Early Life Determinants of Cognitive Ability: A Comparative Study on Madagascar and Senegal

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Abstract

We study the determinants of educational and cognitive outcomes of young adults in Madagascar and Senegal employing a production function approach. Using unique and comparable long-term panel data sets from both countries, we find that cognitive skills measured using test scores in second grade are strong predictors of school attainment and cognitive skills of a cohort of individuals surveyed in their early twenties. The inclusion of early life household wealth, parental education and other household characteristics in the model does not diminish the impact of early cognitive ability on educational and cognitive outcomes in young adult life. Additionally, we find that both early life cognitive ability and health seem to have independent effects on educational attainment and adult cognition. In Senegal, both math and French scores are strong predictors of adult cognitive skills, whereas in Madagascar math plays a relatively stronger role. We find suggestive evidence that the association between early life cognitive ability and later life outcomes is stronger among girls as compared to boys. We also show significant differences in the relationship between early ability and later life test scores for those cohort members according to their height, which we consider a proxy for health status – shorter individuals show a stronger relationship between second grade performance and later life outcomes. These findings highlight the importance of how falling behind in early life may be critical in determining long-term outcomes, particularly for vulnerable groups, that is girls and shorter individuals.

JEL Classification Codes: I21, O12

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1. Introduction

Cognitive ability has important implications not only for individual well-being (Heckman et al 2006), but also for economic growth (Hanushek and Woessmann 2008, 2012; Hanushek 2013). In this paper, we study the determinants of grade attainment and cognitive ability among young adults in two francophone African countries, Madagascar and Senegal. Primarily, we examine the importance of early life cognitive ability in determining the educational level and cognitive capacity of young adults. Additionally, we explore the role of other early life conditions, such as health, wealth and parental education in shaping these young adult outcomes. We do so by using two unique and similar panel surveys from Madagascar and Senegal that follow children from second grade until they are young adults. The cohorts are followed over a period of 17 years in Senegal and 15 years in Madagascar, an unusually long period for survey data, especially in the African context.

Our study adds to the literature in economics and psychology that discusses the positive relationship between cognitive performance of children in elementary school and academic performance later in life (Cunningham and Stanovich 1997; Feinstein 2003; Bourne et al. 2007; Duncan et al. 2007).[1] For the most part, these studies measure academic performance in terms of school attainment and test scores. We also compare the relative importance of the impact of early math and language scores on later life outcomes across the two countries. This comparison is possible because the language of instruction (French) is the same across the two countries in our sample. Our results closely mirror those of Duncan et al. (2007), who use data from US, Canada and UK to find that math skills at school entry are a stronger predictor of later achievement than language skills.[2]

[1] For a review article on effects of early life attributes to adult outcomes see Heckman and Mosso (2014).

[2] Our results should interpreted keeping in mind that French, which is the language of instruction in our sample, might not be the first language learned by the children at home while the language of instruction might have been the same as the primary language at home in in Duncan et al. (2007), who present evidence of predominantly Anglophone developed countries.

Apart from contributing to the literature on the persistence of cognitive skills from school-age to later life, we also discuss the importance of the impact that early life cognitive skills have on the level of schooling acquired by early adulthood. Glick and Sahn (2010) found that skills in early primary school (second grade) in 1995–6 are strongly positively associated with school progression eight years later.[3] Similarly, Singh and Mukherjee (2016) using panel data from India find that early primary school skills contribute to the likelihood of completing secondary schooling.[4] In our analysis, we document similar relationships with the added dimension that we use data sets that span a longer period of time, as compared to the aforementioned studies. This allows us to examine the impact that second grade test scores have on educational and cognitive outcomes of a cohort of young adults last surveyed when they are in early twenties.

While the primary focus of our research is on the effect of early life cognitive ability on schooling and cognition later in life, we are also interested in the important role played by early childhood health in determining later life outcomes.[5] Therefore, we include height in our models to first, examine the role of childhood health in shaping adult cognitive ability and grade attainment as well as to control for the confounding effect it might have on our primary question of interest – the effect of cognitive ability in second grade on cognitive ability and grade attainment in young adulthood.

In this regard, we build upon the related evidence of the impact of health, measured using height, on both schooling outcomes and cognitive ability. More specifically, Alderman et al. (2006) show that childhood health status (as measured by height for age) has a positive impact on completed schooling as an adult. Behrman et al. (2014) also find that height for age at the age of six affects adult cognitive skills, and further make the point that excluding height from a cognitive production function will result in an overestimation of the effect of schooling on cognitive ability. Similarly,

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[3] This study uses the same data set (for Senegal) as our analysis.

[4] This study uses data from the Young Lives project, which has followed a cohort of children for 11 years as of the time of the writing of this paper. Details: http://www.younglives-india.org/ findings-and-data

[5] See, for example, Almond & Mazumdar 2013 and Currie & Vogl 2013 for excellent reviews on this topic. In addition, there is a substantial literature, primarily from developed countries, which looks at the development of human capital before the age of five (Currie & Almond 2011).

Case and Paxson (2008), Lundborg et al. (2014), Vogl (2014), Sohn (2015) and LaFave and Thomas (2016) all find a strong correlation between height and cognitive ability of adults.[6] Like these other papers, the health indicator we use is adult height, which is determined by a confluence of genetic and environmental factors (Tanner 1979).

Family background, particularly wealth and parental education, also plays a critical role in the cognition development process. Our paper builds on this literature which provides strong evidence that parents' education affects grade progression and cognitive skills of their children, both in developing and developed countries (Cunha and Heckman 2007; Todd and Wolpin 2007; Cunha et al. 2010; Glick et al. 2011; Behrman et al. 2014; Jones et al. 2014). Moreover, Fiorini and Keane (2014) found evidence that cognitive skill formation depends heavily on the amount of time spent in educational activities after school, mostly provided for by parents. In a similar vein, Zhang et al. (2014) find parental absence affects children's cognitive skills in rural China, while Helmers and Patnam (2011) find that parental investment has an impact on skill levels of children of primary school age or lower in India. In the context of Sub-Saharan Africa, Glick et al. (2011) and Jones et al. (2014) find that parental background plays a significant role in the determination of children's ability, and similarly, children of educated (and non-poor parents) have been found to perform much better than their peers on cognitive tests (Dumas and Lambert, 2011).

In terms of wealth, or other money metric measures of income, there is evidence that material well-being matters for education and cognition outcomes (Cunha and Heckman 2007; Todd and Wolpin 2007; Cunha and Heckman 2008; Helmers and Patnam 2011; Schady et al. 2015). However, in most studies from developing countries, income, expenditure, or wealth is measured contemporaneously with the cognitive indicator. This provides the impact of contemporaneous household resources on cognition outcomes. In contrast to the preponderance of

[6] Lundborg et al. (2014) also finds that height at age 18 has a significant impact on wages even after controlling for cognitive and non-cognitive skills in Sweden. Other literature investigating the height premium without taking into account cognitive skills include Persico et al. (2004), who show that controlling for height in teenage years nearly eliminates all of the contemporaneous effect of adult height on wages. Similarly, Vogl (2014) and Sohn (2015) find large height premium in wages in Mexico and Indonesia, respectively.

this literature, we explore the impact of wealth (measured by assets) in early childhood on later life cognition outcome.

To explore the impact of aforementioned socioeconomic factors, height and cognitive ability in second grade on young adult outcomes, we build upon a standard cognitive production function framework (Todd and Wolpin 2003; 2007; Cunha and Heckman 2007; Cunha et al. 2010), in which cognitive skills are developed over time and are a function of inputs received by the child, such as parents' education, wealth, and the schooling environment. The unique nature of our data set permits us to assess this relationship while controlling for the impact of a variety of household and school level factors. We also discuss heterogeneous effects on dimensions related to gender, height and household wealth.

Another distinguishing characteristic of our work is the fact that we study these research questions in the context of two Sub-Saharan African countries from which we have comparable data sets. There is a relative lack of evidence with respect to Africa, especially in a comparative context. To strengthen the comparability of our results from Madagascar and Senegal, we use Item Response Theory (IRT)[7] to create joint test score indices for the two countries, which we use to compare performance across the two countries in two points of time. Such comparisons of human capital formation, especially from developing countries, are quite rare (Singh 2017, Schady et al. 2015, Jones et al. 2014). Our analysis is different from these papers insofar as our data covers a longer time period effectively spanning the entire course of schooling experience from second grade to early adulthood.

We find that school attainment and cognitive skills of young adults are strongly related to cognition in second grade in both countries. We observe heterogeneous effects of math and French skills in second grade, where math scores have a stronger impact on later life outcomes than French scores. These results confirm patterns observed in Duncan et al. (2007). The results also suggest that taller individuals have higher cognitive test scores, evidence similar to Case & Paxson (2008)

[7] How we render the test scores comparable by constructing the IRT scores is explained in detail in Appendix A.

and LaFave & Thomas (2016). We also find that height plays an important role in grade attainment among young adults in Senegal, but its effect is not statistically significant in Madagascar. This effect of child health is independent of the effect of early childhood cognitive ability. In addition, our results indicate that wealth of the household when children are entering school has an effect on schooling and cognitive skills measured over 15 years later when they turn young adults. Furthermore, we find that parents' education matters more in Madagascar than in Senegal. Finally, our heterogeneity analysis shows that early life test scores matter more for later life outcomes for shorter individuals and females, groups that are potentially more vulnerable. This finding implies that lagging behind in second grade is more detrimental to certain groups as compared to others.

The remainder of this paper is organized as follows. Section 2 presents the country contexts, while section 3 expands on the data and some comparative descriptive statistics on Madagascar and Senegal. In Section 4 we discuss the conceptual framework and the empirical strategy used. Section 5 presents the results and section 6 discusses robustness checks. Finally section 7 concludes.

2. The Context

Our comparative study examines the production of human capital among young adults in two poor sub-Saharan African countries, Madagascar and Senegal. Although these countries differ in their nature of schooling, the role of skills, the social context and other related social norms, there are many similarities. Both are low-income countries that struggle with low primary school enrollment and completion rates. This is the case despite significant improvements in primary school completion rates over the study period (1996–2012)—from 40 to 59 percent in Senegal and from 31 to 70 percent in Madagascar. In the same period, gross enrollment rates in primary schools have also risen in both countries - in Senegal from 59 percent to 81 percent, and in Madagascar from 86 percent to 145 percent (World Bank 2016).[8] Additionally, in the 1990s, grade repetition and dropout rates were high in both countries (Michaelowa 2001; Glick and Sahn 2010).

Since both countries follow educational systems modeled after the French system, the primary language of instruction is French. However, there are some differences between the educational systems of the two countries. One of the more important distinctions is the presence of a large network of Koranic schools in Senegal which offers religious education. These schools enroll a large proportion of preschool children. Despite attending these schools, most students subsequently enroll in secular schools after their stint in these koranic schools is finished.[9]

The Malagasy and Senegalese economies differ in many important respects. Madagascar is an island economy that has experienced almost two decades of political turmoil since 1998, with average GDP per capita growth being zero during the period of our study (World Bank 2016). In contrast, Senegal is one of the more dynamic economies in West Africa, with GDP per capita growth averaging 1.2 percent between 1995–2012. Likewise, the poverty headcount ratio has increased slightly in Madagascar, to nearly 75 percent in 2010. However, in Senegal the headcount ratio stood at 47 percent in 2010 (World Bank 2016). Madagascar has lower levels of intergenerational mobility of education and occupation than a number of other African countries (Bossuroy and Cogneau 2013; Azomahou and Yitbarek 2016). Further, Glick et al. (2011) find that parents' education and schooling are important determinants of learning in the case of Madagascar. In the case of Senegal, Glick and Sahn (2009) show that conditional on a child's level of schooling at the age of 14–17 years, having better educated parents or a higher level of household resources have only modest benefits for academic performance. They found similar

[8] Net enrollment rate is not available for Madagascar after 2003. The large disparity in the gross enrollment rates indicates that, in Madagascar, there is potentially much more enrollment of overaged or underaged children, as well as rampant grade repetition.

[9] Recent analyses show that the opening of formal schools in Senegal reduced the enrollment and the amount of time spent in Koranic schools (André and Demonsant 2013). This would imply that koranic schools act as substitutes to the formal secular schooling system. But, whether Koranic schools complement or substitute formal education is still an open question. Madagascar is different from Senegal because of the absence of such a system.

results for school-level variables.[10] Therefore, even though children in Madagascar and Senegal are exposed to potentially similar schooling systems, they differ critically in the opportunities they may encounter and the extent to which their background matters for their achievements in later life.

3. Data

The first round of the long-term panel data sets was conducted in 1995–6 in Senegal and in 1997–8 in Madagascar. Math and French tests were administered to children at the beginning and end of second grade, when they were in the age range of 7 to 10 years.[11] These school-based tests were administered as part of a multi-country study called the Program on the Analysis of the Conference of Francophone Ministers of Education, which is referred to by its French acronym, PASEC.[12] Both urban and rural communities were included in the PASEC sample, which was designed to be a nationally representative selection of communities. The PASEC tests were conducted with children in schools, therefore restricting the sample to those who were enrolled. Hence, the sample is not representative of the entire cohort of children in the relevant age range since there were some children in each country that never enrolled in school. Among communities with more than one school, a school was chosen randomly to be part of the sample. An important qualification in selecting the schools in the sample was that they had to have a class size of at least 20 students, although, that could include multi-grade classrooms. In practice, this meant that rural PASEC clusters were larger than the average-sized rural communities in Madagascar. In Senegal almost all schools had sufficient number of children in the classroom and thus were eligible to be included in the sample.

[10] In the case of Senegal, Dumas and Lambert (2011) found that family characteristics do matter for enrollment and the level of education, but they do not have information on cognitive skills, as we do.
[11] Some children were older or younger because of early or delayed enrollment.
[12] In French, the study name is Programme d'analyse des systèmes éducatifs de la Confemen. They were conducted under the authority of the Conference of Education Ministers for Francophone Africa, CONFEMEN. For more information on the PASEC, see PASEC (2016) and Michaelowa (2001).

A subset of the children attending second grade in 1995–6 in Senegal and 1997–8 in Madagascar were resurveyed in the early 2000s when they were adolescents,[13] and again in 2011–12. The 2011–12 data set used in this paper is referred to as the Life Course Transition of Young Adults Surveys in the two respective countries, and it consists of young adults who were 21 to 23 years old at the time of the survey. The children in this long-term cohort were randomly selected from slightly less than half the original clusters included in the mid-1990s' PASEC surveys. Our final sample includes 333 and 447 children that were in second grade in the 1990s in Madagascar and Senegal, respectively, and were subsequently interviewed in 2012 and 2013.[14]

As indicated above, cognitive skills assessments, in the form of math and French tests, were administered in both survey rounds. It should be noted that the tests administered in the two countries were either the same, or had a subset of common questions. However, the tests for children and for adults were different, reflecting the different periods in the cohort members' life course. The common questions in the tests administered in both countries in second grade, and then again as adults, allow us to construct comparable test scores based on the Item Response Theory (IRT). For a descriptive comparison of the levels of test performance, we create the common IRT scores using the joint distribution of the two tests. The parameters of IRT are thus estimated jointly for the common items, which renders the scores comparable at each time period.[15],[16] The IRT also has the benefit of being a cardinal measure of test performance, while the more commonly used measure of percentage of correct answers merely yields an ordinal measure.

[13] These surveys are referred to as the Progression Through School and Academic Performance in Madagascar Study (EPSPAM) and Senegal Household Education and Welfare Survey (EBMS) in Senegal. The limited number of clusters, or so-called PASEC communities, revisited resulted from budgetary constraints in carrying out the survey, especially since the cost of finding the original children was quite high.

[14] The main reason for the smaller sample size in Madagascar is that we only attempted to find 15 randomly selected children from the original PASEC sample per community, compared to 20 in Senegal.

[15] The details of which tests were merely similar and which were the same is given in Appendix A alongside with the description of the IRT methodology.

[16] While we can compare the performance across countries, we cannot do so across time. This is because as the tests administered to adults have no common items with the tests administered to children.

Figures 1.a, 1.b and 1.c plot the cumulative density functions (CDF) of the test scores for the two time periods, using the IRT estimated from the joint distribution of the test scores. The distribution of second grade composite scores (Figure 1.a) for Madagascar first order stochastically dominates the distribution for Senegal. This pattern holds for both math (Figure 1.b) and French (Figure 1.c) scores separately. By 2012, there has been considerable convergence in the distribution of the scores across the countries.

In Figure 2 we provide descriptive evidence on the relationship between the 2^{nd} grade and early adulthood scores using the jointly estimated (comparable) IRT scores. A strong implication from Figure 2 is that the relationship between the 2^{nd} grade and early adulthood scores is stronger in Senegal than in Madagascar, as the slopes of the curves are steeper. Furthermore, the narrower confidence bounds show that the relationship is stronger in Senegal than in Madagascar.[17]

Figures 3a and 3b show the non-parametric relationship of test scores measured as young adults in relation to height in young adulthood. We can see from the graphs that in both countries test scores are increasing in height, taller individuals did better in cognitive tests as adults. The evidence is similar to that presented in Case and Paxson (2008) and LaFave and Thomas (2017).

While the IRT scores based on the joint distribution are especially useful for descriptive comparisons of test scores across countries, in the regression analysis presented below we employ IRT scores that were estimated separately for each country. This allows us to better model changes in cognition across time in Madagascar and Senegal since the country specific IRT scores better estimate country- specific measures of ability.

Appendix Tables B.1.a and B.1.b present summary statistics of the variables of interest in Senegal and Madagascar, respectively. The test score variables are the country-specific IRT transformations with mean being close to zero, both in the 1990s and in 2012. In Senegal, the

[17] The larger confidence bounds in the low and high ends of the test score distribution reflect the fact that there are less observations at the ends of the distributions.

sample of adults on average has completed 9 grades of school, compared to 10 grades in Madagascar. In Senegal the sample has a slight majority of males, whereas in Madagascar, it is the other way around. On average, the Senegalese sample (24 years) is slightly older than the Malagasy sample (22 years). This is consistent with the second grade baseline data having been collected two years earlier in Senegal. In addition, the Malagasy sample is roughly 10 centimeters shorter than the Senegalese sample. The discrepancy is similar to that found in the DHS data for women (Subramanian et al. 2011). The discrepancy is large, and likely finds partial explanation in the different ethnic compositions of the populations. The largest ethnic groups in Madagascar are of Asian descent. Additional information on household characteristics were collected in the original PASEC surveys conducted in the mid–90s, including a detailed listing of all the assets owned by the household. This allows us to create a household asset index using factor analysis.

One considerable challenge with the data sets is attrition. Nearly 50 percent of the cohort first interviewed in the 1990s was resurveyed in 2011-12. Given the 15-to-17-year interval between the surveys and the challenges of tracking young teens over time in these remote populations, this rate of attrition is not surprising. Additionally, there was no intention of following the PASEC cohort when that survey was originally undertaken. Thus, we faced the challenge of returning to communities many years after the original PASEC survey and searching for the original children included in the surveys in the mid-1990s. The difficultly of doing so was exacerbated by the exceedingly low living standards, volatility in economic conditions and the constant social transformation in the communities surveyed. Having said that, we are of course concerned about the high attrition rate in our data. To better understand the implications of this attrition rate, we compared the current sample of children in the cohort with those in the original PASEC samples, which were designed to be representative of school-aged children in the respective countries at that point of time. Appendix Tables C.1.a and C.1.b show a comparison of means for key variables between these samples. We find that there are no statistically significant differences for most variables between the full sample and the sample in our analysis. In the case of Senegal, there are no statistically significant differences at the levels of one per cent. In the case of Madagascar, the children in the panel come from households with slightly less wealth. The cohort members included in the sample are also slightly younger than the overall sample. More importantly, we see no systematic differences in their test scores. To alleviate concerns related to attrition driving our results, we run a robustness check of our results by estimating the probability of attrition based on different characteristics in the 2nd grade data and then weight the main estimation equation using the inverse of these weights. This is described in detail in section 6.

Despite the checks intended to alleviate concerns over attrition, we want to emphasize that we do not make any claims regarding our cohort being representative of the entire population in this age group. This is because, as noted above, this is a school-based sample where children in second grade were administered these tests. Therefore, by design the sample excludes children who had not completed at least one year of schooling at the time of the first survey and those from the smallest, most remote villages in Madagascar. We would still argue that we have a unique long-term panel data set from two developing sub-Saharan African countries where we were able to follow individuals' cognitive ability from second grade until young adulthood and explain the evolution of scores with information on socioeconomic background. Therefore, despite the recognized limitations in terms of size and attrition there is much to learn from these data sets.[18]

4. Conceptual Framework

In this section, we first present a simple theoretical framework of cognitive production function, and thereafter present the empirical framework we use to estimate it.

4.1. Theoretical framework

Our theoretical framework builds on the work of Todd and Wolpin (2003, 2007), which is also the analytical point of departure of Aubery and Sahn (2014); Fiorini and Keane (2014); and

[18] We should note that other unique panels of this type of duration and detail from developing countries, such as the Guatemalan studies (Grajeda et al. 2005; Behrman et al. 2014) and Young Lives studies (see http://www.younglives.org.uk/content/sampling-and-attrition), suffer from similar attrition problems. For a discussion, see Alderman et al. (2001).

Singh (2017). We also draw on literature studying the effect of height on later life outcomes, which for the most part finds a strong correlation between height and cognitive skills in adulthood (Case and Paxson 2008, LaFave & Thomas 2017).

If we were to consider childhood and adulthood as two periods of life, then the following would be a simple illustration of the two-period mechanism pertaining to grade attainment:

$$Y_2 = f(\,\beta_1\, A_1(\mu_0) + \,\beta_2\, P_1 + \,\beta_3\, H_1(\mu_o) + \,\beta_4\, S_1)\,, \qquad (1a)$$

where the grade attainment Y_2 in Period 2 is a function of cognitive ability A_1 and height H_1 in Period 1, which is largely determined by health/nutritional endowment and socioeconomic factors in the first few years of life (Martorell & Habicht 1986). In turn, both of these are functions of a genetic component, μ_o, at the time of conception. In Period 1, S_1 denotes the school inputs and P_1 denotes parental investments, including factors such as household wealth and the education of parents.

In terms of cognitive skills, the model is

$$A_2 = g(\,\gamma_1 A_1(\mu_0) + \,\gamma_2 P_1 + \,\gamma_3 H_1(\mu_o) + \,\gamma_4\, S_1) \qquad (1b)$$

in which we explain the stock of skills in Period 2, A_2, using cognition level in Period 1, A_1, as one of the explanatory variables. Otherwise, the function is similar to equation (1a).

The dynamic nature of this theoretical framework allows parental investments in a given period to be a function of the previous period's test score. Therefore, this framework allows parents to invest more (less) in better (less well) performing children, which would then potentially lead the children to perform even better (or not as well) in the next period, and so on (Glick and Sahn 2009; 2010). This is a relevant point to keep in mind in resource-constrained environments, such as Madagascar and Senegal, where the opportunity cost of schooling, child labor, could also be high. Parents, who are assumed to be maximizing their lifetime utility, are faced with this challenge wherein they might have to choose between short-term gains and potential long-term benefits.

Therefore, in families with several children, as is most often the case in these countries, the parents might be inclined to invest in the schooling of the best performing child.

4.2. Empirical framework

In the simplest version, the empirical counterpart of equation (1a) is a reduced form that can be estimated using an OLS model of the following form:

$$Y_{i,t+1} = \beta_o + \beta_1 A_{i,t} + \beta_2 Height_{i,t+1} + \beta_3 HH_i + \beta_5 X_i + \gamma_j + \varepsilon_i \qquad (2a)$$

In this regression, $Y_{i,t+1}$ stands for the highest grade attained by the cohort member in 2012, and $A_{i,t}$ stands for a measure of early life ability of the children, which in our case is measured using math and French scores at the beginning and end of second grade (called pretest and posttest, respectively). $Height_{i,t+1}$ refers to height measured in 2012, which is a function of both health inputs received during the life-cycle, particularly in early childhood, as well as genetics (Martorell & Habicht 1986). We include it in our model, as evidence suggests that height has an impact on later life outcomes, and hence omitting it from the model could potentially lead to inflated coefficient estimates for other covariates in the model (Case and Paxson 2008, LaFave & Thomas 2017). HH_i is a vector of household level (time-invariant) inputs, γ_j, are school fixed effects in school j, and X_i denotes time-invariant control variables.

Estimating equation (1b) leads to a very similar reduced form regression

$$A_{i,t+1} = \beta_o + \beta_1 A_{i,t} + \beta_2 Height_{i,t+1} + \beta_3 HH_i + \beta_4 X_i + \gamma_j + \varepsilon_i \qquad (2a)$$

Our dependent variables $A_{i,t+1}$ are performances on French and math tests in 2012, both used individually and in the form of composite scores.

This setup is analogous to a Value Added (VA) specification where current outcomes are regressed on past realizations of these outcomes and their determinants. These specifications have primarily been used in modeling skill acquisition from one grade to another. Such a framework has been used, for example, in estimating teacher/school effects in learning. Even though our model framework has these similarities, it differs conceptually because we are interested in explaining cognitive skills in early adulthood—a time during which the cohort is no longer in school. This is also the reason why including contemporaneous inputs in our estimation is not relevant.[19]

Our model takes school inputs into account through the inclusion of school fixed effects. The school assigned to each individual is based on the school they attended in second grade. The school fixed effects control for all time invariant school level factors, as well as class-level time-invariant unobservables, as our data has only one class per school. The fixed effects arguably also control for time invariant community-level factors, as students from one school roughly belong to the same community and each community mostly had one school in the sample. The fixed effects specification implies that our coefficients of interest comes from comparisons among children who attended the same school (and class) when in second grade. Hence, it is plausible that we are comparing among children who were exposed to roughly the same socioeconomic and environmental factors in their childhood, thus making the comparisons even more relevant. We include asset index of the household in second grade in our specification, which controls for the effects that the household wealth could have on later life outcomes. We also use height in early adulthood as a proxy for the health status of the child in early life. Additionally, we control for some individual specific attributes (parents' education and age of the individual in 2012), which further reduces concerns regarding omitted variables in this specification.

We measure early life ability of the individual using second-grade math and French test scores. As explained earlier, the richness of our data provides us with information on test scores from two different points of time- a pretest score and a posttest score. The pretest was administered to students at the start of second grade, and the posttest was administered at the end of second grade. In addition to capturing "ability endowment," the second-grade scores are a function of

[19] See Fiorini and Keane (2014) for an overview of different specifications of VA models to explain cognitive skill formation for school-aged children with contemporaneous and lagged inputs.

household and school inputs that the children received from the point of conception up until the time the test was conducted. Here we have a choice of using scores from a test conducted at the start of the school year or at the end of the school year. We use the score from the test conducted at the end of the school year in our specifications, since they are comparable across the two countries.

Our empirical specification includes lagged inputs and lagged achievement. It can therefore be thought of as a "combination of cumulative and value-added models," as described in Fiorini and Keane (2014). It generalizes the value-added (VA) model, which was preferred in Todd and Wolpin (2007) because it minimized the out-of-sample root mean squared error.[20] Even though our framework is statistically equivalent to a VA model with lagged inputs, it differs conceptually as the time period between our waves is fairly large, 15–18 years.

We also estimate a model with only lagged inputs and no lagged test scores, which in Todd and Wolpin (2007) and Fiorini and Keane (2014) is referred to as the "cumulative model." This model assumes that the lagged inputs incorporate the innate ability and unobserved inputs. Our estimations clearly show that this is not the preferred specification, as the lagged test scores are statistically significant.[21]

In the main specifications, we use test score variables that are created based on Item Response Theory (IRT). We use this method to create three separate sets of test scores – math, French and composite scores. In latter specifications, we explore whether math and French test scores obtained during early childhood are equally strong predictors for adult skills, or if, as found

[20] In addition, Fiorini and Keane (2014) also discuss data intensiveness of these procedures and the associated sample size issues in their analysis. We also face similar challenges but still end up with nearly the same sample size as their specifications.

[21] Another potential specification for studying the effect of lagged inputs on cognitive ability in early adulthood is the fixed effects framework (Fiorini and Keane 2014). The underlying assumption is that the lagged coefficient of the test score is equal to one (Singh 2017). Our results show that this is not a valid assumption, as the coefficient estimates are much lower (as in Singh (2017) and Fiorini and Keane (2014)), and also not feasible due to the fact that we do not have time-varying inputs in our regressions. We argue, hence, that omitting this specification is not a concern.

in some literature from the predominantly English speaking world, math ability is a stronger predictor of skills in later life (Duncan et al. 2007; Duncan and Magnuson 2011).

4.3. Correcting for measurement error

Test scores typically suffer from measurement error, as they are based on one-time spot performances of students, which could be impacted by many factors relating to the test day environment. If these factors are idiosyncratic, then they would bias the coefficient on the test score variable towards zero. We address this measurement error concern by using an instrumental variable approach. Since we have test score data at the beginning (pre-test) and at the end (post-test) of second grade, we use the second grade pretest scores to instrument for the posttest scores. Similar strategies have been employed by Ladd and Walsh (2002) and Andrabi et al. (2011). In our main specification, we use the composite score of French and math as the main independent variable of interest, thereby correcting the measurement error by using the pretest composite score as an instrument for the posttest composite score. Our 2SLS model takes the following form:

$$TS_i^{post} = \alpha_o + \alpha_1 TS_i^{pre} + \alpha_2 Height_i + \alpha_3 HH_i + \alpha_4 X_i + \gamma_j + \tau_i \qquad (2b)$$

$$Y_i = \delta_o + \delta_1 TS_i^{post} + \delta_2 Height_i + \delta_3 HH_i + \delta_4 X_i + \gamma_j + \theta_i \qquad (2c)$$

where posttest and pretest scores are denoted by TS_i^{post} and TS_i^{pre}, respectively; γ_j denotes school fixed effects; HH_i refers to household level inputs (parents' education and assets); and X_i denotes individual-specific controls.

We can only control for the observed individual, household, and school factors, thus the unobserved factors are part of the error term. These unobserved factors might in turn be correlated with both our outcome of interest (such as later life schooling) and the early life test scores, thus leading to endogeneity bias. It is important to note that the previously discussed instrumental variable strategy does not necessarily correct for this endogeneity bias, and simply addresses systematic measurement errors. Thus, like other literature that has looked at early childhood ability and how it affects outcomes in adult life, we rely on the usage of an extensive set of controls. While we acknowledge the possibility of endogeneity in our specification, we also note that several recent papers have looked at the comparison between value-added estimates of the type explored here and estimates from experimental or quasi-experimental analyses. They have all mostly concluded that the non-experimental estimates are unbiased, when compared with estimates from experiments (Angrist et al. 2013; Kane et al. 2013; Deming 2014; Deming et al. 2014). Also, the long duration of our panel mitigates concerns related to endogeneity and, to our knowledge, there is no research that covers this large a span of time that has fully addressed these endogeneity concerns.

5. Results

5.1. Highest grade attained

Now we turn our attention to the models in Tables 1.a and 1.b where we show the relationship between early life cognitive ability and the highest grade attained by young adults in Senegal and Madagascar, respectively. It is important to note that the highest grade attained might be different from the number of years of schooling. This is because repeating grades is quite common in both countries, as it is in most African countries that follow the French educational model. The first column of Tables 1.a and 1.b display the results from simple OLS regressions with a single covariate, the composite French and math score from second grade. As pointed out previously, the test score variables have been created using IRT; thus, the test score mean and standard deviation are close to zero and one respectively. In Senegal, a composite test score one standard deviation above the mean in the second grade implies an increase in the highest grade attained by around 1.64 years. In Madagascar, the coefficient is 0.99 (Table 1b column 1). Both of these coefficients are significant at the one percent level.

In columns 2-5, we introduce school fixed effects into the model. School fixed effects account for all time-invariant school characteristics and, hence, control for school-specific factors that impact young adult life cognitive scores. The coefficients in column (2) change a little relative to column (1), but remain significant at the one per cent level in both countries.

In columns (3) and (4), we add a series of household and individual covariates, which do not lead to noteworthy change in the coefficient of the early life cognitive ability in either country- it remains strongly statistically significant in these specifications. Father's education level has a positive impact on grade attainment in Madagascar, with mother's education level having a modest additional impact. In Senegal, the average level of parents' education is low, so we use dummies for whether each parent has any education or not instead of using a continuous measure.[22] The results for Senegal indicate that parents' education has a positive and statistically insignificant impact on grade attainment.

The second-grade household asset index, created using factor analysis, has a large positive and significant association with the highest grade attained in Senegal. We find that an increase of one unit in the asset index raises schooling by around 0.50 years in Senegal. In Madagascar, we do not see any such effects of assets in early childhood. This might be because the households in Madagascar have on average lower levels of assets than in Senegal.[23] This might also be because the coefficient estimate of the asset index is obtained while controlling for parental education.[24] We also tried adding interaction terms of the early life scores separately with assets and parents' education to these models. These variables were not significant and therefore were omitted from the specifications reported here.

In columns (4) and (5), we add the height of the cohort member into the model. As discussed in Case and Paxson (2008), Vogl (2014) and LaFave and Thomas (2017), this is used as a measure of childhood health and nutritional status, particularly as effected by in utero and early childhood inputs. Thus, this coefficient controls for the effects of early childhood health

[22] In Senegal, mother's education is 1.3 years and father's 2.7 on average. In Madagascar, mothers and fathers have 5.6 and 6.2 years of education, respectively.
[23] Summary statistics on the number of assets owned are available from the authors by request.
[24] The coefficient of asset index is significant when we remove the parental education variable.

inputs and human capital that might have an impact on adult cognitive ability. We see that, in both countries, the coefficient on second grade test score is largely unaffected by the inclusion of height. In Senegal, height has a significant positive effect on highest grade attained, whereas in Madagascar the coefficient is positive, much smaller in magnitude, and not significant. Our results indicate that being one centimeter taller is associated with an increase of 0.04 years of schooling in Senegal. The fact that we find that the impact of cognition is unaffected by the inclusion of the height variable shows that they both have independent effects. [25] This is largely consistent with the current literature, which finds an effect of height on human capital formation (Perisco et al. 2004; Case and Paxson 2008, 2010, Spears 2012).[26]

As explained earlier, the second-grade test score suffers from idiosyncratic measurement error problems, which could lead to a biased estimate of its coefficient. In column (5) of Tables 1.a and 1.b, we report the results from the IV strategy that corrects for this measurement error by instrumenting the math/French composite test score taken at the end of second grade with the test score taken at the beginning of the second grade. The F-statistic for the excluded instrument (labeled "widstat") is 254.8 in Senegal and 82.7 in Madagascar, which is well above the conventional threshold of 10 considered for classify the instrument as weak.

The magnitudes of the IV coefficients are similar in both countries- 1.38 and 1.29 (Senegal and Madagascar respectively) higher years of grade attainment per standard deviation increase in the test score. While the IV results paint a consistent narrative of a significant positive relationship between early life test scores and educational achievement later in life, it is not clear why the idiosyncratic measurement error correction matters more in Madagascar than in Senegal. This may reflect that the measurement error correction seems to work better with the pre-test conducted in Madagascar than it does with that in Senegal, or that there might have been greater measurement

[25] In the case of Madagascar, we have also run the model with controlling for ethnicity, which should be correlated with height given that there is a mix of ethnic groups both Asian and African origin. The results remain similar, when ethnicity is controlled for. Results are available from the authors by request.
[26] Victor et al. (2008) and Grantham-McGregor et al. (2007) provided reviews of this literature in the context of underdeveloped and developing countries. Indeed, Victor et al. (2008) showed that height at the age of 2 is the best biological predictor of later life human capital.

error in Madagascar to start with. In addition, the difference in the correction from the IV can also stem from the fact that the questions in the pre-tests (used as the instrument) differed across the two countries.

5.2. Test scores

In Tables 2.a and 2.b, we estimate the effect of early cognitive ability on composite test scores of French and math (columns 1 and 2), as well as math (columns 3 and 4) and French (columns 5 and 6) separately. The findings in these tables are consistent with the results discussed previously in terms of grade attainment – early life cognitive ability has a strong and persistent impact on later life cognition. More specifically, columns 1 and 2 show evidence of a robust positive and significant relationship between early life cognitive ability and later life composite French and math scores in Senegal and Madagascar. Consistent with the attainment models, the magnitude on the test score parameter rises in Madagascar when we adjust for measurement error using IV regressions (column 2). Based on the IV model in column 2, in Tables 2.a and 2.b, the results show that a one standard deviation increase in composite scores in second grade is associated with higher composite score by 0.27 and 0.32 standard deviations among young adults in Senegal and Madagascar, respectively. The Senegal results are statistically significant at the one percent level, whereas the Madagascar results are significant at the five percent level.

As expected, results in Table 2.a suggest that, in Senegal, the assets of the household when the cohort member was in second grade has a positive and significant impact on later life cognition, even controlling for parents' education. A one standard deviation increase in the assets index is associated with an increase in composite test scores of 0.14 standard deviations. In Madagascar, although the asset index variable is positive in all the models, it is not statistically significant. Mother's education has a positive and marginally significant relationship with the composite test score in Madagascar.

We observe similar patterns in the results in columns 3–6 in Tables 2.a and 2.b, where the individual scores on 2012 math and French tests are modeled separately. Early life cognitive ability has a statistically significant positive impact on both math and French scores in Senegal and

Madagascar. However, the effect is far stronger in the case of math than in the case of French.[27] Overall, the results describe a situation where early life cognitive ability, measured by test scores, has a strong and persistent effect on later life educational and cognitive outcomes. These effects remain despite the addition of a rich set of control variables, the introduction of an IV strategy to correct for measurement error and the use of school fixed effects. Thus, we provide persuasive evidence of the importance of better performance on tests in as early as second grade on adult schooling and cognitive outcomes.

5.3. Heterogeneity Tests

5.3.1. Differential effect of French and math scores

In order to explore another dimension of this relationship, we replicate the regressions discussed above using a slightly modified empirical strategy. Instead of using the composite math and French scores as the measure of early childhood ability, we enter the math and French scores separately as independent variables in different regression models. In the corresponding IV regressions, we use the French (math) test administered before second grade as an instrument for the French (math) test scores for the tests taken at the end of second grade.[28]

We are motivated to do so because math and French tests potentially capture different types of abilities. It has been found that math ability in childhood is a stronger predictor of later life skills than language skills, although this evidence is from predominantly English speaking countries (Duncan et al. 2007; Duncan and Magnuson 2011). The results show that there is a strong and positive association of highest grade attained with second-grade math scores in both countries (Tables 3.a and 3.b, column 1). This is consistent with our main results based on using the composite score (Tables 1.a and 1.b). In Senegal, the effect of a one standard deviation rise in the second-grade math score leads to a rise in highest grade attained by 1.4 years, whereas the

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[27] Using the z-scores of the percentage of correct answers as a dependent variable yields very similar results to the ones presented here. This is due to the fact that the z-scores and the IRT scores are very highly correlated. The results are available from the authors by request.

[28] The results are qualitatively similar if we were to use pre-test as the independent variable and post-test as the instrument. The results available from the authors by request.

corresponding effect in Madagascar is 1.18 years (column 2 of Tables 3a and 3b, respectively). The effect size in each country is comparable to the coefficient estimate of the composite score (Tables 1.a and 1.b) in each country – 1.38 (Senegal) and 1.29 (Madagascar).

In the first two columns of Tables 4.a and 4.b we present evidence on the relationship between second-grade French score and later life grade attainment. The effect of a one standard deviation rise in second-grade French test score on highest grade attained is around 1.6 and 1.7 years in Senegal and Madagascar, respectively (column 2 in Tables 4.a and 4.b). These effects are similar to the results using composite test score (Tables 1.a and 1.b).

In columns 3 to 8 of Tables 3.a, 3.b, 4.a and 4.b, we run similar models, but this time the dependent variables are composite scores, math scores and French test scores in the second grade, respectively. In Senegal, the French scores have a statistically significant impact on all the cognition outcomes, while the magnitudes are similar to the coefficients we get from the main specifications (Tables 1.a and 1.b). The results with second grade French tests are relatively weaker in Madagascar (Table 4.b). These results thus seem to suggest that early life math scores are stronger predictors of later life math scores than they are of later life French scores, particularly in Senegal. Additionally, early life math scores predict later life French scores better than early life French scores do, in the case of Madagascar. For Senegal, later life French scores are equally well predicted by both early life French and math scores. In crux, there is suggestive evidence that the math scores are driving the persistent impact of composite scores on later life outcomes in Madagascar (Table 1.b). We also note that the importance of other background characteristics is similar in the models with math and French, separately. This is in turn similar to the results where the composite score is used as an independent variable (Tables 1.a and 1.b).

5.3.2. Gender differences

We also explore whether there are any gender differences in the impact of early life cognition on later life outcomes. We do this by running separate models for boys and girls, but keep all other aspects of the model specification identical to the one in our main results (Tables

1.a and 1.b). The results in Tables 5.a and 5.b indicate that the test score coefficient differs in magnitude between girls and boys in both the two countries. Across all outcomes in both countries, the coefficient for early life test score is consistently higher for girls than for boys. This effect is especially pronounced in Senegal. We conduct a t-test to check for the equality of the test score coefficient in the male and the female regressions. This test was able to reject the null of equality of coefficients in one case in Madagascar and in two cases in Senegal.[29] This provides suggestive evidence that early life performance is potentially more persistent in its impact on later life cognitive ability for girls. This potentially implies larger negative consequences for girls who fall behind in early grades. In other words, catching up from early cognitive deficits may be harder for girls as compared to boys. This is a consistent result that we find in both countries.

5.3.3. Differences in Height

We next divide the sample into two groups based on the gender specific median height in the sample for each country (Tables 6.a and 6.b). In Senegal, the coefficients for the below median group (relatively shorter) is greater than the coefficients for the above median (relatively taller) group for early life composite test score in the case of all outcomes–highest grade attained, and the different test scores. These differences, however, are not statistically significant at standard levels. In Madagascar, the patterns are similar, with the exception of the highest grade attained outcome. Here again, we do not find statistically significant differences in the coefficient of the two groups. Taken together, these results suggest that there is more persistence in early life scores among shorter individuals. Thus, as with girls, the group of shorter and less healthy cohort members are not only more vulnerable in early childhood, but have a higher persistence in their poor cognitive performance over time suggesting early deficits are unlikely to be overcome. [30]

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[29] There may be multiple reasons why this might be the case. Firstly, sample size is relatively small in both countries, but it is larger in Senegal, as compared to Madagascar. This paired with a fall in the number of degrees of freedom in the equation for each gender, might imply the lack of differences that are visually different but statistically not significant. Another potential reason could be that the gender effects may in reality be smaller in Madagascar, as compared to Senegal.

[30] Due to the large ethnic diversity in Madagascar, we also ran the model in Madagascar controlling for ethnicity. The results are qualitatively similar and not reported here.

5.3.4. Differences in household assets

Finally, we check whether differences in household assets in second grade matter for the persistence in the impact of early life scores on later life outcomes. To do so we divide the sample into two parts based on the median level of assets in second grade. The results in tables 7.a and 7.b suggest that having a higher level of assets in childhood leads to a larger persistence in the impact of second grade test scores across the two countries. This potentially implies that children from relatively richer households are able to sustain their better performance in second grade into their later life outcomes – potentially through higher investments in them. Although, another interpretation is that among children from more economically disadvantaged households there is lower persistence in this relationship, over time they are able to overcome the disadvantage through more schooling and improvements in cognitive performance. However, the fact that the t-test of difference in the coefficients is significant in only one case at the five percent level in Madagascar, and not significant in any case in Senegal once again admonishes caution in drawing firm conclusions.

6. Robustness Checks

6.1. Accounting for attrition

The attrition rates described in section 2 might raise a concern that our results could be driven by some form of sample selection. Therefore, in Appendix C, we investigate the robustness of our findings to adjustments for attrition. First, we test whether the samples are balanced across the attrited and non-attrited individuals in Table C-1. As discussed in section 2, we do not find systematic significant differences across the samples in both countries.

Second, we estimate inverse probability weighed regressions, where the weights are obtained from a logit regression, on the baseline data as robustness checks for the main results. This logit regression uses a dummy variable denoting attrition as the dependent variable and has a variety of household and individual level covariates from the first round of data as covariates.[31] Tables C-2.a and C-2.b replicate results of Tables 1.a and 1.b columns 1-5 for Senegal and Madagascar, respectively, using the sample adjusted with the inverse probability weights. By comparing Tables 1.a and C-2.a, the models where highest grade obtained is estimated for Senegal, we see that the significance levels are exactly the same in all of the regressions, and the magnitudes are very close to each other. A comparison between Tables 1.b and C-2.b shows that the magnitudes are very similar in the case of Madagascar as well, and most of the significance levels remain similar.[32] Thus the results do not change considerably when adjustments are made for attrition, hence demonstrating the robustness of this relationship across the two countries.

6.2. Lewbel (2012) Corrections

In another robustness check, we complement our main IV strategy with a novel methodological approach. Lewbel (2012) describes an empirical framework in which identification is achieved using heteroscedascticity, in place of imposing the standard exclusion restrictions in the two-stage least squares framework. There are two main conditions that need to be satisfied for this model to be applicable: the presence of some exogenous variable in the structural equation and the heteroscedasticity of the error terms. This set of exogenous variables (Z) could be a subset of the independent variables (X) or could be the same as them. Under this method, one regresses each endogenous regressor on the set of exogenous variables. The residuals from these regressions are used along with the demeaned set of exogenous variables to construct "*generated instruments*". This estimation framework is similar in nature to other approaches where heteroscedascticity is used as a source of identification (King et al 1994; Sentana & Fiorentini 2001; Heckman & Vytlacil 1998 among others).

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[31] Namely the test scores on 2nd grade, gender, asset index, a school level infrastructure index constructed with factor analysis, and the education level of the teacher.

[32] Robustness check results using IRW are similar when using test score variables as outcome variables. Results are available from the authors by request.

We present results using the pre-test and the generated instruments as instrumental variables in our model[33]. These results can be compared to the IV regression results in Tables 1 and 2, which use only the pre-test as an instrument. The inclusion of an extra instrument allows us to conduct the Sargan-Hansen overidentification test. Under the null that the over-identifying restrictions are valid, the test has a chi-square distribution. We are unable to compute this statistic in our main tables because the IV models are exactly identified, that is, the number of instruments is equal to the number of endogenous regressors. The usage of Lewbel (2012) method allows us to conduct this test as the generated instruments make the model over-identified.

The results in Table 8 indicate that the addition of the generated instrument using this method does not significantly alter the IV results. This is especially the case in Senegal where the impact of test score on all the outcomes remains relatively stable (as compared to Tables 1.a and 2.a) and statistically significant at the one percent level. The results for Madagascar lose a little bit of statistical significance but still retain the correct sign and similar magnitude as the IV results in Tables 1b and 2b. In addition, the J-statistic p-value shows that the null hypothesis of valid over-identifying restrictions is valid for all outcomes across both countries. Therefore, we conclude that our main IV specification is robust to the Lewbel (2012) instrumental variables strategy.

7. Conclusions

We find persuasive evidence of the impact of early life cognitive ability on educational and cognitive outcomes in early adult life in two francophone sub-Saharan African countries, Senegal and Madagascar. Using different measures of early life cognitive skills in a production function framework for human capital, we find that composite math and French test scores measured in second grade have large and significant positive associations with the highest grade attained and math and French test scores in young adulthood in both countries. Therefore, cognitive ability in second grade has an enduring effect on cognitive skills developed into young adulthood. This

[33] We do not present the models with only the generated instruments.

relationship is stronger in Senegal than in Madagascar. We find that early life math scores are stronger predictors of later life cognitive outcomes, as compared to early life French scores. This finding is consistent with results reported elsewhere that indicate certain types of abilities in childhood are more important in predicting human capital outcomes later in life.

We also explore whether child health, measured using adult height, has a significant positive impact on adult human capital, and whether its inclusion in the models affects the strength of the relationship between early test scores and adult cognition. We only find a statistically significant effect of health in Senegal, although, in Madagascar the sign and magnitude of the coefficient is quite similar. These effects of early cognitive ability and health on later life outcomes are robust to the inclusion of each other in the specification, indicating they are operating through independent channels.

The results we report are robust to the addition of other childhood inputs, namely parental education and asset levels when the cohort was in second grade, as well as school fixed effects. Parental inputs have an independent effect on early adulthood outcomes in both countries. Household asset measured in second grade have a significant positive impact on adulthood outcomes in Senegal, whereas in Madagascar, parents' education matters more.

We also run a series of heterogeneity tests and find that there are larger negative consequences for girls who fall behind in early grades. We similarly find that shorter and less healthy cohort members have a higher persistence in their poor cognitive performance over time. In other words, catching up from early cognitive deficits may be harder for girls and unhealthy children. In contrast, low levels of assets early in life do not seem imply that children from relatively richer households are better able to sustain their better performance in second grade later into life.

We also discuss challenges that arose due the ambitions of examining cognition over a span of time of over 15 years between our two surveys, including issues of attrition, as well the potential for measurement error in using the second grade test as a measure of ability. By employing techniques such as estimating inverse probability weighed regressions and employing Lewbel (2012) instrumental variable method, add to the strength of the findings.

While we do not directly address policies to improve cognitive outcomes of young adults, our results imply that early life ability is a very powerful predictor of young adulthood cognitive outcomes. This would then imply that policies should target preschool-aged children who are lagging behind other children in terms of their cognitive skills and health status, and that such interventions are particularly important for young girls who seem less able to catch up from early cognitive disadvantage. It is important to note that although the analysis argues for early childhood interventions, it does not provide insights into the exact nature of the interventions required. Even so, the ability to target interventions more effectively not only optimizes allocation of scarce resources but also leads to more people getting the benefits of these programmes.

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Tables

Table 1: Impact of early life composite French and math scores on grade completed

a. Senegal

VARIABLES	(1) No School FE OLS	(2) School FE OLS	(3) School FE OLS	(4) School FE OLS	(5) School FE IV
2nd grade composite score	1.645***	1.783***	1.728***	1.695***	1.380***
	(0.185)	(0.207)	(0.194)	(0.195)	(0.310)
Height 2012				0.042*	0.045**
				(0.023)	(0.021)
Assets 2nd grade			0.495*	0.487*	0.549**
			(0.285)	(0.285)	(0.271)
Mother's education (dummy)			0.616	0.473	0.459
			(0.582)	(0.596)	(0.559)
Father's education (dummy)			0.331	0.285	0.285
			(0.516)	(0.516)	(0.481)
Age 2012			-0.496***	-0.498***	-0.497***
			(0.080)	(0.080)	(0.074)
Female			-0.151	0.262	0.227
			(0.330)	(0.406)	(0.380)
Observations	447	447	447	447	447
R-squared	0.143	0.349	0.413	0.419	0.235
F					10.95
Widstat					254.8

b. Madagascar

VARIABLES	(1) No school FE OLS	(2) School FE OLS	(3) School FE OLS	(4) School FE OLS	(5) School FE IV
2nd grade composite score	0.993***	0.716***	0.666***	0.665***	1.285***
	(0.193)	(0.273)	(0.232)	(0.232)	(0.462)
Height 2012				0.019	0.019
				(0.020)	(0.018)
Assets 2nd grade			-0.063	-0.059	-0.119
			(0.246)	(0.248)	(0.242)
Mother's education			0.090*	0.087	0.077
			(0.053)	(0.053)	(0.050)
Father's education			0.145***	0.141***	0.137***
			(0.049)	(0.049)	(0.045)
Age 2012			-0.707***	-0.711***	-0.733***
			(0.123)	(0.123)	(0.113)
Female			-0.267	-0.116	-0.096
			(0.301)	(0.327)	(0.300)
Observations	333	333	333	333	333
R-squared	0.085	0.366	0.496	0.498	0.209
F					13.86
widstat					82.71

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother’s and father’s education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis. The row “widstat” denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Impact of early life composite French and math scores on adult test scores

a. Senegal

VARIABLES	(1) Math and French OLS	(2) Math and French IV	(3) Math OLS	(4) Math IV	(5) French OLS	(6) French IV
2nd grade composite score	0.362***	0.269***	0.625***	0.556***	0.307***	0.210***
	(0.051)	(0.070)	(0.080)	(0.117)	(0.048)	(0.068)
Height 2012	0.007	0.008	0.012	0.012	0.006	0.007
	(0.006)	(0.005)	(0.008)	(0.008)	(0.006)	(0.005)
Assets 2nd grade	0.123*	0.141**	0.200*	0.213**	0.134**	0.152**
	(0.067)	(0.063)	(0.105)	(0.101)	(0.065)	(0.061)
Mother's education (dummy)	-0.078	-0.072	-0.068	-0.071	-0.024	-0.018
	(0.145)	(0.135)	(0.212)	(0.199)	(0.138)	(0.128)
Father's education (dummy)	0.016	0.016	0.028	0.028	0.045	0.046
	(0.128)	(0.118)	(0.177)	(0.165)	(0.128)	(0.118)
Age 2012	-0.061***	-0.061***	-0.105***	-0.105***	-0.057***	-0.058***
	(0.021)	(0.019)	(0.030)	(0.028)	(0.020)	(0.018)
Female	0.072	0.060	-0.069	-0.077	0.101	0.089
	(0.106)	(0.098)	(0.153)	(0.142)	(0.103)	(0.095)
Observations	381	381	447	447	381	381
R-squared	0.351	0.166	0.327	0.193	0.342	0.140
F		4.649		7.898		3.836
Widstat		232.9		254.8		232.9

b. Madagascar

VARIABLES	(1) Math and French OLS	(2) Math and French IV	(3) Math OLS	(4) Math IV	(5) French OLS	(6) French IV
2nd grade composite score	0.146**	0.316**	0.154**	0.349**	0.127*	0.260*
	(0.064)	(0.134)	(0.070)	(0.139)	(0.068)	(0.142)
Height 2012	0.005	0.005	-0.001	-0.001	0.005	0.005
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Assets 2nd grade	0.064	0.052	0.088	0.074	0.019	0.009
	(0.070)	(0.065)	(0.067)	(0.063)	(0.082)	(0.077)
Mother's education	0.026*	0.023*	0.024	0.021	0.030**	0.028**
	(0.014)	(0.013)	(0.016)	(0.015)	(0.013)	(0.012)
Father's education	0.017	0.016	-0.002	-0.004	0.036***	0.035***
	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)	(0.011)
Age 2012	-0.130***	-0.139***	-0.118***	-0.129***	-0.099**	-0.106***
	(0.036)	(0.034)	(0.037)	(0.035)	(0.039)	(0.036)
Female	-0.029	-0.025	-0.150	-0.143	0.070	0.073
	(0.101)	(0.092)	(0.102)	(0.095)	(0.107)	(0.097)
Observations	310	310	318	318	312	312
R-squared	0.490	0.118	0.377	0.071	0.529	0.133
F		6.555		4.154		6.744
Widstat		57.80		60.01		57.39

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis. The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Impact of early life math scores on adult outcomes

a. Senegal

VARIABLES	(1) Grade OLS	(2) Grade IV	(3) Composite OLS	(4) Composite IV	(5) Math OLS	(6) Math IV	(7) French OLS	(8) French IV
2nd grade math score	1.383***	1.406***	0.284***	0.267***	0.532***	0.566***	0.223***	0.211***
	(0.202)	(0.330)	(0.052)	(0.077)	(0.079)	(0.125)	(0.048)	(0.073)
Height 2012	0.041*	0.041*	0.007	0.007	0.011	0.011	0.007	0.007
	(0.023)	(0.022)	(0.006)	(0.005)	(0.008)	(0.008)	(0.006)	(0.005)
Assets 2nd grade	0.575**	0.571**	0.135**	0.138**	0.228**	0.222**	0.147**	0.150**
	(0.285)	(0.268)	(0.068)	(0.064)	(0.104)	(0.100)	(0.067)	(0.062)
Mother's education (dummy)	0.560	0.563	-0.055	-0.055	-0.033	-0.029	-0.005	-0.005
	(0.616)	(0.576)	(0.146)	(0.134)	(0.212)	(0.197)	(0.140)	(0.129)
Father's education (dummy)	0.309	0.309	0.011	0.012	0.037	0.038	0.042	0.042
	(0.531)	(0.493)	(0.131)	(0.120)	(0.183)	(0.170)	(0.131)	(0.120)
Age 2012	-0.500***	-0.501***	-0.062***	-0.062***	-0.106***	-0.106***	-0.058***	-0.058***
	(0.082)	(0.076)	(0.021)	(0.019)	(0.030)	(0.028)	(0.020)	(0.018)
Female	0.397	0.403	0.098	0.093	-0.014	-0.006	0.118	0.115
	(0.414)	(0.392)	(0.107)	(0.101)	(0.153)	(0.145)	(0.104)	(0.097)
Observations	447	447	381	381	447	447	381	381
R-squared	0.396	0.210	0.323	0.138	0.310	0.173	0.312	0.111
F		10.33		4.268		7.435		3.681
Widstat		191.9		169.3		191.9		169.3

b. Madagascar

VARIABLES	(1) Grade OLS	(2) Grade IV	(3) Composite OLS	(4) Composite IV	(5) Math OLS	(6) Math IV	(7) French OLS	(8) French IV
2nd grade math score	0.617***	1.179**	0.161***	0.356**	0.190***	0.336*	0.125**	0.355**
	(0.194)	(0.471)	(0.055)	(0.173)	(0.061)	(0.180)	(0.057)	(0.173)
Height 2012	0.018	0.017	0.005	0.005	-0.002	-0.002	0.005	0.005
	(0.020)	(0.019)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Assets 2nd grade	-0.045	-0.090	0.065	0.053	0.088	0.079	0.021	0.007
	(0.245)	(0.238)	(0.069)	(0.064)	(0.066)	(0.060)	(0.082)	(0.079)
Mother's education	0.092*	0.087*	0.027*	0.025*	0.024	0.023	0.031**	0.029**
	(0.052)	(0.049)	(0.014)	(0.013)	(0.016)	(0.015)	(0.013)	(0.013)
Father's education	0.140***	0.135***	0.017	0.015	-0.003	-0.004	0.036***	0.033***
	(0.049)	(0.045)	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)	(0.012)
Age 2012	-0.715***	-0.739***	-0.134***	-0.147***	-0.123***	-0.133***	-0.101***	-0.117***
	(0.122)	(0.114)	(0.036)	(0.035)	(0.037)	(0.037)	(0.039)	(0.039)
Female	-0.085	-0.038	-0.020	-0.005	-0.140	-0.128	0.076	0.094
	(0.329)	(0.306)	(0.101)	(0.094)	(0.103)	(0.095)	(0.107)	(0.099)
Observations	333	333	310	310	318	318	312	312
R-squared	0.500	0.210	0.496	0.112	0.388	0.093	0.531	0.099
F		12.95		6.260		3.695		6.709
widstat		51.28		45.16		45.84		44.94

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis. The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Impact of early life French scores on adult outcomes

a. Senegal

VARIABLES	(1) Grade OLS	(2) Grade IV	(3) Composite OLS	(4) Composite IV	(5) Math OLS	(6) Math IV	(7) French OLS	(8) French IV
2nd grade French Score	1.652***	1.592***	0.363***	0.333***	0.595***	0.650***	0.327***	0.251***
	(0.203)	(0.409)	(0.052)	(0.099)	(0.081)	(0.157)	(0.050)	(0.096)
Height 2012	0.048**	0.049**	0.008	0.008	0.014*	0.014*	0.007	0.007
	(0.023)	(0.021)	(0.006)	(0.005)	(0.008)	(0.008)	(0.006)	(0.005)
Assets 2nd grade	0.511*	0.522*	0.136**	0.140**	0.211*	0.201*	0.141**	0.153**
	(0.293)	(0.286)	(0.069)	(0.064)	(0.108)	(0.106)	(0.066)	(0.062)
Mother's education (dummy)	0.439	0.437	-0.083	-0.081	-0.081	-0.080	-0.030	-0.024
	(0.600)	(0.558)	(0.150)	(0.137)	(0.220)	(0.204)	(0.140)	(0.129)
Father's education (dummy)	0.220	0.222	0.013	0.013	0.004	0.002	0.042	0.044
	(0.516)	(0.479)	(0.128)	(0.117)	(0.178)	(0.164)	(0.127)	(0.117)
Age 2012	-0.499***	-0.499***	-0.062***	-0.062***	-0.105***	-0.106***	-0.059***	-0.059***
	(0.081)	(0.075)	(0.021)	(0.019)	(0.031)	(0.029)	(0.020)	(0.018)
Female	0.033	0.035	0.031	0.030	-0.153	-0.154	0.066	0.065
	(0.414)	(0.386)	(0.108)	(0.099)	(0.156)	(0.145)	(0.104)	(0.095)
Observations	447	447	381	381	447	447	381	381
R-squared	0.405	0.221	0.343	0.163	0.308	0.171	0.344	0.148
F		10.57		4.304		7.009		3.467
widstat		121.4		101.3		121.4		101.3

b. Madagascar

VARIABLES	(1) Grade OLS	(2) Grade IV	(3) Composite OLS	(4) Composite IV	(5) Math OLS	(6) Math IV	(7) French OLS	(8) French IV
2nd grade French Score	0.424	1.696*	0.047	0.303	0.006	0.420*	0.083	0.208
	(0.265)	(0.876)	(0.075)	(0.215)	(0.081)	(0.232)	(0.077)	(0.222)
Height 2012	0.019	0.020	0.005	0.005	-0.002	-0.001	0.005	0.005
	(0.021)	(0.019)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Assets 2nd grade	-0.027	-0.122	0.072	0.059	0.099	0.077	0.024	0.017
	(0.248)	(0.254)	(0.071)	(0.067)	(0.069)	(0.067)	(0.083)	(0.077)
Mother's education	0.092*	0.075	0.028*	0.024*	0.026*	0.021	0.031**	0.030**
	(0.053)	(0.053)	(0.014)	(0.013)	(0.016)	(0.016)	(0.014)	(0.013)
Father's education	0.144***	0.141***	0.018	0.017	-0.001	-0.003	0.036***	0.036***
	(0.049)	(0.047)	(0.013)	(0.012)	(0.014)	(0.013)	(0.012)	(0.011)
Age 2012	-0.692***	-0.704***	-0.123***	-0.127***	-0.109***	-0.116***	-0.094**	-0.095***
	(0.126)	(0.117)	(0.036)	(0.034)	(0.037)	(0.035)	(0.039)	(0.036)
Female	-0.153	-0.201	-0.034	-0.046	-0.156	-0.168*	0.063	0.058
	(0.333)	(0.312)	(0.102)	(0.092)	(0.103)	(0.097)	(0.107)	(0.097)
Observations	333	333	310	310	318	318	312	312
R-squared	0.488	0.156	0.481	0.088	0.366	-0.006	0.525	0.130
F		12.95		5.923		3.646		6.411
widstat		31.73		25.56		26.65		25.19

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis. The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Gender Heterogeneity

a.Senegal

	Years Edu		Composite		French		Math	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV	IV	IV	IV	IV	IV	IV	IV
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
2nd grade composite score	2.264***	1.231***	0.507***	0.259***	0.470***	0.201**	0.866***	0.578***
	(0.538)	(0.401)	(0.121)	(0.088)	(0.106)	(0.090)	(0.196)	(0.140)
Observations	188	259	161	220	161	220	188	259
R-squared	0.344	0.184	0.273	0.156	0.279	0.125	0.256	0.183
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	67.03	180.8	66.58	149.3	66.58	149.3	67.03	180.8
P-value gender diff.		0.123		0.0970		0.0540		0.232

b. Madagascar

	Years Edu		Composite		French		Math	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV	IV	IV	IV	IV	IV	IV	IV
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
2nd grade composite score	2.448***	0.586	0.620**	0.221	0.559*	0.161	0.685**	0.282
	(0.660)	(0.591)	(0.283)	(0.178)	(0.300)	(0.172)	(0.271)	(0.200)
Observations	179	154	164	146	165	147	170	148
R-squared	0.216	0.201	0.114	0.142	0.153	0.144	0.035	0.079
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	41.94	30.97	20.45	25.94	20.58	25.17	24.00	25.27
P-value gender diff.		0.0360		0.233		0.251		0.232

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Variables height, age, mother's and father's education and asset index are included similarly as in Tables 1,2 and 3, but not reported in this table (excluding female). The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Height Heterogeneity
a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years Edu		Composite		French		Math	
	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median
2nd grade composite score	1.495***	1.638***	0.304***	0.319***	0.210*	0.259***	0.545***	0.648***
	(0.437)	(0.385)	(0.116)	(0.105)	(0.118)	(0.098)	(0.186)	(0.149)
Observations	234	213	198	183	198	183	234	213
R-squared	0.313	0.275	0.183	0.236	0.156	0.232	0.194	0.219
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	100.3	156.1	84.57	156.3	84.57	156.3	100.3	156.1
P-value height diff.		0.807		0.924		0.751		0.667

b. Madagascar

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years Edu		Composite		French		Math	
	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median
2nd grade composite score	0.983**	1.105	0.220	0.443**	0.125	0.452*	0.312	0.476***
	(0.471)	(0.829)	(0.168)	(0.201)	(0.151)	(0.254)	(0.209)	(0.181)
Observations	172	161	160	150	161	151	164	154
R-squared	0.192	0.225	0.080	0.136	0.120	0.117	0.029	0.090
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	55.84	25.34	30.63	23.05	30.68	22.93	33.28	23.15
P-value height diff.		0.898		0.393		0.268		0.554

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Variables female, age, mother's and father's education and asset index are included similarly as in Tables 1,2 and 3, but not reported in this table (excluding height). The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Asset Heterogeneity

a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years Edu		Composite		French		Math	
	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median
2nd grade composite score	1.820***	0.893*	0.300**	0.180	0.221*	0.143	0.707***	0.476***
	(0.513)	(0.467)	(0.125)	(0.113)	(0.121)	(0.112)	(0.202)	(0.168)
Observations	224	223	190	191	190	191	224	223
R-squared	0.294	0.145	0.212	0.089	0.184	0.061	0.254	0.136
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	81.96	128.4	74.90	117.7	74.90	117.7	81.96	128.4
P-value asset diff.		0.181		0.477		0.636		0.379

b. Madagascar

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years Edu		Composite		French		Math	
	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median	IV Above Median	IV Below Median
2nd grade composite score	1.296*	0.964*	0.583***	-0.041	0.496***	-0.010	0.520**	0.043
	(0.757)	(0.579)	(0.211)	(0.168)	(0.188)	(0.194)	(0.221)	(0.185)
Observations	167	166	156	154	156	156	157	161
R-squared	0.028	0.320	-0.019	0.210	0.044	0.220	0.009	0.117
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Widstat	27.06	43.63	23.31	22.23	23.31	21.58	23.84	24.59
P-value asset diff.		0.727		0.0210		0.0620		0.0970

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school level fixed effects. All test scores are constructed using country-specific IRT. Variables female, age, mother's and father's education as well as school FE's are included similarly as in Tables 1,2 and 3, but not reported in this table (excluding asset index). The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Robustness Check (Lewbel 2012) – Senegal and Madagascar

	SENEGAL				MADAGASCAR			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Grade	Composite	Math	French	Grade	Composite	Math	French
2nd grade composite score	1.338***	0.265***	0.570***	0.203***	1.023**	0.240*	0.239*	0.196
	(0.327)	(0.076)	(0.127)	(0.074)	(0.478)	(0.128)	(0.133)	(0.137)
Height 2012	0.045**	0.008	0.013	0.007	0.019	0.005	-0.001	0.005
	(0.023)	(0.006)	(0.008)	(0.006)	(0.020)	(0.006)	(0.006)	(0.006)
Assets 2nd grade	0.557*	0.141**	0.226**	0.153**	-0.093	0.057	0.084	0.015
	(0.290)	(0.068)	(0.110)	(0.066)	(0.258)	(0.069)	(0.067)	(0.083)
Age 2012	-0.497***	-0.061***	-0.105***	-0.058***	0.081	0.024*	0.023	0.029**
	(0.080)	(0.020)	(0.031)	(0.020)	(0.054)	(0.014)	(0.016)	(0.013)
Female	0.223	0.060	-0.069	0.088	0.139***	0.017	-0.002	0.035***
	(0.407)	(0.106)	(0.154)	(0.103)	(0.048)	(0.012)	(0.014)	(0.012)
Mother's education	0.457	-0.072	-0.083	-0.018	-0.724***	-0.135***	-0.119***	-0.103***
	(0.598)	(0.147)	(0.216)	(0.139)	(0.121)	(0.036)	(0.038)	(0.039)
Father's education	0.284	0.016	0.005	0.046	-0.104	-0.027	-0.145	0.070
	(0.514)	(0.127)	(0.181)	(0.127)	(0.321)	(0.099)	(0.103)	(0.105)
Observations	447	381	447	381	333	310	318	312
R-squared	0.234	0.165	0.196	0.139	0.221	0.133	0.086	0.142
Widstat	41.75	38.07	42.32	38.07	13.55	6.254	3.825	6.496
J	9.026	3.708	1.906	5.148	6.260	3.835	4.337	4.103
Jp	0.172	0.716	0.928	0.525	0.395	0.699	0.631	0.663

Notes: All these models are IV models where the instruments are the pretest score in second grade and the generated instrument based on the Lewbel (2012) method. These specifications contain school fixed effects. The mother's and father's education variables in Senegal are dummy variables for whether they have any education or not. In Madagascar, those variables are based on the number of years of education they have.

Figures

Figure 1a: Cumulative distribution functions of composite scores

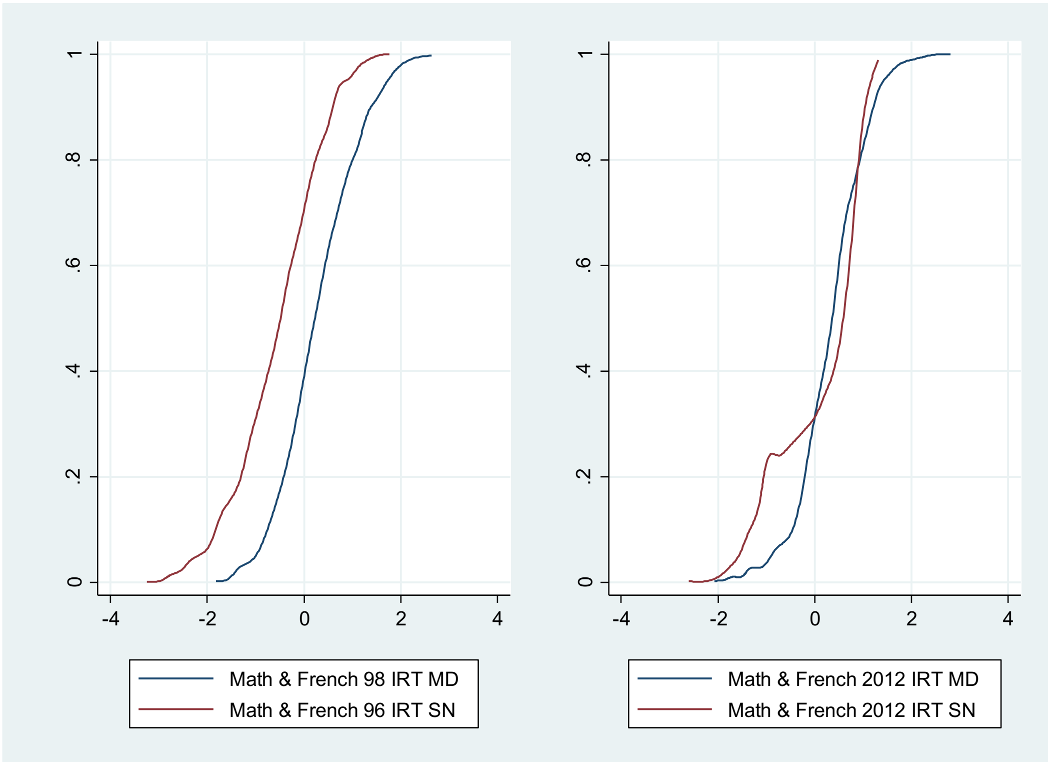


Figure 1b: Cumulative distribution functions of math

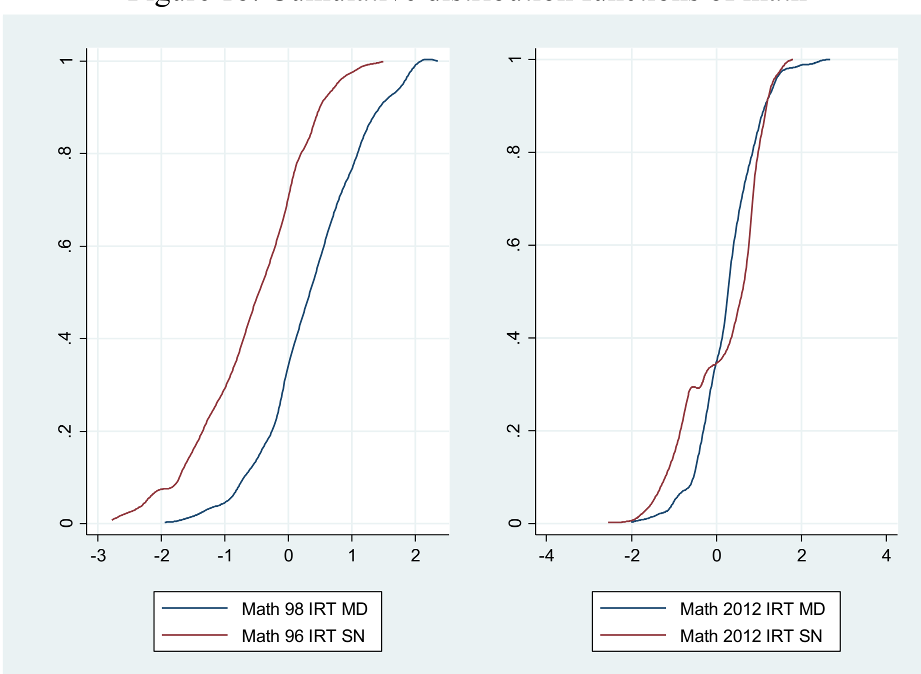
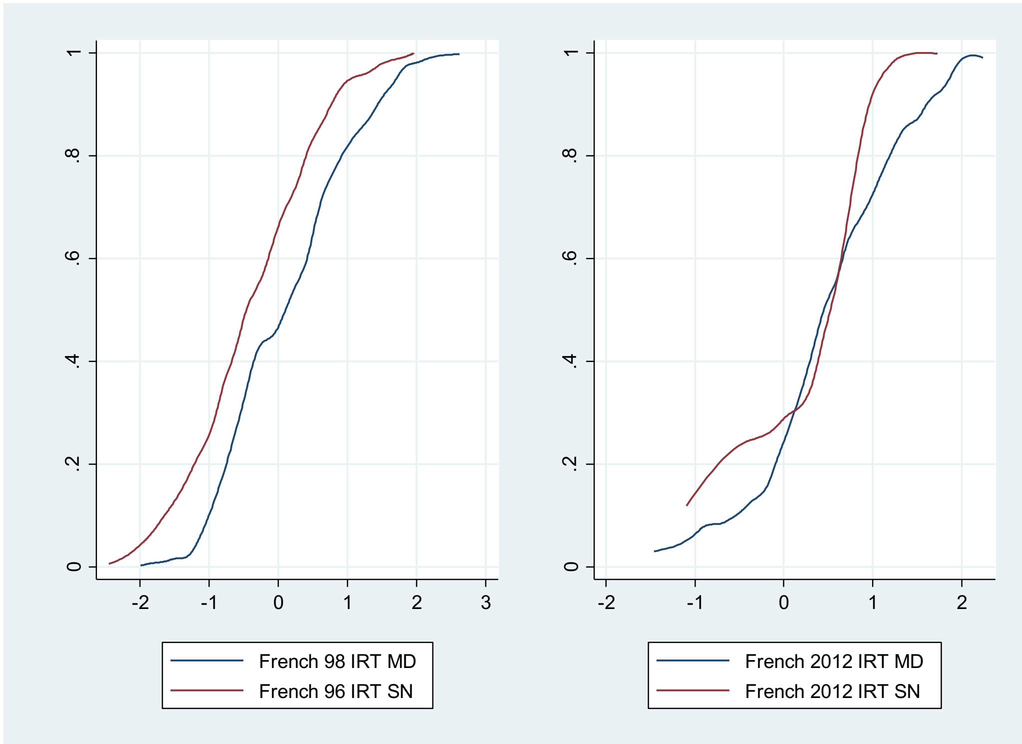
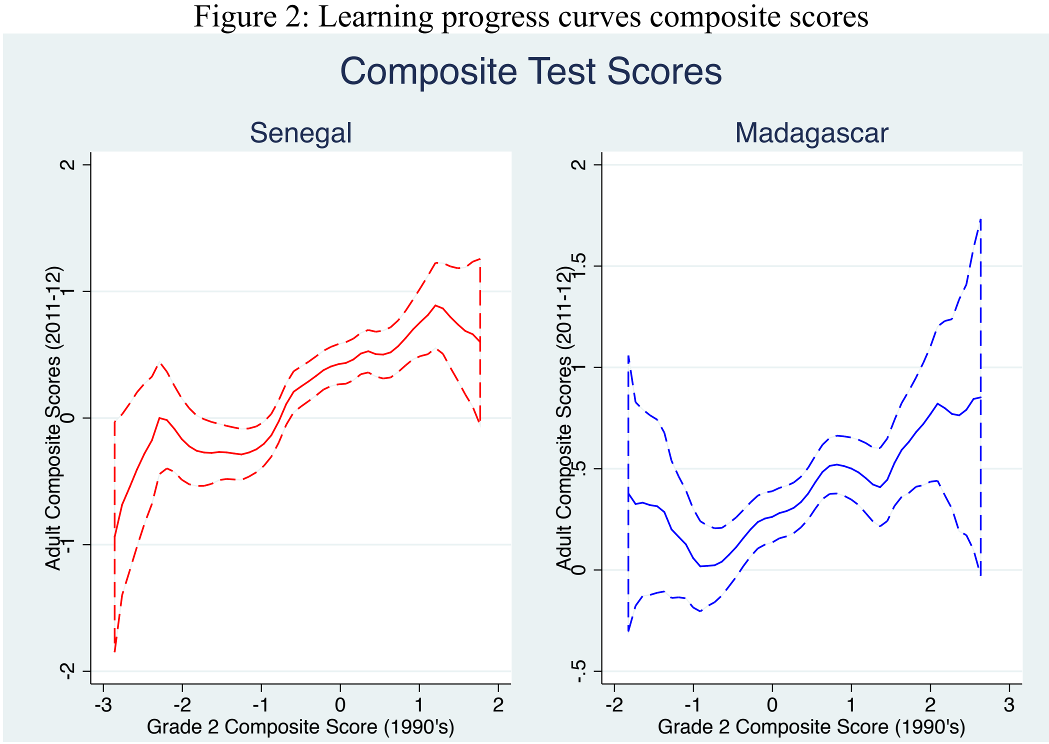


Figure 1c: Cumulative distribution functions of French



Notes: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round.

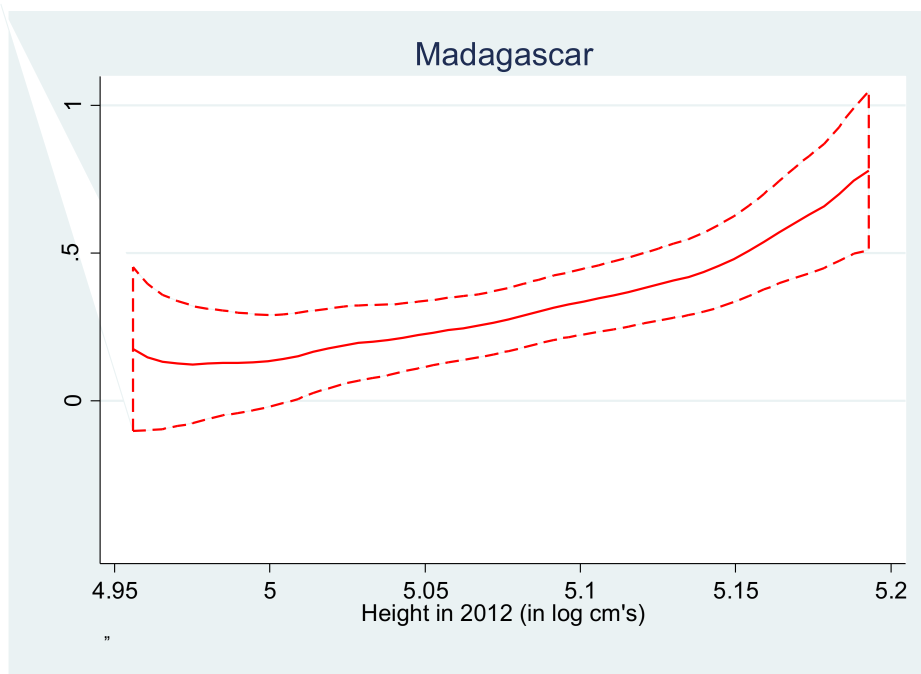
Figure 2: Learning progress curves composite scores



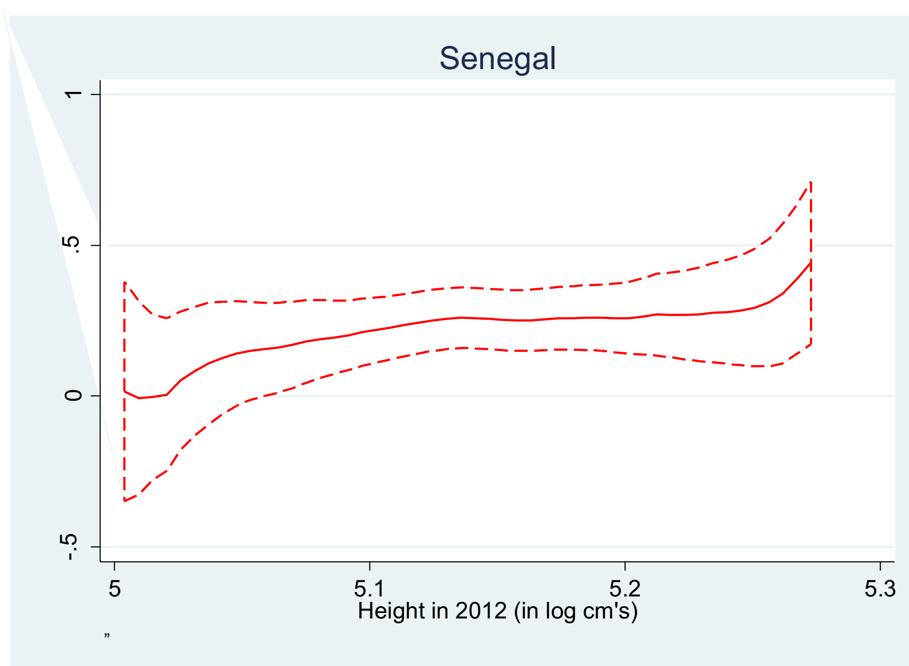
Notes: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round. Kernel: epanechnikov, degree=0, bandwidth=0.2, pwidth=0.65

Figure 3: Height and composite test scores in 2012

a. Madagascar



b. Senegal



Notes: Kernel: epanechnikov, degree=0, bandwidth=0.03, pwidth=1.2

APPENDIX

A. Item response theory

The test scores used in this paper are constructed using Item Response Theory (IRT). IRT is still an uncommon measure in the education economics literature, apart from a few exceptions (Singh 2017; Das and Zajonc 2010). It is, however, used in evaluating results from large-scale tests, such as the PISA, TIMMS and GRE.

The main principle of IRT is to differentiate between the latent ability of any given student to answer a question correctly and the actual response given. This is done by three different parameters for any given item: the difficulty, discrimination, and the pseudo-guessing parameters.

The Item Response Function (IRF) links the latent ability to the probability of success in that item for any given respondent. Following Singh (2017); Das and Zajonc (2010), we use the three-parameter (3PL) logistic model introduced by Birnbaum (1968). Given the probability of a correct response $X_{ig} = 1$ for a given item g, and given ability level θ, the probability of successful response is:

$$P_g\left(X_{ig} = 1 \middle| \theta\right) = c_g + \frac{1-c_g}{1+exp\left[1.7a_g\left(\theta_i - b_g\right)\right]} \ ,$$

where b_g is the difficulty parameter, a_g is the discrimination parameter, and c_g is the pseudo-guessing parameter. The difficulty parameter measures the overall difficulty of the item; the discrimination parameter tells how well a given item can differentiate between different levels of ability. Finally, the pseudo-guessing parameter tells how much success in a given item is random and, thus, unrelated to the respondent's ability. Setting the pseudo-guessing parameter to zero will yield a two-parameter model (2PL), which we have used in the cases where the maximum likelihood function of the 3PL-model was not converging. We argue this is not an issue, since for the test scores that we were able to estimate with the 2PL and 3PL models are very strongly correlated (close to 99%).

For comparing the levels of the test scores between the two countries (Section 5.1), we construct the IRT scores from the joint distribution of the scores of the two countries.

The advantage of doing this is that the parameters of IRT are estimated jointly for the common items, which renders the scores comparable. For all the regression analysis, we employ IRT scores that were estimated separately for each country, as we estimate country-specific regression models.

Test score comparability across time and space

The test scores in the second grade were administered in Senegal in 95-96 and in Madagascar in 97-98 for both French and math. During those school years, there were two tests for both French and math, one at the beginning of the second grade and one at the end of the second grade, which we call "pre-test" and "post-test", respectively. During 2012, French and Math tests were administered in both Senegal and Madagascar. These tests were different from the tests administered by PASEC for the second graders.

The below Table A1 reports which data sets are similar across space and time. In the regressions we use IRT scores that are calculated for that country alone, hence we do not exploit the comparability in the regressions, given that we run regressions separately for each country. In comparing the difference in performances across Senegal and Madagascar, we use the property that the tests are either fully or partially the same (Figure 1). The below Table A1 explains what are the similarities in different tests across time and space. Notice that tests administered on the 2nd grade are different from those administered in 2012.

Table A1. Comparison of tests questions

		Madagascar		Senegal	
		Math	**French**	**Math**	**French**
Children	**2nd grade pre-test**	Not same with anything	Not same with anything	Partially same as post in SN and post in MD	Same as post in SN and post in MD
	2nd grade post-test	Partially same as pre in SN, same as post in SN	Same as post and pre in SN	Partially same as pre in SN, same as post in MD	Same as pre in SN and post in MD
Adults	**2012**	Partially same in SN	Partially same in SN	Partially same in MD	Partially same in MD

B. Summary statistics

Table B.1: Summary statistics

a. Senegal

	Obs	Mean	Std. Dev.	Min	Max
Highest Grade in 2012	405	8.93	3.83	0.00	15.00
French 2nd grade (pre)	405	-0.09	0.84	-1.47	1.89
French 2nd grade (post)	405	-0.12	0.86	-2.14	2.19
Math 2nd grade (pre)	405	-0.09	0.92	-1.69	2.60
Math 2nd grade (post)	405	-0.08	0.93	-2.59	2.22
Math and French 2nd grade (post)	405	-0.11	0.88	-2.65	2.16
Math and French 2nd grade (pre)	405	-0.07	0.92	-2.02	2.52
2012 Math score	349	0.45	1.44	-3.24	2.90
2012 French score	349	0.46	0.79	-0.86	1.91
2012 Math-French score	349	0.23	0.83	-2.48	1.30
Height in 2012	405	171.91	8.76	149.00	195.00
Female	405	0.41	0.49	0.00	1.00
Age 2012	405	23.76	2.04	16.00	29.00
Mother Education (Dummy)	405	0.09	0.28	0.00	1.00
Father Education (Dummy)	405	0.18	0.38	0.00	1.00
Assets 2nd grade	405	0.02	0.94	-1.09	1.92

b. Madagascar

	Observations	Mean	Std. Dev.	Minimum	Maximum
Highest grade in 2012	333	10.04	3.22	1.00	15.00
French 2nd grade (pre)	333	0.10	1.00	-2.11	2.70
French 2nd grade (post)	333	-0.09	0.99	-2.36	2.51
Math 2nd grade (pre)	333	0.06	0.96	-2.79	1.80
Math 2nd grade (post)	333	0.01	0.89	-2.42	2.15
Math and French 2nd grade (post)	333	-0.04	0.94	-2.43	2.54
Math and French 2nd grade (pre)	333	0.07	1.03	-2.89	3.00
2012 Math score	318	0.28	0.81	-2.01	2.75
2012 French score	312	0.28	0.88	-1.76	2.13
2012 Math and French score	310	0.31	0.83	-2.37	3.03
Height in 2012	333	160.17	7.91	142.00	180.00
Female	333	0.54	0.50	0.00	1.00
Age 2012	333	21.85	1.39	19.00	26.00
Mother's education	333	5.62	3.65	0.00	17.00
Father's education	333	6.21	3.92	0.00	17.00
Assets 2nd grade	333	-0.08	0.79	-0.76	3.26

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All test scores are constructed using country-specific IRT. Height is reported in centimeters Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis.

C. Tests for attrition

Table C.1: Mean comparison across panel and full sample of students at baseline

a. Senegal 1995-96

	Not in panel	Panel	Difference
French 2nd grade (pre)	-0.10	-0.09	-0.01
French 2nd grade (post)	-0.18	-0.12	-0.06
Math 2nd grade (pre)	-0.14	-0.09	-0.05
Math 2nd grade (post)	-0.17	-0.08	-0.09
Math and French 2nd grade (post)	-0.21	-0.11	-0.10
Math and French 2nd grade (pre)	-0.19	-0.07	-0.12*
Assets 2nd grade	-0.05	0.02	-0.07
Female 1995–96	0.36	0.40	-0.04
Age 2nd grade	8.19	8.31	-0.12*

b. Madagascar: 1997–98

	Not in panel	Panel	Difference
French 2nd grade (pre)	-0.01	0.10	-0.11*
French 2nd grade (post)	0.02	-0.09	0.11*
Math 2nd grade (pre)	-0.01	0.06	-0.06
Math 2nd grade (post)	0.01	0.01	-0.00
Math and French 2nd grade (pre)	-0.01	0.07	-0.08
Math and French 2nd grade (post)	0.01	-0.04	0.06
Assets 2nd grade	0.02	-0.08	0.10**
Female	0.51	0.53	-0.03
Age 2nd grade	8.74	8.21	0.53***

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis.

Table C-2: Impact of early life composite French and math scores on grade completed: Inverse Probability Weights

a. Senegal

VARIABLES	(1) No School FE OLS	(2) School FE OLS	(3) School FE OLS	(4) School FE OLS	(5) School FE IV
Math and French 2nd grade (post)	1.594***	1.756***	1.710***	1.675***	1.357***
	(0.203)	(0.221)	(0.211)	(0.215)	(0.328)
Height in 2012				0.037	0.041*
				(0.025)	(0.023)
Assets 2nd grade			0.593*	0.581*	0.630**
			(0.322)	(0.321)	(0.301)
2012 Age (in years)			-0.453***	-0.460***	-0.458***
			(0.092)	(0.092)	(0.085)
Female (=1)			-0.186	0.173	0.125
			(0.360)	(0.445)	(0.417)
Mother Education (Dummy)			0.844	0.676	0.659
			(0.657)	(0.667)	(0.624)
Father Education (Dummy)			0.375	0.334	0.345
			(0.579)	(0.567)	(0.527)
Observations	400	400	400	400	400
R-squared	0.141	0.362	0.420	0.424	0.227
F					8.641
Widstat					226.9

b. Madagascar

VARIABLES	(1) No School FE OLS	(2) School FE OLS	(3) School FE OLS	(4) School FE OLS	(5) School FE IV
Math and French 2nd grade (post)	0.961***	0.382	0.419	0.425	1.352**
	(0.247)	(0.321)	(0.279)	(0.279)	(0.545)
Height in 2012				0.028	0.030
				(0.027)	(0.025)
Assets 2nd grade			-0.033	-0.021	-0.026
			(0.325)	(0.326)	(0.329)
2012 Age (in years)			-0.730***	-0.735***	-0.773***
			(0.166)	(0.163)	(0.152)
Female (=1)			-0.461	-0.214	-0.176
			(0.367)	(0.415)	(0.376)
Mother's education			0.102*	0.096*	0.077
			(0.057)	(0.057)	(0.056)
Father's education			0.091	0.085	0.087
			(0.062)	(0.062)	(0.059)
Observations	323	323	323	323	323
R-squared	0.084	0.413	0.515	0.517	0.139
F					6.779
widstat					64.84

Notes: All regressions weighted with inverse probability weights. Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All test scores are constructed using country-specific IRT. Height is reported in centimeters. Age is reported in years. Mother's and father's education are continuous variables measured in years for Madagascar, and dummies for Senegal for any education. Household asset index is constructed using factor analysis. The row "widstat" denotes the Kleibergen-Paap Wald rk F statistic for weak instruments. Heteroscedasticity-robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.