0.78	0.98	0.20	0.76	0.85	0.09	0.98	1.00	0.02	0.91	1.00	0.09
OC 15Y*	0.84	0.96	0.12	0.62	0.94	0.32	0.43	0.72	0.29	0.84	0.99	0.15	0.54	0.95	0.41
OC 19Y	0.48	0.73	0.25	0.32	0.74	0.42				0.39	0.65	0.26	0.21	0.74	0.53

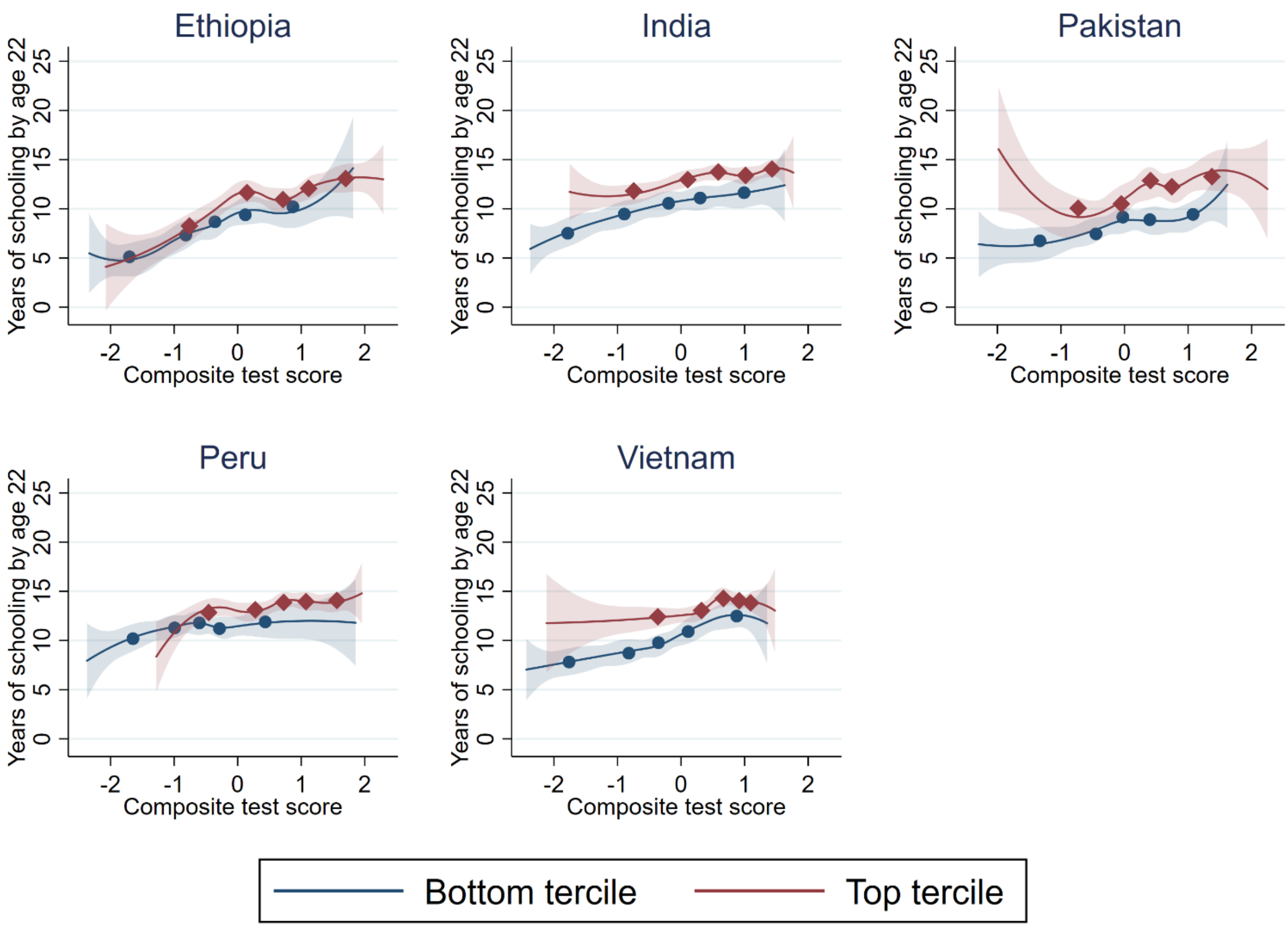
Panel B - SES Gaps in Test Scores

8Y	-1.14	-0.39	0.75	-1.27	-0.63	0.64	-0.65	-0.29	0.36	-1.54	-0.70	0.84	-1.23	-0.24	0.99
12Y	-0.52	0.44	0.96	-0.20	0.53	0.73	0.41	0.91	0.50	-0.10	0.55	0.65	-0.30	0.43	0.73
15Y*	0.01	0.89	0.88	0.07	0.82	0.75	1.12	2.27	1.15	0.14	0.85	0.71	-0.10	0.75	0.85

Note: Young Lives Older Cohort 15 year olds (OC 15Y*) are compared to 17 year olds in Pakistan. For Pakistan, the test scores aggregate scores in Math, Urdu and English; for the other countries, taken from the Young Lives data, the test scores refer to mathematics test scores.

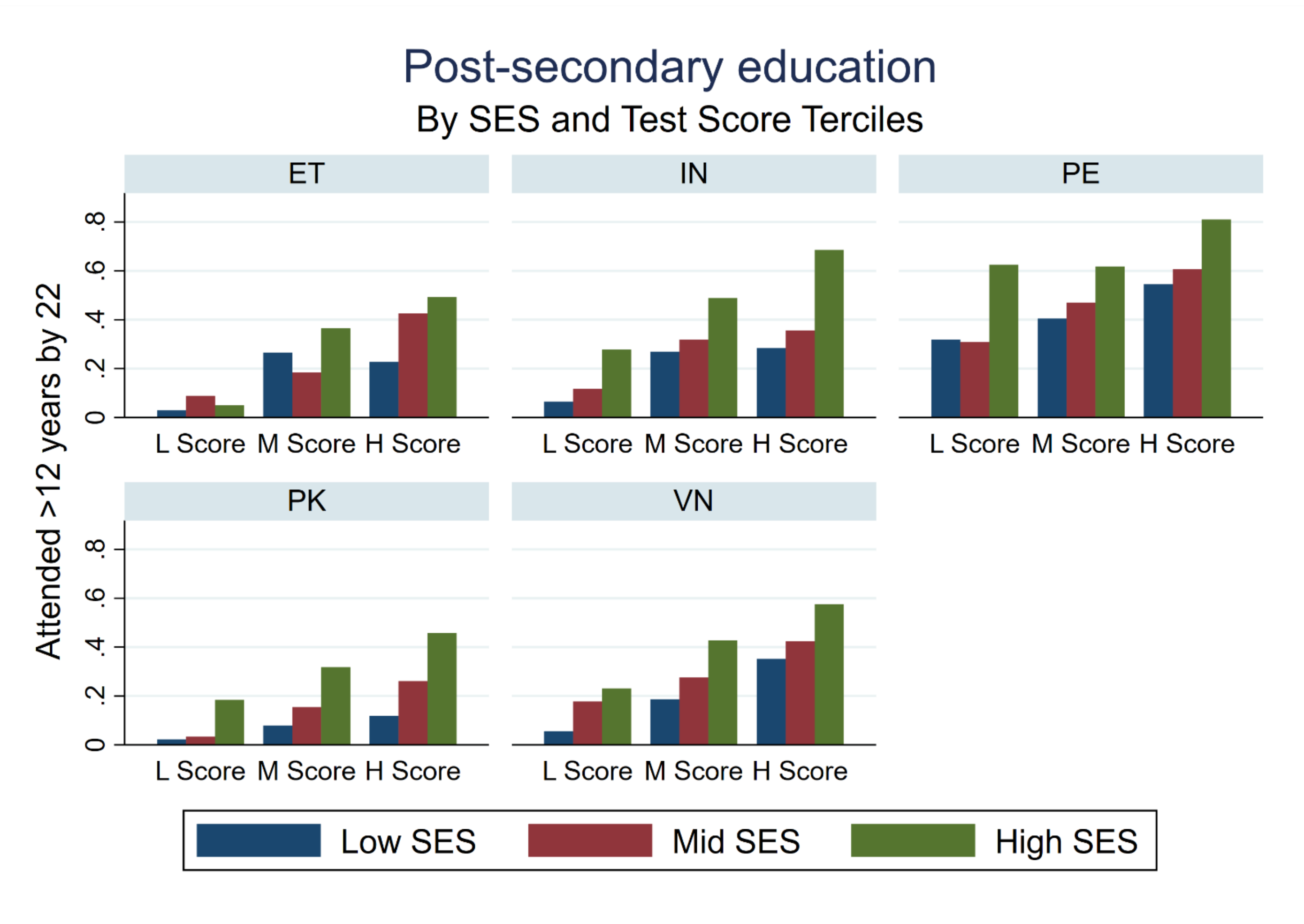
Appendix A: Supplementary figures and tables

Figure A.1: Predicted final schooling by achievement and SES, with 95% confidence intervals



Note: See notes for Figure 2.The confidence bands account for clustering at the site level and impose the same smoothness requirements at the boundary as the non-parametric fit.

Figure A.2: Difference in post-secondary education, by SES and test score terciles



Note: Post-secondary education here is defined as having more than 12 years of education as a binary indicator. SES- and test-score terciles are defined as in Figure 1.

Table A.1: Characteristics of households in top and bottom SES terciles

	Ethiopia			**India**			**Pakistan**			**Peru**			**Vietnam**		
	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff
Test scores (12y/G6), all subjects	0.58	-0.38	0.96	0.47	-0.37	0.84	0.32	-0.18	0.50	0.64	-0.75	1.39	0.53	-0.59	1.11
Maximum parental education	8.67	1.44	7.23	10.52	0.53	9.99	9.33	0.96	8.38	13.38	5.43	7.95	11.73	4.51	7.22
Wealth Index PCA	0.95	-0.65	1.61	1.00	-0.88	1.88	0.78	-0.90	1.68	1.04	-0.99	2.02	1.02	-0.89	1.90
Years of schooling at 22	11.20	8.14	3.06	13.19	9.96	3.24	11.58	7.87	3.71	13.57	11.00	2.57	13.52	9.69	3.84
Attended >12 years of schooling	0.39	0.14	0.26	0.55	0.18	0.38	0.34	0.06	0.28	0.73	0.35	0.38	0.50	0.14	0.35
Household Assets															
Owns bedstead	0.90	0.36	0.55	0.89	0.71	0.18	0.98	0.97	0.00				0.87	0.97	-0.10
Owns Sewing machine	0.02	0.00	0.02	0.25	0.01	0.24	0.85	0.72	0.13	0.21	0.13	0.08	0.21	0.13	0.08
Owns fan	0.01	0.00	0.01	0.96	0.30	0.66	0.95	0.94	0.00	0.20	0.00	0.20	0.99	0.68	0.31
Owns TV	0.43	0.00	0.43	0.87	0.12	0.75	0.85	0.75	0.10	0.97	0.43	0.55	0.99	0.68	0.31
Owns radio	0.84	0.30	0.54	0.20	0.07	0.13	0.19	0.08	0.11	0.68	0.76	-0.08	0.29	0.19	0.10
Owns car	0.01	0.00	0.01	0.01	0.00	0.01	0.20	0.04	0.16	0.07	0.01	0.07	0.04	0.00	0.04
Owns motorbike/scooter	0.00	0.00	0.00	0.31	0.00	0.31	0.73	0.67	0.07	0.06	0.04	0.02	0.92	0.39	0.53
Owns bicycle	0.11	0.01	0.10	0.57	0.19	0.38	0.45	0.46	-0.01	0.56	0.28	0.29	0.91	0.78	0.13
Owns refrigerator	0.06	0.00	0.06	0.17	0.00	0.17	0.85	0.59	0.27	0.52	0.03	0.48	0.54	0.02	0.52
Owns landline phone	0.39	0.01	0.38	0.23	0.00	0.23				0.45	0.01	0.44	0.76	0.04	0.72
Owns mobile phone	0.20	0.00	0.20	0.46	0.01	0.45				0.68	0.08	0.60	0.51	0.01	0.50
Monthly expenditure per capita	181.43	102.61	78.82	1151.57	753.36	398.21	1325.42	980.56	344.86	281.70	130.25	151.45	541.44	240.17	301.26
Observations*	270	266		301	299		289	289		200	202		301	292	

The table displays differences in means for the top and bottom SES terciles in each country. The wealth index PCA presented here is standardized by country with mean zero and standard deviation 1. The SES measure used in this table is based on the standardized wealth index PCA. Monthly expenditure per capita is reported in real 2006 local currency for each country, deflated to account for differences in prices across clusters. The number of observations for Pakistan is lower for the household asset variables (255 and 250 observations for the top and bottom terciles) and for the test score variable (242 and 239 observations for the top and bottom terciles).

Table A.2: Correlates of attending college for top and bottom SES Terciles

Panel A: Correlates of attending college

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	ET	IN	PK	PE	VN	ET	IN	PK	PE	VN
Wealth index PCA	0.07**	0.08***	0.08***	0.10***	0.02	0.04*	0.11***	0.08***	0.15***	0.06**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)
Maximum parental education	0.00	0.01*	0.01***	0.00	0.03***	0.00	0.01	0.01***	0.00	0.02**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Test scores (12y/G6), all subjects	0.13***	0.13***	0.07***	0.11***	0.09***	0.12***	0.14***	0.08***	0.13***	0.09***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Constant	0.22***	0.29***	0.13***	0.51***	0.11	0.23***	0.31***	0.14***	0.54***	0.13*
	(0.04)	(0.04)	(0.03)	(0.08)	(0.07)	(0.02)	(0.03)	(0.03)	(0.07)	(0.07)
R-squared	0.20	0.25	0.17	0.20	0.19	0.27	0.29	0.18	0.26	0.24

Panel B: Oaxaca-blinder decomposition

Difference	**0.26*** **	**0.38*** **	**0.28*** **	**0.38*** **	**0.35*** **	**0.26*** **	**0.38*** **	**0.28*** **	**0.38*** **	**0.35*** **
	(0.06)	**(0.05)**	**(0.03)**	**(0.06)**	**(0.06)**	**(0.06)**	**(0.05)**	**(0.03)**	**(0.07)**	**(0.07)**
Wealth index PCA	0.11**	0.16***	0.13***	0.20***	0.04	0.06	0.21***	0.13***	0.31	0.11
	(0.05)	(0.05)	(0.03)	(0.06)	(0.06)	(0.10)	(0.07)	(0.03)	(0.20)	(0.12)
Maximum parental education	0.03	0.11**	0.12***	0.03	0.19***	0.03	0.08	0.11***	0.01	0.16***
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)	(0.04)	(0.06)	(0.04)	(0.07)	(0.06)
Test scores (12y/G6), all subjects	0.13***	0.11***	0.03***	0.15***	0.10***	0.12***	0.12***	0.04***	0.18***	0.11**
	(0.03)	(0.02)	(0.01)	(0.04)	(0.03)	(0.03)	(0.03)	(0.01)	(0.05)	(0.04)
Cluster FE						Yes	Yes	Yes	Yes	Yes
Observations	536	600	480	402	593	536	600	480	402	593

Robust standard errors, clustered at the site level, in parentheses *** p<0.01, ** p<0.05, * p<0.1Dependent variable is a binary indicator equal to 1 if an individual has attended more than 12 years of schooling Wealth index PCA is standardized within country with mean zero and standard deviation 1. The estimations are run with the bottom and top SES terciles in each country

Appendix B: Using terciles of per capita real monthly expenditure as measure of SES

Figure B.1: Difference in years of schooling, by MPCE and test score terciles

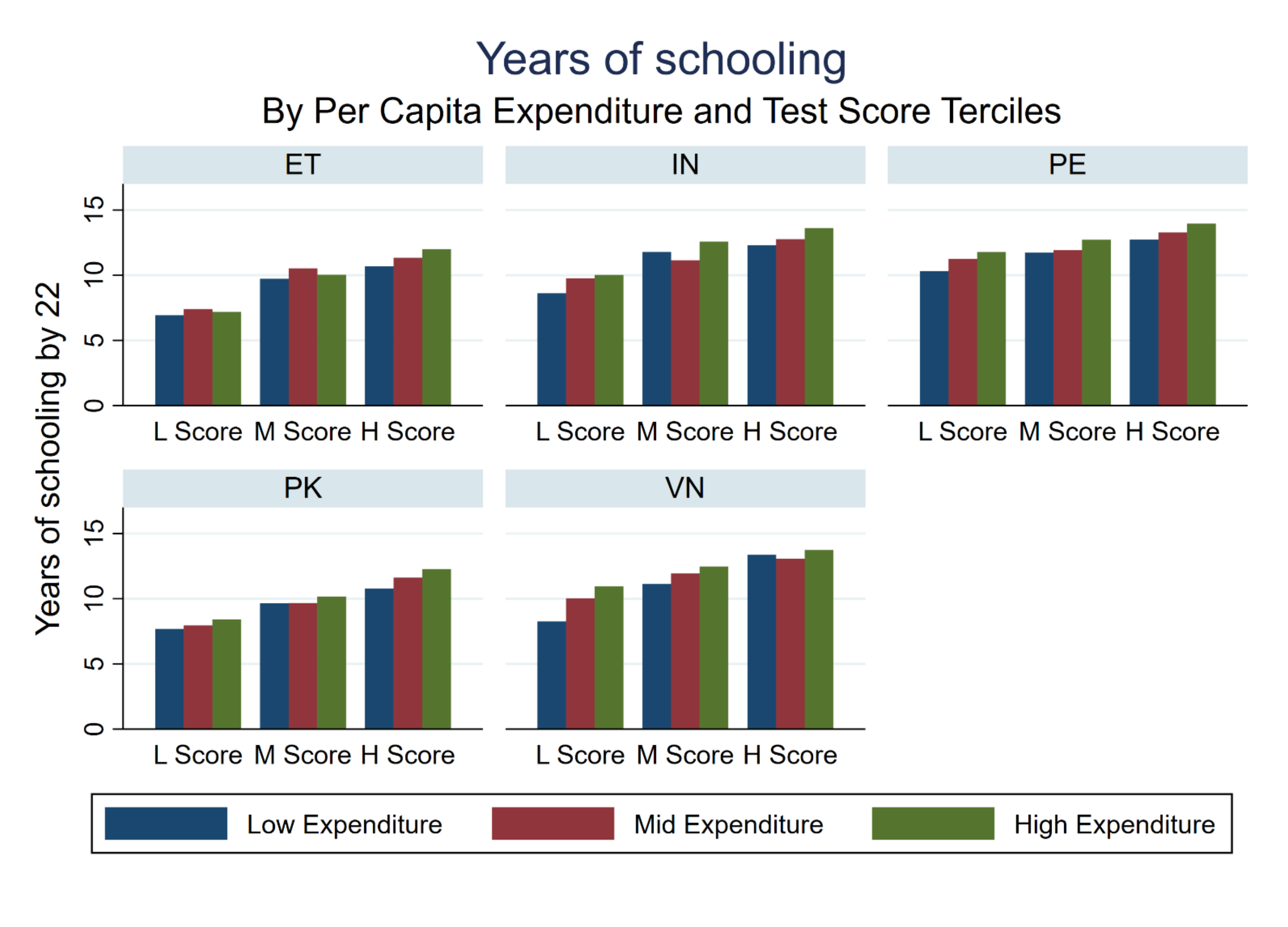


Figure B.2: Predicted years of schooling, by MPCE and test score terciles

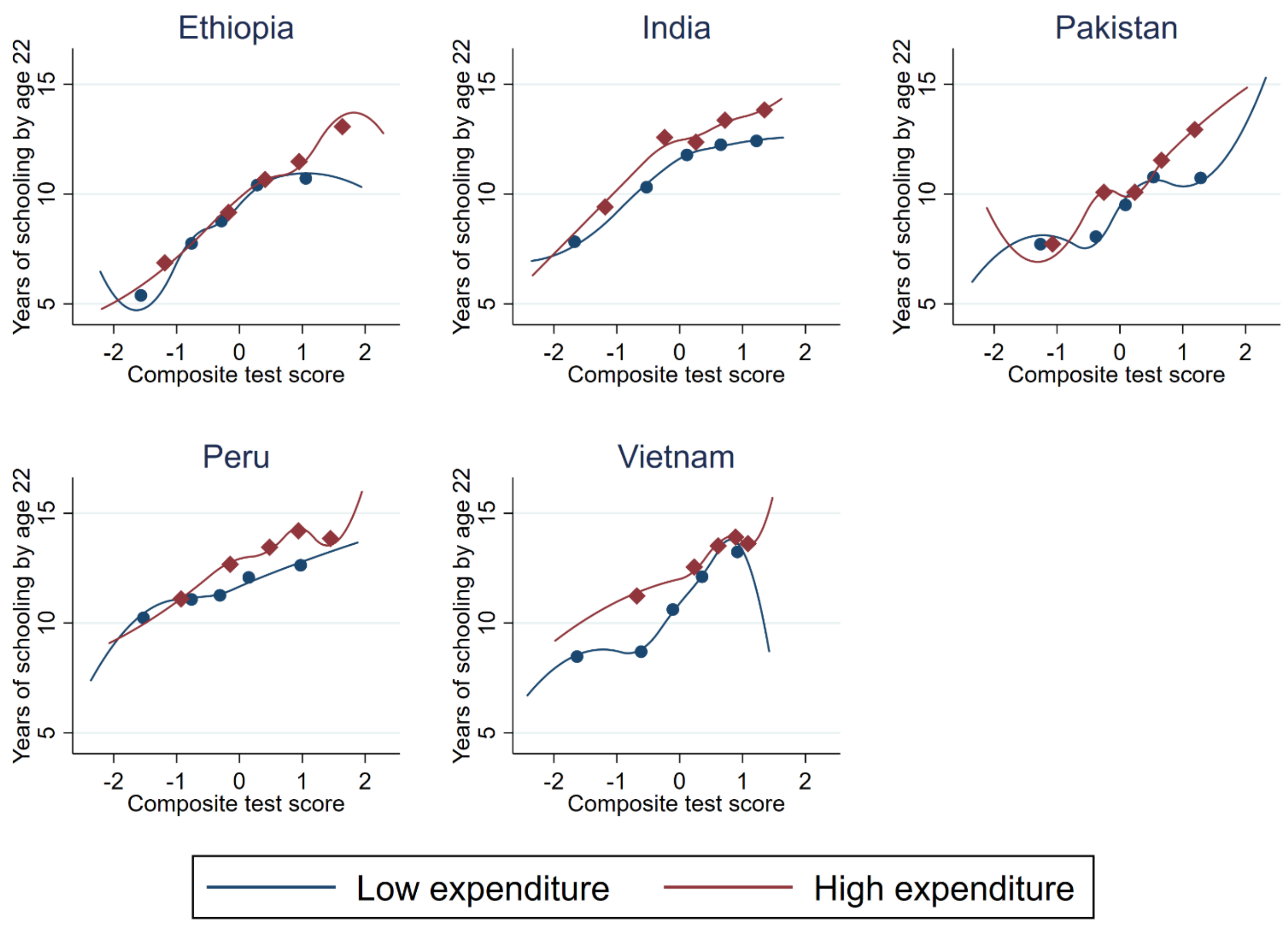


Fig B.3: Divergence in learning between 8-12 years across high- and low-MPCE students

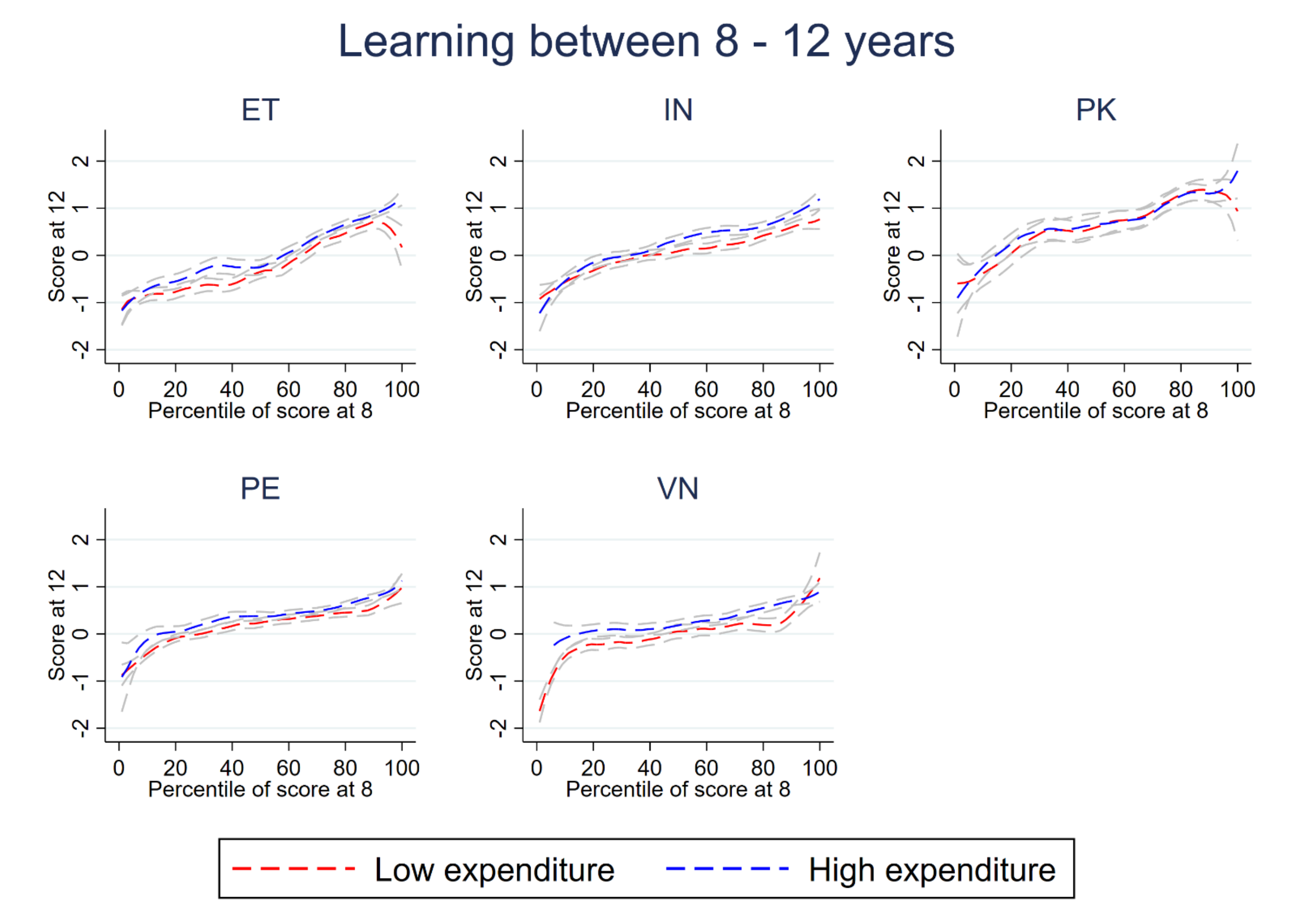
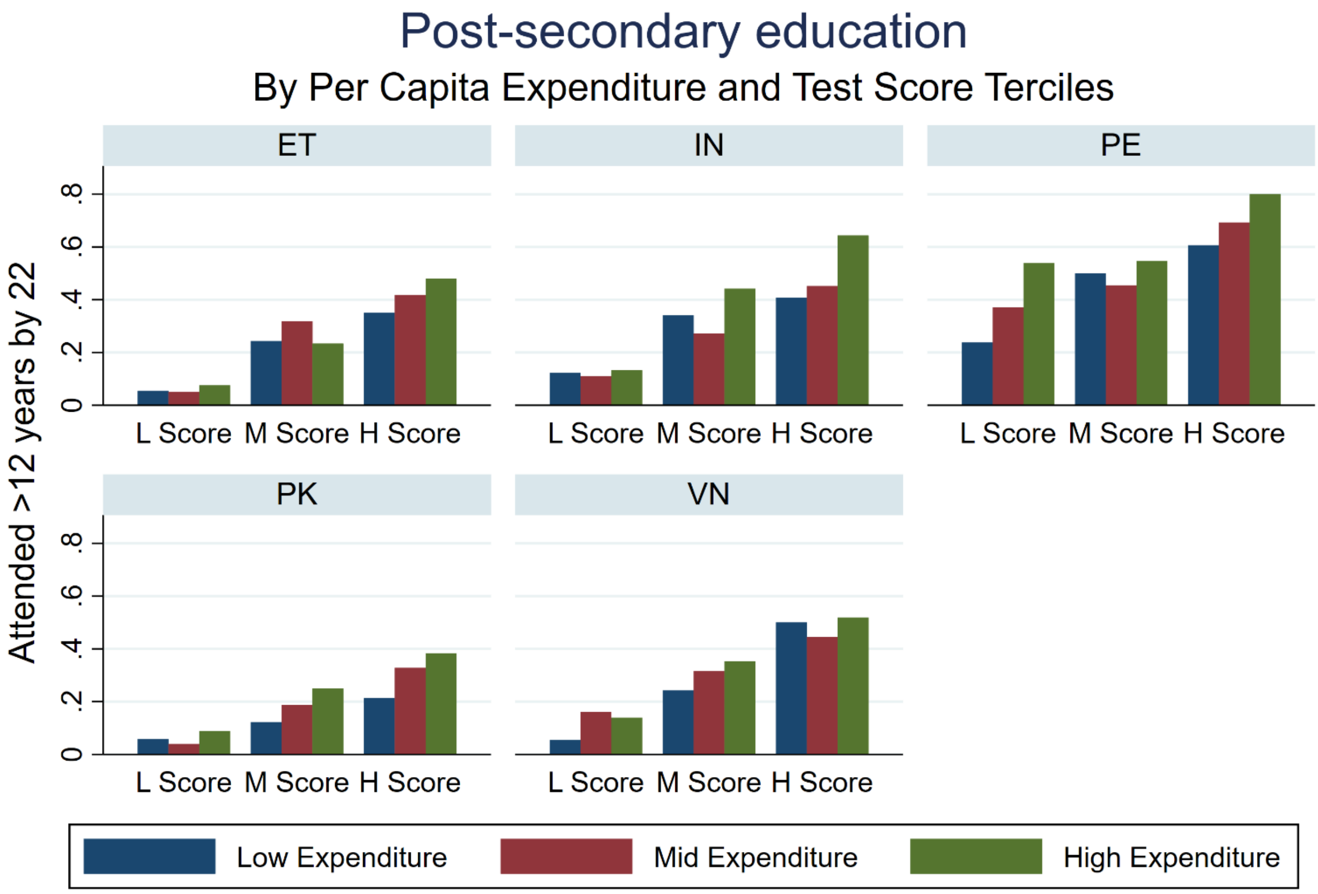


Fig B.4: Difference in post-secondary education, by MPCE and test score terciles



Post-secondary education
By Per Capita Expenditure and Test Score Terciles
ET
IN
PE
PK
VN
Attended >12 years by 22
0
.2
.4
.6
.8
L Score
M Score
H Score
Low Expenditure
Mid Expenditure
High Expenditure

Table B.1: Characteristics of households in top and bottom MPCE terciles

	Ethiopia			India			Pakistan			Peru			Vietnam		
	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff	Top	Bottom	Diff
Test scores (12y/G6), all subjects	0.33	-0.27	0.59	0.16	-0.07	0.23	0.13	-0.02	0.15	0.36	-0.42	0.77	0.43	-0.43	0.85
Maximum parental education	6.75	3.89	2.86	7.03	3.41	3.62	5.94	3.96	1.98	11.69	7.59	4.10	10.62	6.20	4.42
Wealth Index PCA	0.61	-0.42	1.03	0.48	-0.39	0.87	0.40	-0.27	0.67	0.64	-0.63	1.27	0.86	-0.71	1.57
Years of schooling at 22	10.25	8.58	1.67	12.27	10.85	1.42	10.50	8.96	1.54	13.05	11.17	1.89	12.97	10.34	2.63
Attended >12 years of schooling	0.31	0.18	0.14	0.43	0.29	0.15	0.25	0.12	0.13	0.67	0.39	0.28	0.42	0.22	0.20
Household Assets															
Owns bedstead	0.76	0.53	0.23	0.78	0.77	0.02	0.98	0.96	0.03				0.88	0.96	-0.08
Owns Sewing machine	0.01	0.01	-0.00	0.15	0.08	0.07	0.84	0.76	0.07	0.20	0.12	0.07	0.20	0.13	0.06
Owns fan	0.03	0.00	0.03	0.78	0.51	0.27	0.98	0.91	0.07	0.18	0.01	0.17	0.97	0.76	0.21
Owns TV	0.34	0.03	0.31	0.63	0.32	0.31	0.85	0.76	0.09	0.94	0.54	0.40	0.99	0.75	0.24
Owns radio	0.74	0.40	0.34	0.19	0.11	0.09	0.18	0.16	0.02	0.69	0.73	-0.05	0.29	0.16	0.14
Owns car	0.01	0.00	0.01	0.01	0.00	0.01	0.15	0.06	0.09	0.09	0.00	0.09	0.03	0.00	0.03
Owns motorbike/scooter	0.00	0.00	0.00	0.27	0.02	0.25	0.77	0.68	0.09	0.07	0.04	0.04	0.87	0.39	0.48
Owns bicycle	0.07	0.02	0.05	0.46	0.33	0.14	0.53	0.42	0.11	0.53	0.25	0.28	0.91	0.81	0.10
Owns refrigerator	0.05	0.00	0.05	0.14	0.00	0.14	0.82	0.69	0.13	0.42	0.09	0.34	0.51	0.02	0.50
Owns landline phone	0.29	0.04	0.24	0.17	0.01	0.16				0.34	0.10	0.23	0.67	0.05	0.62
Owns mobile phone	0.18	0.01	0.17	0.38	0.06	0.31				0.61	0.13	0.48	0.47	0.02	0.45
Monthly expenditure per capita	227.98	63.11	164.86	1525.06	461.08	1063.98	2123.98	513.53	1610.45	367.78	84.98	282.80	606.02	188.86	417.16
Observations*	270	267		302	302		290	291		200	200		300	293	

Table B.2 - Correlates of years of schooling for top and bottom per capita expenditure terciles

Panel A - Correlates of years of schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	ET	IN	PK	PE	VN	ET	IN	PK	PE	VN
Wealth index PCA Standardized	0.51**	0.45***	0.87***	0.27*	0.30	0.32**	0.51***	0.85***	0.74***	0.68***
	(0.18)	(0.15)	(0.17)	(0.14)	(0.20)	(0.14)	(0.15)	(0.17)	(0.16)	(0.20)
Maximum parental education	0.08**	0.07*	0.22***	0.06	0.19***	0.07**	0.06*	0.21***	0.07*	0.16***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Test scores (12y/G6), all subjects	1.81***	1.46***	1.28***	1.23***	1.30***	1.85***	1.72***	1.30***	1.31***	1.37***
	(0.16)	(0.20)	(0.15)	(0.25)	(0.23)	(0.20)	(0.15)	(0.15)	(0.22)	(0.24)
Constant	8.92***	11.10***	8.93***	11.59***	10.03***	8.98***	11.13***	8.98***	11.49***	10.29***
	(0.33)	(0.36)	(0.26)	(0.45)	(0.40)	(0.17)	(0.18)	(0.26)	(0.35)	(0.33)
R-squared	0.36	0.34	0.30	0.34	0.40	0.43	0.43	0.31	0.44	0.46

Panel B - Oaxaca-Blinder Decompositions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Difference	**1.68*** **	**1.41*** **	**1.74*** **	**1.88*** **	**2.63*** **	**1.68*** **	**1.41*** **	**1.74*** **	**1.88*** **	**2.63*** **
	(0.46)	**(0.39)**	**(0.37)**	**(0.30)**	**(0.50)**	**(0.46)**	**(0.44)**	**(0.37)**	**(0.37)**	**(0.53)**
Wealth index PCA Standardized	0.51**	0.39**	0.67***	0.35*	0.47	0.32	0.45*	0.65***	0.94*	1.06
	(0.20)	(0.16)	(0.16)	(0.18)	(0.32)	(0.34)	(0.23)	(0.16)	(0.52)	(0.71)
Maximum parental education	0.22**	0.26*	0.52***	0.24	0.84***	0.20*	0.23	0.50***	0.28	0.69***
	(0.10)	(0.14)	(0.14)	(0.17)	(0.24)	(0.11)	(0.16)	(0.14)	(0.23)	(0.26)
Test scores (12y/G6), all subjects	1.07***	0.34	0.27**	0.95***	1.11***	1.09***	0.39	0.27**	1.01***	1.17***
	(0.29)	(0.24)	(0.13)	(0.24)	(0.32)	(0.31)	(0.28)	(0.13)	(0.28)	(0.40)
Cluster FE						Yes	Yes	Yes	Yes	Yes
Observations	530	602	490	400	593	530	602	490	400	593

Table B.3 Gaps in Enrolment and Test Scores, by MPCE terciles

Panel A - Gaps in Enrolment

	Ethiopia			India			Pakistan			Peru			Vietnam		
Cohort	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff	Bottom	Top	Diff
YC 5Y	0.03	0.05	0.02	0.51	0.36	-0.15				0.00	0.02	0.02	0.01	0.01	0.00
YC 8Y	0.66	0.87	0.21	0.99	0.99	0.00				0.97	0.99	0.02	0.96	1.00	0.04
YC 12Y	0.92	0.96	0.04	0.95	0.99	0.04				0.98	0.99	0.01	0.94	1.00	0.06
YC 15Y	0.88	0.94	0.06	0.82	0.95	0.13				0.93	0.99	0.06	0.70	0.91	0.21
OC 8Y	0.61	0.76	0.15	0.98	0.97	-0.01	1.00	1.00	0.00	0.98	1.00	0.02	0.95	1.00	0.05
OC 12Y	0.93	0.94	0.01	0.82	0.94	0.12	0.76	0.83	0.07	0.98	1.00	0.02	0.91	0.99	0.08
OC 15Y*	0.87	0.91	0.04	0.69	0.85	0.16	0.56	0.62	0.06	0.85	0.97	0.12	0.59	0.93	0.34
OC 19Y	0.54	0.62	0.08	0.41	0.60	0.19				0.40	0.59	0.19	0.25	0.67	0.42

Panel B - Gaps in test scores

OC 8Y	-1.03	-0.55	0.48	-1.02	-0.83	0.19	-0.53	-0.37	0.16	-1.40	-0.77	0.63	-1.10	-0.33	0.77
OC 12Y	-0.41	0.24	0.65	0.01	0.32	0.31	0.58	0.69	0.11	0.02	0.51	0.49	-0.17	0.37	0.54
OC 15Y*	0.17	0.71	0.54	0.28	0.61	0.33	1.60	2.12	0.52	0.25	0.81	0.56	0.03	0.66	0.63

Note: Young Lives Older Cohort 15 year olds (OC 15Y*) are compared to 17 year olds in Pakistan. For Pakistan, the test scores aggregate scores in Math, Urdu and English; for the other countries, taken from the Young Lives data, the test scores refer to mathematics test scores.