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Late-Childhood Foundational Cognitive Skills Predict Educational Outcomes Through Adolescence and Into Young Adulthood: Evidence from Ethiopia and Peru

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Keywords

Human Capital, Cognitive Skills, Education, Executive Function, Ethiopia, Peru, Memory

Disciplines

Cognitive Science | Demography, Population, and Ecology | Family, Life Course, and Society | Place and Environment | Social and Behavioral Sciences | Sociology

Late-childhood foundational cognitive skills predict educational outcomes through adolescence and into young adulthood: evidence from Ethiopia and Peru

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Abstract

We estimate the associations between a set of foundational cognitive skills (inhibitory control, working memory, long-term memory, and implicit learning) measured at age 12 and educational outcomes measured at ages 15 and 19-20 in Ethiopia and Peru (the Young Lives study). The estimates adjust for a rich set of lagged controls and include measurements of children's general abilities. For a subset of the outcomes, we exploit within-household variation. Working memory and long-term memory are consistently and positively associated with subsequent domain-specific cognitive achievement tests in both countries, university enrolment in Peru (working memory) and lower secondary-school completion in Ethiopia (long-term memory). Inhibitory control predicts subsequent math-test scores in both countries, and grade attainment in Ethiopia. These results provide additional evidence to justify the importance of promoting investments in cognitive skills throughout childhood and adolescence, and these results potentially elucidate how investments in children impact their educational achievements.

Keywords: human capital, cognitive skills; education; executive function; Ethiopia; Peru

JEL codes: I25, I24, I23

1. Introduction

The promotion of learning opportunities for all is an important challenge for developing countries, as recognized by the Sustainable Development Goals (Goal N° 4) (United Nations, 2015). Most of the studies carried out in low-and-middle-income countries (LMICs) about the impact of educational inputs have focused on school resources and processes, including, for example, the role of teachers (Glewwe et al., 2011; McEwan, 2015). However, there is little evidence about the basic or foundational cognitive skills developed by children and adolescents that could in turn help them take better advantage of the school environment.

Cognitive skills (CSs) are thought to play important roles in educational attainment, which in turn determines how well children can perform in economic outcomes later in life (Hanushek, 2009; Hanushek & Woessmann, 2008; Reynolds et al., 2010). However there are limited data available about the CSs accumulated by children in LMICs—they are not fully captured by domain-specific achievement tests. CSs include working and long-term memory, planning and problem solving, attention control, processing speed, spatial and numerical processing, and social cognition, among others. Recent theoretical and empirical developments have suggested the importance of a group of these skills under the umbrella of what has been called executive function (EF). While there is not unanimous agreement among researchers of which skills form EF, most definitions include working memory, inhibition control, and attention flexibility or control (Carlson, 2005; Garon et al., 2008). EF permits the regulation of thought and action (Miyake & Friedman, 2012), which allows children to adapt and perform well in classroom environments. EF is also malleable through adolescence due to the associations with connections in the prefrontal cortex, an area that undergoes changes into young adulthood (Benes, 2001).

Although CSs, including EF, are essential to learning and thus expected to be linked to a variety of learning outcomes over the life cycle, there is limited evidence available about which CSs predict different domain-specific learning outcomes in LMICs. We aim to fill some of these gaps by analysing longitudinal data collected in late childhood in two LMICs using a novel computerized method that allowed us to measure inhibitory control, working memory, long-term memory, and implicit learning. We refer to these four skills as Foundational Cognitive Skills (FCSs) throughout this paper—and use the term CSs to refer to research of other authors measuring only some of these skills, as well as other skills including domain-specific skills. Specifically, our purpose is to investigate the predictive value of this set of skills on educational achievements among adolescents and young adults growing-up in poverty in Ethiopia and Peru. To do this, we assessed the relationships between FCSs in late childhood at age 12 with cognitive test scores and grade attainments in adolescence at age 15 and with lower-secondary-school completion in Ethiopia and university enrolment in Peru in young adulthood at ages 19 and 20, respectively. We used longitudinal data from the Young Lives study (YL); specifically, we used information from a sample of children tracked from age 1 (in 2002) to age 20 (in 2021) in both Ethiopia and Peru. FCSs were measured by the Rapid Assessment of Cognitive and Emotional Regulation (RACER) (Behrman et al., 2022; Hamoudi & Sheridan, 2015), which is a tablet-based assessment application administered in the Ethiopian and Peruvian YL samples in 2013. Even though the two samples are not representative of the general populations of these countries, they capture a wide spectrum of the living standard conditions observed in both countries (Escobal & Flores, 2008; Outes-Leon & Sánchez, 2008). To our knowledge, this is the first data set with a longitudinal design that has measured CSs in late childhood in LMICs.

Our study offers three main contributions. First, we use unique data on FCSs collected as part of a large cohort study in LMICs. Unlike achievement tests, these measures are not domain-specific, and should, therefore, be relatively free of bias due to the language of implementation or cultural differences. Second, most research has focused on the development of CSs (see, for instance, Garon et al., 2008, Best & Miller, 2010) and its relationship with achievement (e.g., Cain et al., 2004) during the preschool period. However, there is evidence that the latent organization of CSs components changes from preschool to adulthood (Lee et al., 2013; Miller et al., 2012; Miyake et al., 2000; Monette et al., 2015; Usai et al., 2014). We measure FCSs and EF in late childhood and assess their importance for educational achievements during adolescence and early adulthood. Third, our evidence suggests the importance of promoting the development of CSs for children early in life. Limited learning opportunities and the lack of stimulating and adequate learning environments have repercussions on children's cognitive development with long-term consequences on their school performance (Geary, 2013, Reynolds et al., 2010). Emerging evidence from LMICs shows that CSs can be affected and negatively impacted by limited access to early quality education (Araujo et al., 2016), vulnerabilities associated with poor households (Behrman et al., 2022), and undernutrition (Sánchez et al, 2022). Documenting the relationships of CSs with school performance in countries where children face these challenges and struggle with cognitive disadvantages can be helpful to generate insights about the mechanisms through which early-life poverty shapes educational achievement.

The remainder of this paper is structured as follows. Section 2 discusses key findings from the main literature about CSs and their relationships with academic achievements. Section 3 describes the YLS samples in Ethiopia and Peru and the data obtained through RACER. Sections 4 and 5 present our estimation strategy and present the main results, respectively. Section 6 reports the robustness checks performed, and Section 7 concludes with a discussion of the main results.

2. Literature review

There has been much research on the relationships between CSs and domain-specific test scores. However, most of it focuses on evaluating these relationships for children observed during the preschool period, while there are only a few studies that assess these relationships in late childhood and adolescence (Riggs et al., 2015, Friedman et al., 2016; Friedman et al, 2011; Friedman et al., 2008, Huizinga et al., 2006; McAuley & White, 2011). Furthermore, most of the studies focus on populations from high-income countries (HICs, predominantly the United States and the United Kingdom), whereas there are not many studies using data from LMICs (Christopher et al., 2012; Evans & Popova, 2016). We present a brief review of studies -most of them from HICs- investigating relationships between CSs and domain-specific cognitive achievement mainly during the preschool period. We also include here a review of studies assessing the relevance of EF in early numeracy and literacy, to be able to establish general patterns of associations that might help in the interpretation of our results for adolescents.

The relationship between EF and early numeracy and early literacy have been widely studied (Blair & Razza, 2007; Bull et al., 2008; Lan et al., 2011; Dilworth-Bart, 2012; Schmitt et al., 2017). Since EF is a construct, different authors considered different CS for their conception of EF. Most of the studies found a positive correlation between EF and both math and language skills. For example, Blair and Razza (2007) assessed the relationships between inhibitory control and attention shifting and academic ability (math and reading comprehension) in preschool and kindergarten US children and found that inhibitory control had strong correlations with both math and reading skills. Likewise, Bull et al. (2008) considered inhibition, shifting and updating as part of EF, and treated working memory as a separate skill. They concluded that higher levels of EF were associated with advantages in math and literacy skills in a sample of preschool children from Scotland. Additionally, Lan et al. (2011) and Dilworth-Bart (2012) found that EF (inhibitory control, working memory and attentional control), was a significant predictor of both mathematics and literacy achievement, using data from sample of pre-school-aged children in China and the US.

When referring to CSs in general, most empirical studies on relationships between CSs and educational achievements focus on domain-specific vocabulary, math, and reading-comprehension skills. For instance, Cain et al. (2004) found that working memory predicts reading comprehension for a longitudinal sample of children in England evaluated at ages eight, nine and 11 years. This finding is consistent with what Christopher et al. (2012) found. In this case, the authors found that working memory is not only important for reading-comprehension, but also for processing speed, for a sample of US children, ages eight to 16 years. McClelland´s investigation (2000) of associations between behavioural regulation, and literacy, vocabulary and math test scores concluded that behavioural aspects of self-regulation are important for the development of early domain-specific skills and school success in US children ages four to five years. In this case, the main component of behavioural regulation was inhibitory control. Consistent with that, Merkley et al. (2016) found that inhibitory control was correlated with performance on a math test for a sample of UK children, ages three to five years.

Some studies show that household socioeconomic status (SES) predicts CSs, partly by defining the environment in which the children develop. An environment that can provide the means for children to improve their cognitive skills is more often found in richer households, in comparison with poorer households that lack the resources to stimulate cognitive growth. In many cases, poorer households have parents with lower levels of education, which can also limit their children´s development (Stipek & Ryan, 1997; Griffin & Morrison, 1997). Additionally, richer households can also provide better schooling, which can further develop children´s CSs, since it is at school where they continually repeat tasks that develop basic abilities such as working and long-term memory, and attention (Blair, 2002).[i] Nevertheless, there are many studies that only evaluate the relationships between cognitive skills and educational outcomes for children from low-income households (Blair et al., 2007; Howse et al. 2003), which allows for conclusions only for this specific group.

Beyond childhood and adolescence, there is evidence of the predictive power of CSs on outcomes later in life (Roberts et al., 2011). Many studies, as reviewed by Farkas (2003), have approached this topic by assessing the impact of different skills and personal characteristics in the achievement of general long-term goals such us the pursuit of post-secondary education. A starting point is how to interpret the differences in higher-education enrolment between high and low SES groups. According to Carneiro and Heckman (2002), both short-term financial constraints and other long-term factors associated with the family income (and parental education) can explain the differences in higher-education enrolment in the US. The role of CSs fits with the latter, since higher-income households can provide better education and development of CSs early in life. This is also consistent with evidence from other HICs as shown by Jerrim & Vignoles (2015), that found that what makes a difference is the CSs developed before 15 years old for participants from England, Canada, Australia and the US. For LMICs, it is sometimes argued that financial constraints impose a greater deterrent for enrolment in higher education, which is what Castro et al. (2016) found when accessing this relationship for Peru. Nonetheless, they also found that CSs (numeracy and problem-solving capacity, working memory, verbal fluency, and receptive language) were also significant in explaining enrolments in universities.

Overall, the existing evidence suggest that CSs are positively associated with domain-specific cognitive achievements, specifically math, vocabulary and literacy skills. However, most of the studies evaluated samples from HICs and generally in the early stages of education, like kindergarten or preschool. Moreover, even when the authors refer to academic attainment, this did not include schooling grade attainment, which is an important indicator of educational success in LMICs.

3. Data

YL has been tracking ~12,000 children in Ethiopia, India, Vietnam and Peru since 2002. It has collected information for two cohorts: a younger cohort born in 2001-2, and an older cohort born in 1994-5. Our analysis focuses on the younger cohort in Ethiopia and Peru because only for them were the RACER data collected. In 2002, respectively 2,052 and 1,999 participants (henceforth, index children) in Ethiopia and Peru were visited in their homes for the first time (Round 1) at ~ age 1. These samples were selected through a two-stage procedure. First, in both countries, 20 clusters were selected (districts in Peru, woredas in Ethiopia). Then, approximately 100 children and their families were randomly selected in each cluster. The selection of clusters aimed at capturing the diversity of each country in terms of geography, climate, ethnicity, and living standards, while also over-representing poor households.[ii] Although samples were not designed to be nationally representative, comparisons of the distributions of the YL samples with those in Demographic Health Survey (DHS) samples in both cases show that the YL samples capture the diversity of living standards of each country (Escobal & Flores, 2008; Outes-León & Sánchez, 2008).

After the first visit in 2002, follow-up in-person visits took place in 2006, 2009, 2013 and 2016 (Rounds 2-5). During each of these visits, rich information on household socio-demographic characteristics, children's health and nutrition, educational attainment, achievement test scores, among others, was collected for the index children chosen in the first visit at ~ ages 5, 8, 12 and 15, respectively. In addition, a phone survey was administered in 2020-2021 to gather information about the impacts of the COVID-19 pandemic on the index children when they were young adults. The phone survey was composed of five calls, three administered in 2020, and two in 2021. Information on schooling attainment was also obtained through this phone survey. For our analysis we used information collected in 2013 (Round 4), 2016 (Round 5), 2020 and 2021 (Call 2 and Call 5 of the phone survey), when the younger cohort was age 12, 15, 19, and 20 years old, respectively. Information from Rounds 1-2 is also used to construct some of our control variables.

At the time of the last in-person visit (Round 5), attrition was relatively low compared to other longitudinal studies: 5.4% in Ethiopia and 8.2% in Peru excluding deaths, which represents annual attrition rates of 0.6% and 0.4% (see Sánchez and Escobal, 2020). The attrition rate of the phone survey was higher due the remote nature of the phone survey and the impossibility to contact those with outdated contact information. Furthermore, in the case of Ethiopia, the civil conflict that started in late 2020 in some parts of the country led to the decision to not collect data in the Tigray region and in some clusters in the nearby regions. As a result, the attrition rate for Ethiopia increased substantially between late 2020 and 2021. For this reason, for our analysis we used data from Call 2 for Ethiopia (administered between August and October 2020, when the entire sample was contacted) and Call 5 for Peru (administered between October and December 2021). Attrition rates for Ethiopia and Peru in these calls are 13.0% and 17.9%, respectively (with respect to the original sample, excluding deaths).

YL also has collected data from siblings of the original participants since Round 3 in 2009. In Peru, data were collected for 861 younger siblings ages 2 to 8 years of the index children, whereas in Ethiopia information was collected for the 1550 siblings closest in age, 1001 younger siblings ages 3 to 8 years and 449 older siblings ages 8 to 17 years, to the index children. We use data from the younger siblings from both country samples when introducing estimates that exploit within-household variation.

Descriptive statistics of the analytical sample for both countries are reported in Table 1. The Ethiopian sample is mainly rural, whereas the Peruvian sample is mainly urban, reflecting the state of development and urbanization of each country; more than one third of the index children in Ethiopia come from households where the mother has no formal education, compared to less than one tenth in the Peruvian sample (Panel A).

INSERT TABLE 1 HERE

Panel B reports descriptive statistics of the index children, including schooling attainment. By the time of the last in-person visit in 2016 (Round 5), the average age was 15, and 19-20 by the time of the phone survey in 2020-2021. Assuming on-age enrolment and no grade repetition, by age 15, all index children should have reached the 9th grade in Ethiopia and the 10th grade in Peru. However, only 18% and 26% reached these levels by Round 5, respectively.[iii] The variance of grade attainment is larger in Ethiopia, reflecting a more difficult transition through schools for children in this country, due to delayed enrolment and grade repetition. In Round 5, 40% of index children had reached grades 8 and 9 in the Ethiopian sample, whereas in the Peruvian sample 75% of the sample had reached grades 9 and 10. Differences in schooling attainment between the two countries become more pronounced in the transition to young adulthood. According to information collected in Peru during the phone survey, 90.0% had completed secondary school, 58.8% were enrolled or had been enrolled in higher education, and 31.8% had ever been enrolled in a university at age 20 (in 2021). In the case of Ethiopia, 45.5% had completed lower secondary school, while only 11.7% had completed upper secondary education. Furthermore, only 3.1% had ever been enrolled in higher education and only 2.5% were or had been enrolled in a university at age 19 (in 2020).[iv]

Domain-specific cognitive achievement has been measured in YL starting from the age of 5. The cognitive measures used are the Peabody Picture Vocabulary Test (PPVT), which measures knowledge of vocabulary, and math and reading comprehension tests. Both the math and reading comprehension tests were designed by the YL educational team, while the Peabody test is a well-known test to measure receptive vocabulary (Cueto et al., 2009; Cueto & León, 2012). For the index children, the PPVT has been administered since the age of 5, and math and reading comprehension tests since the age of 8. For siblings, to keep time administration manageable, only the PPVT was administered starting in Round 3. There is variation in the language of test administration in each country, especially in Ethiopia (Table 1, Panel C). For our analysis, we used the raw scores of each test, which were standardized to have mean zero and variance one within each country sample of index children (who are all very close to the same age). However, for the sample that includes both index children and siblings, the raw scores were standardized by age in years within each country given the wider age ranges for the siblings.

When index children were age 12, the YL research team administered RACER in Ethiopia and Peru. RACER is a self-administered, tablet-based software designed to measure FCS (Sheridan & Hamoudi, 2015). RACER contains tasks designed to measure the following skills: inhibitory control, working memory, long-term memory, and implicit learning. Inhibitory control and working memory are considered executive functions, i.e., they are part of a set of skills that defines persons' capacities to achieve their goals. Specifically, inhibitory control refers to one's ability to stop oneself from exhibiting behaviors that one does not want to exhibit and is related to a person's ability to focus on a single task and suppress distractions. Working memory is the ability to hold in mind and manipulate stimuli that are no longer present in the environment. Long-term memory is the ability to encode and retain new knowledge. As mentioned in Sections 1 and 2, there is evidence linking executive functions and long-term memory to educational outcomes, but mainly for preschool-age children from HICs. Finally, implicit learning is the ability of the motor system to recognize and respond to regularities in the environment even when individuals are not aware of these regularities. Implicit learning is linked to language acquisition in young children as well as learning skills such as riding bikes or swimming.

In each task, we can differentiate between baseline and challenge trials. Both were administrated identically. However, the baseline trial helps to control for other skills, aside from the one being assessed, while the challenge trials yield the performance indicator for the cognitive skill measured through each task. Each of the tasks administered to measure these concepts required 2-3 minutes of instructions and 2-4 minutes for administration, for a total time for all FCS of approximately 30 minutes. Between 96 and 97% of the sample children took the test —for the Peruvian sample this is akin to the proportion that took the cognitive achievement tests (PPVT, math, and reading comprehension) at the same age, whereas in the Ethiopian sample a larger proportion of children took the RACER—compared to the cognitive achievement tests (Table 1, Panel D). RACER was also administered to the siblings.

Table 2 reports more details on each of the tasks, including which aspects of performance are measured in each case. In the case of long-term memory, by its nature the task is presented as the first task and repeated at the end. Detailed information about the data collected in Ethiopia and Peru is reported in Behrman et al. (2022).

INSERT TABLE 2 HERE

As mentioned, the challenge trials were used to calculate the performance indicator for each FCS. However, not all of them were calculated in the same way. Inhibitory control was computed as the average of the inverse of the average Euclidean distance and the inverse of the average response time, long-term memory as the percentage of correct choices, working memory as the inverse of the average Euclidean distance, and implicit learning as the inverse of the average response time. For the purpose of the statistical analysis, each FCS outcome is standardized and re-scaled in such a way that a higher score is linked to higher ability. Standardization was by age in years for the pooled sample of children in Ethiopia and Peru. As a reference, Table 3 reports average performance across skills by socio-economic status (proxied by the household location and the tertiles in the distribution of the wealth index of each country), and by area of location in each country sample. On average, Peruvian children performed better than Ethiopian children (in all tests). As expected, children from urban areas performed better than their counterparts in rural areas, and children from the top tertile of wealth performed better than those from the lower tertiles. For more details, see Behrman et al. (2022).

INSERT TABLE 3 HERE

4. Empirical methodology

We start with the following specification:

$$EO_{i,c} = \theta_0 + FCS_i\Gamma + BT_i\theta_1 + X_i\theta_2 + HC_i\theta_3 + RC_i\theta_4 + \psi_c + \mu_i \qquad (1)$$

where $EO_{i,c}$, is a generic term that represents the outcome of interest observed at around age 15 or 19-20 (highest grade achieved at age 15; standardized scores in the PPVT, math, and reading comprehension tests at age 15; aspirations for higher education at age 15; completed lower-secondary school at age 19 in Ethiopia; ever enrolled in higher education at age 20 in Peru) for child i born in community c. FCS_i is a vector that represents the score of the child in the challenge trial used to measure each of the FCSs covered in RACER when the child was age ~12. BT_i is an analogous vector that controls for the performance of the child in the baseline task. Given the different educational progressions observed in both countries, which in turn are related to differences in their economic development, we choose to focus on the probability of having completed secondary school in Ethiopia and the probability of accessing higher education in Peru. Specifically, for Ethiopia, we consider those that finished lower-secondary school, since general access to secondary education is limited around the nation, as evidenced by the percentages previously shown, and upper-secondary education is focused on university preparation, whereas for Peru we focus on the probability of enrolment in universities as they are the most selective higher-educational institutions in the country. The model also includes basic controls at the child level, denoted as vector X_i (age in months, sex, ethnicity proxied by child's mother's native tongue, and the number of years the child attended pre-school); and, socio-economic characteristics of the household, denoted as vector HC_i (household wealth[v], maternal level of schooling, and area of residence). RC_i contains additional controls to account for heterogeneity in the administration of the RACER task: whether the child completed the tasks during the morning (or not), and during a weekday (or not). ψ_c accounts for community-of-birth fixed effects. Finally, μ_i accounts for unobserved random factors.

The vector Γ includes the parameters of interest. We report two set of results for equation (1), first introducing in the model each FCS at a time, (2) and then altogether. The latter allows us to measure the associations of each of these skills with success at school, conditional on the other FCSs.

Our specification allows control for several sources of bias. First, the fact that the RACER outcomes were measured at age 12, years before the educational outcomes of interest at ages 15, 19 and 20, deals with potential simultaneity bias. Second, although the performance of the child in the challenge task(s) contains information about the general ability of the child, this is conceptually adjusted for by controlling for the performance of the child in the baseline trial(s). Third, the inclusion of the additional controls at the child and household levels adjusts for the role that the socio-economic status of the household and parental education play in the determination of a child's performance at school. Fourth, the role of geographical location—e.g., the quality of the educational services provided in the district—is incorporated through the inclusion of the-community-of-birth fixed effects.

The way the RACER outcomes were measured reduces the likelihood of omitted-variable bias due to unobserved characteristics at the child level—general ability is adjusted for by performance in the baseline tasks. However, results in equation (1) might still be afflicted by omitted-variable bias at the household level. For instance, parental preferences for investing in education might simultaneously explain a child's performance in RACER at age 12 and at school a few years later at age 15 or their probabilities to have completed school or been enrolled in higher education during young adulthood. Parental abilities might play a similar role. This is only partially taken into account by controlling for parental education and household wealth. To deal with this source of possible omitted-variable bias, additional results are reported using household fixed-effects versions of the main model, taking advantage of the fact that RACER was also administered to the (immediate) younger sibling of the index child in Peru, and the sibling closest in age of the index child in Ethiopia. The older siblings in Ethiopia are excluded from the analysis since their age range is very wide and some of them were already in their early adulthood when taking RACER. The household fixed-effects specification is as follows:

$$EO_{i,k} = \theta_0 + FCS_{i,k}\beta + BT_{i,k}\theta_1 + X_{i,k}\theta_2 + HC_k\theta_3 + RC_{i,k}\theta_4 + \psi_k + \mu_{i,k} \qquad (2)$$

where child i=1,2 (1= index child, 2=younger sibling) are siblings living in the same household k and ψ_k is the household fixed effect for the kth household. The advantage of this specification is that all unobserved characteristics that are common across siblings and that might bias the estimation of vector β are purged from the estimation by including ψ_k.

5. Results

Table 4 presents the results for the main model (Equation 1) to assess the relationships between each FCS measured at age 12 and each cognitive-achievement-test score measured at age 15 (column 1). Results are reported separately for Peru (Panel A) and Ethiopia (Panel B). Similar results by language of administration are reported in Appendix A.

Results show that long-term memory and working memory are consistently and positively associated with the three measures of domain-specific cognitive achievement in both country samples. An improvement by one standard deviation in long-term memory is associated with increases in cognitive achievement between 10% and 15% (12% and 14%) of a standard deviation in Ethiopia (Peru), whereas for working memory a one-standard-deviation increase is associated with increases in cognitive achievement between 8% and 14% (14% and 19%) of a standard deviation in Ethiopia (Peru).

INSERT TABLE 4 HERE

For inhibitory control, the signs of the point estimates are as expected but the coefficient estimates are not always statistically significant. A one-standard-deviation higher inhibitory control is associated with increases in math scores in Ethiopia and Peru (by 13% and 12%, respectively); and, in PPVT in Ethiopia (by 8%). Finally, for implicit learning, one-standard-deviation higher scores are associated with higher PPVT and math scores in Ethiopia, by 15% and 10% respectively. In the case of Peru, there are no significant associations observed.

Table 5 presents results including all the FCSs simultaneously, retaining the same adjustment variables included in Equation (1). This allows us to assess the prediction of each FCS partialing-out the associations with the other FCSs. There are four noteworthy results. First, virtually all the point estimates are smaller in magnitude. Second, all the coefficient estimates related to long-term memory and working memory remain statistically significant in both country samples. Third, inhibitory control retains predictive value only for math achievement in Ethiopia and Peru. In contrast, the significant association with PPVT is no longer observed for Ethiopia. Fourth, implicit learning no longer significantly predicts cognitive achievement in Ethiopia, and in Peru counterintuitive results (associations with negative signs) are observed for math and reading comprehension, albeit with marginal significance.

INSERT TABLE 5 HERE

For PPVT and reading comprehension, results could be driven by differences in the language in which the test was administered. For instance, in the Peruvian sample, non-Spanish speakers perform worse in all RACER tasks compared to Spanish speakers (Berhman et al., 2022). To account for this while at the same taking into consideration that tests were administered in the language spoken by the adolescent, in Table A1 and Table A2 (Appendix A) we report results separately by the main languages observed in each sample: Amharic, Tigrinya, and Oromo in Ethiopia; and Spanish in Peru. Overall, our conclusions remain unchanged.[vi]

It is conceivable that our main results are picking up a persistent relationship between FCSs and cognitive achievement over early and middle childhood, i.e., we might be capturing the importance that each FCS once had in cognitive achievement, and that persists through time. To establish whether this is the case, in Table A3 and Table A4 (see Appendix A) we report results of a value-added version of the main model. When the dependent variable is cognitive achievement observed at age 15, the estimation controls for cognitive achievement at age 12. Overall, the results remain very similar to those observed in Table 4 and Table 5, which suggests that the results observed are not an artifact of a persistent relationship in cognitive achievement. Put differently, adjusting for lagged cognitive achievement, FCSs still are associated with changes in cognitive achievement between ages 12 and 15. The only noticeable difference is observed in the relationship between long-term memory and math scores in Ethiopia, which becomes statistically insignificant.

Previous results show a robust association between FCS and achievement test scores. In Table 6, Equation (1) is re-estimated with the highest grade attained at age 15 as the outcome of interest. The results for Ethiopia show that the four FCSs are positively associated with grade attainment (Column (i)), with coefficients that range between 0.26 and 0.35. In the case of Peru, only long-term memory and working memory are positively and significantly associated with the grade attained at age 15, with coefficient estimates of 0.05 and 0.17 respectively. When including all the FCSs simultaneously (Column (ii)), all the coefficient estimates remain statistically significant for Ethiopia, whereas for Peru the coefficient estimates remain statistically significant for working memory and inhibitory control (marginally significant for the latter).

INSERT TABLE 6 HERE

It is possible that a higher FCS might be associated with higher aspirations for higher education—mediated by its impact on achievement test scores, which are predictors of enrolment in higher education (Sánchez and Singh, 2018). We explored this relationship using the same model specification as in Equation (1) but did not find any statistically significant relationship.

Up to this point, all outcomes that have been analyzed were observed in the last visit to the younger cohorts in 2016. We now incorporate outcomes observed during the phone survey in 2020 and 2021. Using this information, it is possible to identify whether YL participants had completed lower-secondary school in Ethiopia or were attending university in Peru when aged approximately 19 and 20 years old, respectively. Results must be qualified given that not all participants were contacted during this period. Notwithstanding this limitation, the relationship between FCSs at age 12 and having completed lower-secondary school (in Ethiopia) or university enrolment in Peru was explored through a linear probability model including the same control variables used in the main model. The results for Ethiopia and Peru are presented in Table 7. When including each FCS individually (columns (1)-(4)), in Ethiopia (Panel B), a one-standard-deviation higher long-term memory is associated with an increase in the probability of completing lower secondary school by 5.0 percentage points, whereas an analogous higher inhibitory control is associated with an increase in the probability of completing lower-secondary school by 3.9 percentage points. In the case of Peru, an improvement of one standard deviation in working memory predicts an increase of 3.3 percentage points in the probability of ever being enrolled in university (Panel A). These results are consistent with the main results (Table 4 and Table 5) that show that skills related to memory have the most relevant associations with educational achievement, while also highlighting the role of inhibitory control in Ethiopia. Additionally, when including all FCSs simultaneously (Column (5)), the results for Ethiopia remain the same, with long-term memory and inhibitory control showing significant associations, while for Peru, there are no significant associations observed.

INSERT TABLE 7 HERE

To understand potential biases that might arise due to sample selection (those with outdated or missing contact information were not called), we made a comparison of average performance in each FCS of those YL participants contacted in the phone survey with those not contacted but that were observed in Round 5 (see Table A5, Appendix A). We find that those not contacted during the phone survey have lower scores in all RACER tasks, compared to those that were contacted. For working memory and inhibitory control, the difference is statistically significant in both country samples. Assuming that those participants are also likely to have a lower educational attainment by age 19-20, these suggests our results in tables 7 and 8 are likely to represent a lower bound of the relationship between FCS and enrolment in higher education.

6. Robustness check

To deal with potential omitted household-level variable bias, Table 8 reports the results of re-estimating the main model including household fixed effects (Equation (2)), considering the pooled sample of index children and younger siblings—who are about three years younger, on average. Due to data availability, this model can only be estimated for PPVT and highest grade attained. Results are reported including each FCS individually (columns (1) and (2)) and all FCSs simultaneously (columns (3) and (4)).

These results confirm that working memory and long-term memory predict cognitive achievement in vocabulary in Ethiopia and Peru, and that inhibitory control predicts vocabulary test scores in Ethiopia. Likewise, working memory (and inhibitory control in this specification) predict grade achievement in Ethiopia, but not in Peru. Overall, these findings provide robust evidence of the associations between executive functioning, working memory and long-term memory and test scores in both countries, and grade achievement in Ethiopia.

INSERT TABLE 8 HERE

7. Discussion

For this study, we focused on the predictive power of cognitive skills in late childhood at age 12 for educational outcomes at age 15 and completing lower-secondary school or entry into higher education. From a policy perspective, skill development and accessing post-secondary education are key areas of interest. Overall, we found that FCSs significantly predict later educational success, which is consistent with the evidence from HICs. To our knowledge, our evidence using longitudinal data is unique for LMIC contexts. Considering the role of FCS 'one at a time', long-term memory and working memory are the only skills that predict subsequent achievement across all domains: math, vocabulary, and reading comprehension. Consistent with this, each skill predicts grade achievement in Ethiopia and Peru. In contrast, implicit learning seems to play a minor role in predicting educational success in both countries. This is not surprising, since implicit learning is linked to very basic aspects of development during infancy (Amso & Davidow, 2012).

Our results also suggest important associations in both countries between inhibitory control and math-test performance, but associations with vocabulary development and reading comprehension are less clear. The importance of inhibitory control for math achievement is consistent with prior evidence from HICs (Merkley et al., 2016; Clark et al., 2013). According to Merkley et al. (2016), this might be because numerical tasks require an ability to inhibit non-numerical stimuli. Despite its seemingly limited roles, inhibitory control is a significant predictor of grade achievement at age 15 and lower-secondary-school completion at age 19 in Ethiopia; in Peru, the coefficient estimate is marginally insignificant. The association between inhibitory control and grade achievement is likely mediated by its contribution to the development of math abilities, but inhibitory control also might play a role in non-cognitive dimensions that matter for school success, such as decisions around time use of children (at school and at home), and risky behaviours (Blair et al., 2008).

Our estimates that simultaneously control for the four FCSs observed in RACER suggest that both long-term memory and working memory remain relevant to predict variation in test scores across all domains (math, vocabulary, and reading comprehension), and the association of inhibitory control with math achievement persists. These results hold for Ethiopia and Peru. The importance of multiple skills for school success is also reflected in the observed significant predictors of grade attainment. The two measures of executive functioning included in RACER—working memory and inhibitory control —appear relevant in both countries. The only meaningful difference observed between countries is that long-term memory does not predict grade attainment in Peru once the other FCSs are controlled for. Implicit learning showed less consistent associations with educational outcomes.

An interesting issue for theoretical purposes is why some cognitive skills are associated with educational performance or outcomes, and some are not. In the case of the memory-related skills, long-term memory is associated with the ability to store new knowledge, while working memory is the ability to use that stored knowledge to complete tasks (Behrman et al., 2022). Those definitions are consistent with the requirements for successful continuous learning such as children hopefully experience at school. So, it is not surprising that higher levels of long-term memory and working memory predict higher scores in learning outcomes and higher-grade attainment. For inhibitory control, a part of its definition is related to the ability to focus on the task at hand by suppressing distracting stimuli while learning, which is another necessary tool to being able to perform well in learning activities. We can speculate that this is why inhibitory control has a significant association with some of the outcomes of interest. Finally, implicit learning is the ability to respond to regularities in the environment without necessarily being aware of them. The fact that we did not find this cognitive skill associated with educational outcomes in the two countries does not mean necessarily that it is not relevant in other outcomes.

While we are unable to establish causal links, the household fixed-effects strategy allows us to purge any bias derived from unobserved household characteristics that are constant over time, including (but not limited to) the role of differences in the quality of parenting. Although we cannot implement this specification for math and reading comprehension, as these tests were not administered to siblings, for vocabulary development our estimates confirm the importance of executive functioning and long-term memory for predicting learning. When applying this strategy, it would appear cognitive skills are no longer relevant to predict grade attainment in Peru; however, this might be an artifact of limited within-household variation in grade attainment for this sample.

Our analysis has some limitations. First, since we observe FCSs during late childhood by which age these measurements could already be affected by access to low-quality schools during the elementary-school period. However, we do not expect this to alter our conclusions because the value-added results show that FCSs still are associated with changes in educational outcomes between ages 12 and 15, and the household fixed-effects specification controls for school experiences that are common across siblings. Second, although our strategy allows us to deal with unobserved household heterogeneity, there might be unobserved child-level characteristics that could bias our results (e.g., innate ability), therefore we are unable to make strong causal claims about the relationships observed. However, arguably the baseline scores and the lagged scores in the value-added estimates control for ability. Third, the long-term analysis using data from the phone survey is afflicted by sample selectivity, as we were unable to contact participants for which we did not have up-to-date contact data, and those affected by the civil war in the Tigray region in Ethiopia. This is likely to generate a downward bias in our results.

From a policy perspective, our results justify the importance of investing in cognitive skills that are relevant for educational success. In particular, the results presented showed robust evidence of the importance of working memory and inhibitory control—two key areas of executive functioning, as well as long-term memory for predicting learning outcomes in LMIC contexts. Furthermore, our results show that FCSs are relevant to predict higher-education enrollment many years later. This poses a challenge for school systems: children need to develop FCSs that allow them to perform well at school tasks (e.g., school assignments) and continue learning; at the same time, school tasks can enhance FCSs. This virtuous circle can become a vicious circle for children from vulnerable backgrounds that start schools without a minimum set of FCSs, and that start falling behind. As shown by our results in LMICs and those from Jerrim and Vignole (2015) in HICs, the impact of low CS development can go as far as to limit post-secondary education achievement.

Initiatives related to designing an educational plan more focused on the development of CSs, rather than just knowledge impartment, should not only be implemented for the first years of education, but could also be extended for older children, working as a remediation policy. Banerjee et al. (2007) provide good examples of the potential of cost-effective remediation policies to increase children´s performance. Both programs evaluated by the authors are found to have gains in the average scores in literacy and numeracy skills of Indian children in elementary grade levels. These results are consistent with what Muralidharan et al. (2019) find in their evaluation of another program implemented in India, with both studies highlighting how children low in the score distribution benefit most. The differential effects of interventions to improve cognitive skills at different ages remains an interesting topic for further research. At the end, both early and later interventions are important investments than can help disadvantaged children overcome their initial difficulties.

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Tables

Table 1: Summary statistics

	Ethiopia	Peru
Panel A		
Child lives in urban area (in %), Round 5 (2016)	36.53%	74.69%
Child is male (in %)	52.86%	50.39%
Maternal schooling (in %)		
None	38.02%	n.a.
Any grade of elementary schooling	49.81%	n.a.
More than elementary schooling	12.16%	n.a.
None	n.a.	8.35%
Any grade of primary schooling	n.a.	36.43%
Any grade of secondary schooling	n.a.	37.12%
More than secondary schooling	n.a.	18.10%
Region of origin / ethnicity		
Mother´s native tongue is Amharic	34.63%	n.a.
Mother´s native tongue is Tigrinya	22.13%	n.a.
Mother´s native tongue is Oromifa	18.69%	n.a.
Mother´s native tongue is Spanish	n.a.	70.27%
Panel B		
Age in Round 5 (2016) (average)	15.1	14.9
Highest grade attained (average)	6.77	8.87
Grade achieved in Round 5 (2016)		
9th grade - Secondary schooling	18.39%	n.a.
8th grade - Elementary schooling	21.57%	n.a.
7th grade - Elementary schooling	13.53%	n.a.
6th grade and below	39.50%	n.a.
10th grade - Secondary schooling	n.a.	26.21%
9th grade - Secondary schooling	n.a.	48.65%
8th grade - Secondary schooling,	n.a.	14.70%
7th grade and below	n.a.	9.76%
Long-term educational outcomes (2020 Ethiopia, 2021 Peru)		
Finished secondary education		90.04%
Finished lower secondary education	45.48%	n.a.
Finished upper secondary education	11.66%	n.a.
Ever enrolled in higher education	3.06%	58.77%
Ever enrolled in university	2.48%	31.77%
Panel C – response rates on cognitive tests		
Took the PPVT, Round 5 (2016)	86.18%	95.65%
Took the math test, Round 5 (2016)	91.25%	96.80%
Took the reading comprehension test, Round 5 (2016)	89.92%	94.95%
Took the RACER, Round 4 (2013)	99.89%	99.04%
Panel D – language of administration (PPVT, math, reading comprehension)		
Amharic	48.09%	n.a.
Tigrinya	21.45%	n.a.
Oromifa	19.36%	n.a.
Spanish	n.a.	98.82%
Quechua	n.a.	0.11%
Spanish and Quechua	n.a.	0.22%

Note: statistics correspond to the sample of index children that are part of the analytical sample.

Table 2: Description of RACER tasks

RACER Task #	Cognitive Task	Cognitive Ability	Definition
Task 1	Paired Associate Learning Task (Part 1) "Memory Game 1"	Long-term Memory/Declarative memory	**Long-term memory/declarative memory**: the ability to encode and retain new knowledge.
Task 2	Simon Task "Sides Game"	Inhibitory Control	**Inhibition**: the ability to stop oneself from exhibiting behaviours one does not want to exhibit and is related to one's ability to focus on a single task and supress distractors.
Task 3	Spatial Delayed-Match-to-Sample Task "Finding the Dots"	Working Memory	**Working memory**: the ability to hold in mind and manipulate stimuli that are no longer present in the environment.
Task 4	Adapted Serial Reaction Time Task "Catching Chickens/ Chasing dots"	Implicit Learning	**Implicit learning**: the ability of the motor system to recognise and respond to regularities in the environment even when individuals are not aware of these regularities.
Task 5	Paired Associate Learning Task (Part 2) "Memory Game 2"	Long-term Memory/Declarative memory	**Long-term memory**/Declarative memory: the ability to encode and retain new knowledge.

Note: this table is taken from Behrman et al. (2022). The table is used with authorization from the authors.

Table 3: Summary statistics

	Inhibitory control		Working memory		Long-term memory		Implicit learning	
	Ethiopia	Peru	Ethiopia	Peru	Ethiopia	Peru	Ethiopia	Peru
Full sample	-0.1303	0.1274	-0.1476	0.1576	-0.1343	0.1259	-0.0951	0.0924
By area of location								
Urban	0.0318	0.2806	-0.0170	0.2957	0.1580	0.2133	0.0934	0.1668
Rural	-0.2169	-0.2108	-0.2174	-0.1682	-0.2905	-0.0670	-0.1958	-0.0718
By tertiles of household wealth								
Bottom	-0.1896	-0.1781	-0.2909	-0.1388	-0.2454	-0.0788	-0.2000	-0.1653
Middle	-0.2425	0.0953	-0.1556	0.1541	-0.3273	0.1320	-0.1725	0.0921
Top	0.0539	0.4664	0.0074	0.4416	0.1810	0.3232	0.0801	0.3513

Note: These results are reported for the balanced sample of participants. The results have been standardized to have mean zero and variance one by age in years within the pooled sample of Ethiopia and Peru.

Table 4:
Association between foundational cognitive skills at age 12 and test scores at age 15 - One skill included at a time (Ordinary Least Squares)

Dependent variables:	**PPVT**	**Math**	**Reading comprehension**
	(1)	**(2)**	**(3)**
Panel A: Peru			
Independent variables			
Long-term memory	0.144***	0.124***	0.141***
	(0.016)	(0.021)	(0.029)
Inhibitory control	0.064	0.124***	0.035
	(0.042)	(0.042)	(0.042)
Working memory	0.193***	0.182***	0.136***
	(0.021)	(0.024)	(0.027)
Implicit learning	0.048	0.026	0.027
	(0.030)	(0.025)	(0.021)
Obs.	1,697	1,718	1,686
Adjusted R2	0.330	0.203	0.203
Adjusted R2	0.341	0.216	0.205
Adjusted R2	0.359	0.244	0.229
Adjusted R2	0.314	0.194	0.185
Panel B: Ethiopia			
Independent variables			
Long-term memory	0.146***	0.095***	0.125***
	(0.038)	(0.026)	(0.024)
Inhibitory control	0.082*	0.128***	0.026
	(0.045)	(0.037)	(0.033)
Working memory	0.141***	0.111***	0.080***
	(0.023)	(0.025)	(0.024)
Implicit learning	0.153**	0.098*	0.092
	(0.071)	(0.049)	(0.054)
Obs.	1,469	1,564	1,541
Adjusted R2	0.464	0.324	0.398
Adjusted R2	0.462	0.329	0.393
Adjusted R2	0.486	0.333	0.401
Adjusted R2	0.454	0.320	0.389

Note: Each coefficient in each cell comes from a different estimated model. Each model controls for the baseline performance in the associated task, child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects. ***p<0.01, **p<0.05, *p<0.10.

Table 5:
Association between foundational cognitive skills at age 12 and test scores at ages 15 – All skills included simultaneously (Ordinary Least Squares)

Dependent variables:	**PPVT**	**Math**	**Reading comprehension**
	(1)	**(2)**	**(3)**
Panel A: Peru			
Independent variables			
Long-term memory	0.116***	0.095***	0.112***
	(0.014)	(0.018)	(0.027)
Inhibitory control	0.044	0.097**	0.034
	(0.044)	(0.044)	(0.042)
Working memory	0.150***	0.142***	0.101***
	(0.023)	(0.029)	(0.028)
Implicit learning	-0.023	-0.050*	-0.036*
	(0.032)	(0.027)	(0.019)
Obs.	1,695	1,716	1,684
Adjusted R2	0.383	0.269	0.249
Panel B: Ethiopia			
Independent variables			
Long-term memory	0.115***	0.073**	0.107***
	(0.033)	(0.027)	(0.024)
Inhibitory control	0.034	0.099**	-0.007
	(0.041)	(0.037)	(0.036)
Working memory	0.115***	0.089***	0.067**
	(0.022)	(0.026)	(0.027)
Implicit learning	0.099	0.054	0.056
	(0.064)	(0.047)	(0.054)
Obs.	1,469	1,564	1,541
Adjusted R2	0.503	0.342	0.412

Note: In each panel, the four coefficients reported in each column come from the same estimated model. Each model controls for the baseline performance in all tasks, child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects. ***p<0.01, **p<0.05, *p<0.10.

Table 6:
Association between foundational cognitive skills at age 12 and highest grade achieved at age 15 (Ordinary Least Squares)

	FCS included one at a time	FCSs included simultaneously
	(i)	(ii)
Panel A: Peru		
Independent variables		
Long-term memory	0.053**	0.021
	(0.021)	(0.022)
Inhibitory control	0.077	0.088*
	(0.046)	(0.047)
Working memory	0.167***	0.119***
	(0.035)	(0.033)
Implicit learning	0.050	-0.030
	(0.030)	(0.028)
Obs.	1,718	1,716
Adjusted R2	0.260	0.318
Adjusted R2	0.293	
Adjusted R2	0.299	
Adjusted R2	0.260	
Panel B: Ethiopia		
Independent variables		
Long-term memory	0.287***	0.211***
	(0.057)	(0.051)
Inhibitory control	0.319***	0.270***
	(0.080)	(0.067)
Working memory	0.260***	0.175***
	(0.062)	(0.059)
Implicit learning	0.351**	0.210*
	(0.136)	(0.117)
Obs.	1,649	1,649
Adjusted R2	0.458	0.494
Adjusted R2	0.472	
Adjusted R2	0.472	
Adjusted R2	0.451	

Note: In column (i), each coefficient comes from a different estimated model, whereas in columns (ii) the four coefficients reported in each panel come from the same estimated model. All models control for child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects. In addition, in columns (i) and (ii), each model controls for the baseline performance in the associated task, whereas in columns (iii) and (iv) each model controls for the baseline performance in all tasks. ***p<0.01, **p<0.05, *p<0.10.

Table 7:
Association between foundational cognitive skills at age 12 and educational attainment at age 19-20 (Ordinary Least Squares)

	(1)	(2)	(3)	(4)	(5)
Panel A: Peru	*Dependent variable: Enrolled in university at age 20 (1 if yes; 0 if no)*				
Independent variables:					
Long-term memory	0.0502***				0.0461**
	(4.49)				(3.71)
Inhibitory control		0.0390*			0.0350*
		(2.36)			(2.11)
Working memory			0.0274		0.0182
			(2.03)		(1.30)
Implicit learning				0.0228	0.00907
				(0.88)	(0.31)
N	1506	1506	1506	1506	1506
Panel B: Ethiopia	*Dependent variable: Finished lower secondary education at age 19 (1 if yes; 0 if no)*				
Independent variables:					
Long-term memory	0.0149				0.0103
	(1.66)				(1.28)
Inhibitory control		0.0317			0.0305
		(1.57)			(1.40)
Working memory			0.0335*		0.0220
			(2.73)		(1.67)
Implicit learning				0.0169	0.00366
				(1.15)	(0.24)
N	1543	1543	1543	1541	1541

Note: In Panel A (Peru), enrolment in university takes the value of 1 if the YL participant is currently enrolled or has been enrolled in a university institution, 0 otherwise. In Panel B (Ethiopia) Having finished lower secondary takes the value of 1 if the YL participant completed at least Grade 10. In columns (1) to (4), each coefficient in each cell comes from a different estimated model. In column (5) the four coefficients reported come from the same estimated model. Each model controls for the baseline performance in the associated task, child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal schooling level, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a weekday, 0 otherwise), and community-of-birth fixed effects. ***p<0.01, **p<0.05, *p<0.10.

Table 8:
Household fixed-effects specification – Foundational cognitive skills at age 12 and educational outcomes at age 15

	FCS included one at a time		FCS included simultaneously	
Dependent variables:	**Highest grade achieved**	**PPVT**	**Highest grade achieved**	**PPVT**
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Peru				
Independent variables:				
Long-term memory	0.020	0.069**	0.003	0.049
	(0.034)	(0.032)	(0.040)	(0.033)
Inhibitory control	0.065	0.006	0.052	-0.001
	(0.063)	(0.041)	(0.067)	(0.042)
Working memory	0.067	0.106***	0.048	0.081**
	(0.050)	(0.030)	(0.050)	(0.033)
Implicit learning	-0.026	0.001	-0.056	-0.030
	(0.065)	(0.035)	(0.068)	(0.032)
Obs.	2,398	2,381	2,395	2,378
Adjusted R2	0.888	0.027	0.890	0.058
Adjusted R2	0.889	0.042		
Adjusted R2	0.889	0.039		
Adjusted R2	0.889	0.022		
Panel B: Ethiopia				
Independent variables:				
Long-term memory	0.067	0.062***	0.031	0.050***
	(0.060)	(0.019)	(0.062)	(0.015)
Inhibitory control	0.433***	0.116**	0.382***	0.101**
	(0.136)	(0.042)	(0.133)	(0.039)
Working memory	0.219***	0.072**	0.178**	0.063*
	(0.063)	(0.034)	(0.066)	(0.032)
Implicit learning	0.164	0.038	0.050	0.001
	(0.095)	(0.040)	(0.090)	(0.039)
Obs.	2,481	2,196	2,481	2,196
Adjusted R2	0.720	0.077	0.740	0.120
Adjusted R2	0.733	0.094		
Adjusted R2	0.730	0.100		
Adjusted R2	0.721	0.071		

Note: ***p<0.01, **p<0.05, *p<0.10. In the table, column (1) and (2) represent different models. Column (1) refers to four different OLS regressions, each one using one FCS as the independent variable. Column (2) indicates only one OLS regression using the four FCS variables in the same specification.

Appendix A

Table A1: Peru - Association between foundational cognitive skills at age 12 and test scores at ages 15 among Spanish speakers

Dependent variables:	**PPVT – Spanish**	**Reading comprehension - Spanish**
	(1)	**(2)**
Panel A		
Independent variables		
Long-term memory	0.148***	0.132***
	(0.017)	(0.025)
Inhibitory control	0.066	0.105**
	(0.041)	(0.038)
Working memory	0.192***	0.157***
	(0.021)	(0.029)
Implicit learning	0.043	0.050*
	(0.030)	(0.024)
Obs.	1,692	1,738
Adjusted R2	0.318	0.260
Adjusted R2	0.330	0.278
Adjusted R2	0.347	0.280
Adjusted R2	0.302	0.250
Panel B		
Independent variables		
Long-term memory	0.119***	0.113***
	(0.014)	(0.028)
Inhibitory control	0.047	0.033
	(0.044)	(0.041)
Working memory	0.149***	0.098***
	(0.024)	(0.027)
Implicit learning	-0.029	-0.039*
	(0.032)	(0.020)
Obs.	1,690	1,678
Adjusted R2	0.373	0.239

Note: ***p<0.01, *p<0.05, *p<0.10. In Panel A, each coefficient in each cell comes from a different estimated model. In Panel B, the four coefficients reported in each column come from the same estimated model. Each model was estimated only for those that answered the tests in Spanish. Each model controls for the baseline performance in the associated task, child´s sex, age in months, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects.

Table A2: Ethiopia - Association between foundational cognitive skills at age 12 and test scores at age 15 by language of administration

Dependent variables:	PPVT – Amharic	PPVT - Tigrinya	PPVT – Oromifa	Reading comprehension - Amharic	Reading comprehension - Tigrinya	Reading comprehension - Oromifa
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
Independent variables:						
Long-term memory	0.111**	0.135**	0.215*	0.148***	0.027	0.149*
	(0.049)	(0.030)	(0.083)	(0.038)	(0.042)	(0.067)
Inhibitory control	0.075	0.146	0.031	0.088*	0.034	-0.018
	(0.073)	(0.083)	(0.088)	(0.046)	(0.075)	(0.091)
Working memory	0.132***	0.119	0.180***	0.066*	0.134	0.060
	(0.034)	(0.059)	(0.017)	(0.031)	(0.081)	(0.030)
Implicit learning	0.086	0.317	0.097	0.038	0.212**	0.047
	(0.086)	(0.159)	(0.119)	(0.058)	(0.060)	(0.240)
Obs.	777	354	320	680	335	274
Adjusted R2	0.570	0.301	0.252	0.385	0.116	0.119
Adjusted R2	0.576	0.308	0.212	0.375	0.138	0.097
Adjusted R2	0.588	0.340	0.267	0.380	0.156	0.111
Adjusted R2	0.561	0.319	0.211	0.367	0.132	0.103
Panel B						
Independent variables:						
Long-term memory	0.076*	0.102*	0.188*	0.127***	0.001	0.135
	(0.039)	(0.040)	(0.076)	(0.034)	(0.032)	(0.064)
Inhibitory control	0.039	0.077	-0.006	0.057	0.004	-0.047
	(0.072)	(0.059)	(0.082)	(0.045)	(0.105)	(0.049)
Working memory	0.102***	0.085	0.163**	0.044	0.112	0.067*
	(0.032)	(0.059)	(0.038)	(0.032)	(0.091)	(0.028)
Implicit learning	0.039	0.236	0.075	0.006	0.131	0.050
	(0.081)	(0.149)	(0.103)	(0.065)	(0.071)	(0.254)
Obs.	777	354	320	680	335	274
Adjusted R2	0.599	0.360	0.295	0.399	0.159	0.118

Note: ***p<0.01, **p<0.05, *p<0.10. In Panel A, each coefficient in each cell comes from a different estimated model. In Panel B, the four coefficients reported in each column come from the same estimated model. Each model was estimated only for those that answered the tests in Amharic, Tigrinya and Oromifa, respectively. Each model controls for the baseline performance in the associated task, child´s sex, age in months, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects.

Table A3:
Associations between foundational cognitive skills at age 12 and test scores at age 15 – One skill included at a time (Value-Added Specification)

Dependent variables:	**PPVT**	**Math**	**Reading comprehension**
	(1)	**(2)**	**(3)**
Panel A: Peru			
Independent variables:			
Long-term memory	0.072***	0.050***	0.073***
	(0.018)	(0.016)	(0.021)
Inhibitory control	0.031	0.060**	-0.018
	(0.028)	(0.027)	(0.034)
Working memory	0.093***	0.057**	0.058**
	(0.014)	(0.022)	(0.024)
Implicit learning	0.013	-0.026	-0.004
	(0.024)	(0.018)	(0.020)
Obs.	1,692	1,710	1,680
Adjusted R2	0.549	0.482	0.400
Adjusted R2	0.550	0.481	0.397
Adjusted R2	0.554	0.486	0.408
Adjusted R2	0.545	0.482	0.395
Panel B: Ethiopia			
Independent variables:			
Long-term memory	0.048*	0.023	0.071***
	(0.027)	(0.028)	(0.019)
Inhibitory control	0.029	0.076***	-0.030
	(0.036)	(0.026)	(0.027)
Working memory	0.066***	0.054**	0.053**
	(0.020)	(0.021)	(0.025)
Implicit learning	0.125*	0.013	0.051
	(0.061)	(0.035)	(0.041)
Obs.	1,439	1,414	1,368
Adjusted R2	0.606	0.478	0.525
Adjusted R2	0.606	0.480	0.521
Adjusted R2	0.616	0.481	0.526
Adjusted R2	0.607	0.478	0.521

Note: In each panel, the four coefficients reported in each column come from the same estimated model. Each model controls for the baseline performance in all (four) tasks, lagged test score, child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects. ***p<0.01, **p<0.05, *p<0.10.

Table A4:
Associations between foundational cognitive skills at age 12 and test scores at age 15 – All skills included simultaneously (Value-Added Specification)

Dependent variables:	**PPVT**	**Math**	**Reading comprehension**
	(1)	**(2)**	**(3)**
Panel A: Peru			
Independent variables			
Long-term memory	0.064***	0.045***	0.061***
	(0.017)	(0.015)	(0.021)
Inhibitory control	0.023	0.052*	-0.008
	(0.032)	(0.029)	(0.034)
Working memory	0.075***	0.051*	0.052*
	(0.017)	(0.025)	(0.025)
Implicit learning	-0.019	-0.046**	-0.028
	(0.027)	(0.021)	(0.022)
Obs.	1,690	1,708	1,678
Adjusted R2	0.560	0.491	0.411
Panel B: Ethiopia			
Independent variables			
Long-term memory	0.038	0.017	0.068***
	(0.027)	(0.029)	(0.019)
Inhibitory control	0.014	0.068**	-0.056*
	(0.036)	(0.025)	(0.029)
Working memory	0.058***	0.045*	0.058**
	(0.019)	(0.024)	(0.026)
Implicit learning	0.099	-0.002	0.040
	(0.057)	(0.035)	(0.044)
Obs.	1,439	1,414	1,368
Adjusted R2	0.619	0.481	0.529

Note: In each panel, the four coefficients reported in each column come from the same estimated model. Each model controls for the baseline performance in all (four) tasks, lagged test score, child´s sex, age in months, ethnicity, and number of years of pre-schooling; household wealth dummies (1 if in the middle tertile, 0 otherwise; 1 if in the top tertile, 0 otherwise), maternal level of schooling, area of residence, time of RACER administration (1 morning, 0 otherwise), date of RACER administration (1 if on a week day, 0 otherwise), and community-of-birth fixed effects. ***p<0.01, **p<0.05, *p<0.10.

Table A5:
Average performance by foundational cognitive skill among those not contacted for the phone survey versus those contacted during the phone survey

	N	Long-term memory	p-value	Inhibitory control	p-value	Working memory	p-value	Implicit learning	p-value
Panel A: Peru									
Full sample (Round 5)	1841	0.13		0.13		0.15		0.09	
(a) Not contacted in Call 5	212	0.03	0.122	-0.05	0.000	-0.11	0.000	0.06	0.618
(b) Contacted in Call 5	1629	0.14		0.15		0.19		0.10	
Panel b: Ethiopia									
Full sample (Round 5)	1795	-0.13		-0.13		-0.15		-0.10	
(a) Not contacted in Call 2	200	-0.20	0.294	-0.26	0.002	-0.35	0.002	-0.14	0.458
(b) Contacted in Call 2	1595	-0.13		-0.11		-0.12		-0.09	

Note: statistics correspond to the sample of index children that are part of the analytical sample. Group (a) are index children that were interviewed in the last in-person visit in 2016 (Round 5) but that were not contacted during the phone survey, whereas group (b) are those interviewed in Round 5 and also contacted for the phone survey.

[i] A recent study that tackled this topic is Micalizzi et al. (2019). These authors focused on a group of four-year-old US children to assess how their performance varied according to SES. They concluded that children with higher SES showed higher levels of inhibitory control, which is associated with better school readiness.

[ii] One criterion from the beginning of the study was that country samples were to be pro-poor. This was implemented in different ways by each country team. The country team in Peru considered the universe of districts excluding the top 5% wealthiest districts, and randomly selected 20 districts from the remaining 95% (Escobal & Flores, 2008). In the case of Ethiopia, the country team used a purposive methodology. Clusters were chosen such that (i) poor areas were oversampled, (ii) the diversity across regions, ethnicity and location was captured; (iii) the costs of sampling were manageable (Outes-León & Sánchez, 2008).

[iii] In Ethiopia, elementary (primary) education officially starts at age 7 and lasts for 8 years, followed by 4 years of secondary education, whereas in Peru primary education is compulsory from age 6 and lasts for 6 years, followed by 5 years of secondary education.

[iv] Higher education is defined in Peru as enrolment in a technical institute or university, and for Ethiopia as any tertiary educational option that grants a Teacher´s certificate, a Diploma/Advanced diploma, a University degree, and a Masters or doctoral degree (it doesn´t include Technical and Vocation Education and Training).

[v] The YL wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017).

[vi] Some coefficients become statistically insignificant, likely due to the lower sample size when each country sample is partitioned. However, similar patterns are observed, except for reading comprehension in the Tigray region where the point estimates are very small.