What You Learned by Second Grade Matters:

A Comparative Study on Human Capital Formation in Madagascar and Senegal[1]

Heidi Kaila,[a] **David E. Sahn,**[b] **Naveen Sunder**[c]

January 2019

Running Title: What You Learned by Second Grade Matters

[a] Cornell University. Email: kaila.heidik@gmail.com

[b] Corresponding author, Division of Nutritional Sciences, Cornell University, 309 Savage Hall, Ithaca, NY, Phone (607) 255-8931, Fax (607) 255-0178, Email: des16@cornell.edu

[c] Cornell University, Email: fn63@cornell.edu

[1] **Acknowledgments**: We thank Sam Jones, Jukka Pirttilä, Pablo Selaya, Patricia Justino, and seminar participants at the University of Copenhagen, DIAL Development Conference in Paris in 2017, and Centre for the Study of African Economies (CSAE) conference in Oxford in 2018 for their useful comments and suggestions. We thank Andinet Woldemichael for his excellent help in organizing the Madagascar data. This work was supported by the World Bank and by IZA/DFID Growth in Labour Markets in Low Income Countries (GLM-LIC) Program, under Grant Agreement GA-C1-RA4-067. Heidi Kaila greatly acknowledges support from Danmarks Frie Forskningsfond (DFF) grant number: 7024-00030B. The views expressed are not necessarily those of any of these institutions.

Abstract

We study the determinants of human capital outcomes of young adults in Madagascar and Senegal, employing a production function approach. Using unique and comparable long-term panel data sets, which span more than 15 years, from both countries, we find that test scores in second grade are strong predictors of school attainment and French/math skills of individuals in their early twenties. The association between second-grade skills and later-life outcomes is stronger among girls than boys, and likewise, stronger for math than French test scores. These findings highlight the importance of not falling behind during early school years, as it can lead to worse long-term outcomes, particularly for vulnerable groups like girls. We also find that height, a proxy measure of childhood health and nutritional status, does not affect the magnitude and significance of the early childhood test score variable, and also has an independent effect on the test scores of young adults in Senegal.

JEL Classification Codes: I21, O12

Keywords: education, cognition, human capital, health, Africa

1. Introduction

Cognitive skills have important implications not only for individual well-being (Heckman, Stixrud, and Urzua 2006), but also for economic growth (Hanushek and Woessmann 2008, 2012; Hanushek 2013). In this paper, we study the determinants of grade attainment and academic performance among young adults in two francophone African countries, Madagascar and Senegal. We examine the importance of second-grade skills, measured by test scores on math and French, in determining the educational level and test scores of young adults.[2] Additionally, we explore the role of other conditions, such as health, wealth, and parental education in shaping the outcomes. We do so by using two unique and comparable 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 15 years in Madagascar and 17 years in Senegal, 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 children's performance in elementary school and their academic performance later in life (Cunningham and Stanovich 1997; Feinstein 2003; Bourne et al. 2007;

[2] We use the term skills to refer to academic skills, that is French and math skills, measured in second grade and early adulthood. Even though these skills strictly measure academic performance, we consider them a proxy for cognitive skills formation in general.

Duncan et al. 2007).[3] For the most part, these studies measure academic performance in terms of school attainment and test scores. We follow this literature and compare the relative importance of the impact of early-life math and language scores on school attainment and young adult test scores across two African countries. Our results closely mirror those of Duncan et al. (2007), who used data from the United States, Canada, and the United Kingdom to show that math skills at school entry were a stronger predictor of later achievement than language skills.[4]

Apart from contributing to the literature on the persistence of academic skills from school entry to young adulthood, we also examine how second-grade skills affect school progression. Glick and Sahn (2010) found that skills in early primary school (second grade) in 1995–6 were strongly positively associated with school progression (measured through grade repetition) eight years later. Similarly, Singh and Mukherjee (2016), using panel data from India found that skills in primary school increased the likelihood of completing secondary schooling. In our analysis, we document similar relationships with the added dimension of using data sets that span a longer period of time, as compared to the aforementioned studies. This allows us to examine the impact

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

[4] Our results should be interpreted while 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. This contrasts with the case of Duncan et al. (2007), who presented evidence from predominantly anglophone developed countries where the language of instruction was likely to have been the same as the primary language at home.

that second grade test scores have on human capital formation of a cohort of young adults who were last surveyed in their early twenties, which other studies have not been able to do.

While the primary focus of our research is on the relationship between second-grade skills and human capital outcomes later in life, we are also interested in the role played by health in determining later-life outcomes. Therefore, we include height in our models to examine the role of childhood health in shaping adult outcomes. The additional benefit of including height in our models is that it controls for the confounding effect it could have on our primary question of interest: the relationship between skills in second grade on grade attainment and academic skills in young adulthood.

In this regard, we build upon the related evidence of the impact of health, measured using adult height, on human capital formation. Adult height is determined largely by a confluence of genetic and environmental factors, especially *in-utero* and during the first 24 months of life (Tanner 1979; Strauss 1997; Currie and Vogl 2013). Adult height has been found to be strongly associated with a variety of adult socioeconomic outcomes (Case and Paxson 2008; Lundborg, Nystedt, and Rooth 2014; Vogl 2014; Sohn 2015; LaFave and Thomas 2017). Case and Paxson (2008) found a strong relationship between adult height and earnings, with the pathway being higher cognitive skills of taller individuals, leading them to select into occupations with higher earnings. Lundborg, Nystedt, and Rooth (2014) also found that height at age 18 has a significant impact on wages, even after controlling for cognitive and noncognitive skills in Sweden. Similarly, Vogl (2014) and Sohn (2015) found a large height premium in wages in Mexico and

Indonesia, respectively.[5]

In our work we control for family background, particularly wealth and parental education, as they play a critical role in the process of mental and physical development. In doing so, our paper builds on the literature that provides strong evidence of parents' education affecting grade progression and academic skills of their children, both in developing and developed countries (Cunha and Heckman 2007; Todd and Wolpin 2007; Cunha, Heckman, and Schennach 2010; Glick, Randrianarisoa, and Sahn 2011; Behrman et al. 2014; Jones et al. 2014; Marchetta and Sahn 2016; Behrman et al. 2017). In the context of India, Helmers and Patnam (2011) found that parental investment had an impact on skill levels of children of primary school age or lower. Glick, Randrianarisoa, and Sahn (2011) and Jones et al. (2014) used data from sub-Saharan African countries to find that parental background plays a significant role in the determination of children's ability, and similarly, children of educated (and nonpoor parents) have been found to perform much better than their peers on cognitive tests (Dumas and Lambert 2011).

[5] With respect to childhood height, it has not only been shown to be a strong determinant of adult height (Case and Paxson 2008), but Alderman, Hoddinott, and Kinsey (2006) reported that childhood health status (as measured by height-for-age) had a positive impact on completed schooling as an adult. Behrman et al. (2014) also found that height-for-age at age six affected adult cognitive skills, and further made the point that excluding height from a cognitive production function will result in the overestimation of the effect of schooling on cognitive ability.

We also control for wealth by having an asset index in our models—there is significant evidence that material well-being matters for education and cognition outcomes (Cunha and Heckman 2007, 2008; Todd and Wolpin 2007; Helmers and Patnam 2011; Schady et al. 2015). However, in most studies from developing countries, income, expenditure, or wealth is measured contemporaneously with the outcome of interest. This association between contemporaneous household resources and skills needs to be interpreted with caution, since causality runs in both directions. In contrast to the preponderance of the related literature, we explore the relationship between wealth (measured by assets) at the time children were in second grade on their human capital as young adults. Although a causal interpretation is still not possible, especially due to the impact of unobserved heterogeneity, using wealth lagged 15 years eliminates, at least, the concern of reverse causality in our context.

To explore the importance of aforementioned socioeconomic factors, height, and skills in second grade on young adult outcomes, we build upon a standard human capital production function framework (Todd and Wolpin 2003, 2007; Cunha and Heckman 2007; Cunha, Heckman, and Schennach 2010), in which 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 these relationships while controlling for 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 using comparable data sets. There is a relative lack of evidence of the type that we present here with respect to Africa, mostly due to the lack of availability of long-term panel data sets. It is even more lacking with respect to being able to provide comparative evidence across countries. Our paper bridges this gap in the literature.

To strengthen the comparability of our results from Madagascar and Senegal, we use Item Response Theory (IRT)[6] to create joint test score indices for the two countries. We use these scores to compare performance across the two countries at two points of time (childhood and adult life). Such comparisons of human capital formation, especially from developing countries, are quite rare (Jones et al. 2014; Schady et al. 2015; Singh 2017). Our analysis is different from these papers insofar as our data covers a longer time period, effectively spanning the entire course of the schooling experience from second grade to early adulthood.

We find that human capital in young adulthood is strongly associated with skills in second grade in both countries. We observe heterogeneous effects of math and French skills in second grade, where math scores have a stronger relationship with later-life outcomes. These results confirm patterns observed in Duncan et al. (2007). The results also suggest that taller individuals have higher test scores, evidence similar to that found in Case and Paxson (2008) and LaFave and Thomas (2017). We also find that height plays an important role in grade attainment among young adults in Senegal, but the coefficient estimate is not statistically significant in the

[6] Appendix A explains the construction of the IRT scores and how this facilitates comparison of test scores across the two countries.

Malagasy case. This coefficient of child health is obtained after controlling for skills in second grade. In addition, our results indicate that wealth of the household when children are entering school is associated with schooling and skills measured more than 15 years later. Furthermore, we find that parents' education matters more in Madagascar than in Senegal. Finally, our heterogeneity analysis shows that second grade test scores are more strongly associated with later-life outcomes for shorter individuals and females, groups that are potentially more vulnerable (akin to the analysis of Glewwe, Krutikova, and Rolleston 2017). This implies that poor performance in second grade is more detrimental to outcomes as an adult for 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. In Section 5 we present the results and discuss robustness checks in Section 6. Finally, in Section 7 we draw conclusions.

2. 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 along many dimensions, they share many similarities. Both are low-income countries that struggle with low school attainment and primary school completion rates. This is still 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 Senegal from 59 percent to 81 percent, and in Madagascar from 86 percent to 145 percent (World Bank 2016).[7] Additionally, in the 1990s, grade repetition and dropout rates were high in both countries (Michaelowa 2001; Glick and Sahn 2010). The educational systems in these countries are modeled after the French system, and the primary language of instruction is French.

Although 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. Madagascar is an island economy that has experienced almost two decades of political turmoil, 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 from 1995 to 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 does Senegal, as well as most other African countries (Bossuroy and Cogneau 2013; Azomahou and Yitbarek 2016). Further, Glick, Randrianarisoa, and Sahn (2011) found that parents' education and schooling are important determinants of

[7] 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.

learning in Madagascar. In Senegal, Glick and Sahn (2009) showed that, conditional on a child's level of schooling at 14–17 years of age, having better educated parents or a higher level of household resources have only modest benefits for academic performance. They found similar results for school-level variables.[8]

3. Data

The first round of the survey 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 the children were between 7 and 10 years of age.[9] These school-based tests were administered as part of a multicountry study called the Program on the Analysis of the Conference of Francophone Ministers of Education, which is referred to by its French acronym, PASEC.[10] Both urban and rural communities were included in the PASEC school-based sample, which was designed to be a nationally representative selection of schools from communities

---

[8] In the case of Senegal, Dumas and Lambert (2011) found that family characteristics do matter for enrollment and the level of education, but they did not have information on cognitive skills, as we do.

[9] Some children were older or younger because of early or delayed enrollment.

[10] 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).

throughout the country. This involved randomly selecting communities from throughout the country, and then if there was more than one school among any of the communities selected, one school from that community was chosen randomly to be part of the sample. Despite the intention to draw a representative sample of students from the entire country, there are two important qualifications. First, while the communities, and then schools within the communities were randomly selected, the PASEC tests were school-based tests that were administered only to schoolchildren. As with all school-based testing for such national testing programs, as well as large cross-national surveys such as the Program for International Student Assessment (PISA),[11] the sample was restricted to those who were enrolled in school. 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 who had never been enrolled in school and other children who had left or dropped out of school before second grade. Second, schools were selected for the sample only if they had a class size of at least 20 students, although that could include multi-grade classrooms. In practice, almost all schools in Senegal had sufficient number of children in the classroom and thus were eligible to be included in the sample, but, in Madagascar, we found that the smallest and most remote communities in the country were underrepresented in the sample of schools that was selected in the mid-1990s.

A subset of the children in the PASEC surveys in Madagascar in 1997–98 and Senegal in 1995–96 were followed up in 2012–13. The 2012–13 data sets are referred to as the Life Course Transition of Young Adults Surveys. The young adults were, on average, 22 years old in

[11] http://www.oecd.org/pisa/test/

Madagascar and 24 years old in Senegal at the time of the surveys in 2012–13. The children in this long-term cohort were randomly selected from slightly less than half the original clusters included in the PASEC surveys of the mid-1990s.[12] Our final sample that spans the period of over 15 years includes 333 and 447 children who were in second grade in the 1990s in Madagascar and Senegal, respectively.[13]

As indicated above, 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 (more details in Appendix Table A.1). However, the tests for children and for adults were different, reflecting the different periods in the cohort members' life courses. The presence of common questions in the tests administered in the two countries allows us to construct test scores based on the Item Response Theory (IRT), using the joint distribution of the two test scores. The parameters of IRT are estimated jointly for the common items, which renders scores comparable across the countries for a given time

[12] Selecting of subset of communities was necessitated by budgetary constraints at the time.

[13] The main reason for the smaller sample size in Madagascar is that fewer communities with PASEC schools were followed up in Madagascar than in Senegal. More information on attrition, along with robustness checks for attrition, is provided in Appendix C.

period.[14],[15] This enables us to conduct a descriptive comparison of the test performance across the two countries. Additionally, the IRT score also has the benefit of being a cardinal measure of test performance, as opposed to the more commonly used measure of percentage of correct answers, which is merely an ordinal measure.

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 estimates 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 had been considerable convergence in the distribution of the scores across the countries.

In Figure 2 we provide descriptive evidence on the relationship between the second grade and early adulthood scores, using the jointly estimated (comparable) IRT scores. A clear implication from Figure 2 is that the relationship between the second 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 further illustrate the strength of this relationship in Senegal,

---

[14] The details of which tests were merely similar, and which were the same, are given in Appendix A along with the description of the IRT methodology.

[15] 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.

compared to Madagascar.[16]

Figures 3a and 3b show the nonparametric relationship of test scores measured for young adults in relation to height in young adulthood. We can see that, in both countries, the test scores are increasing in height, implying taller individuals did better in cognitive tests as adults. This is similar to the findings of 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 test scores within country and across time, since the country-specific IRT scores are a better estimate of the 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.[17] The test score variables are the country-specific IRT

---

[16] 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.

[17] The sample sizes vary slightly depending on the dependent variable, due to missing observations in the test scores. The highest grade completed in Madagascar (Senegal) is available for 333 (447) individuals; the 2012 Math scores are available for 318 (447); the 2012 French scores for 312 (381) individuals; and the joint math and French test scores are available for 310 (381) individuals in Madagascar.

transformations with means close to zero, both in the 1990s and in 2012. In Senegal the adult sample has completed an average of 9 grades in school, compared to 10 grades in Madagascar. In Senegal the sample has a slight majority of males, whereas in Madagascar, it is the opposite. On average, the Senegalese sample is 24 years of age, slightly older than the Malagasy sample of 22 years of age. 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 cm shorter than the Senegalese sample. The discrepancy is similar to that found in the DHS data (Subramanian et al. 2011). The difference is large and is likely to be partially explained by different ethnic compositions of the populations, where 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–1990s, 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 concern with the data sets we use is attrition. We faced the challenge of returning to communities many years after the original PASEC survey was conducted in the mid-1990s and searching for the original children over 15 years later. The difficultly of doing so was exacerbated by the exceedingly low living standards, volatility in economic conditions, and the constant social transformation in the original communities surveyed. Despite these challenges, we began by randomly selecting a subset of the communities and a subset of the children in each community to be included in our follow up surveys. Despite our efforts to identify as many of the children as possible, the attrition rates in both in Senegal and in Madagascar were just under 50 percent for the 17- and the 15-year intervals, respectively.

To better understand the implications of this attrition rate, we compared the sample of children in the cohort included in our analysis with those in the original PASEC samples, recalling that the original surveys conducted in the mid-1990s were designed to be representative of school-aged children in the countries. Appendix Tables C.1.a and C.1.b show a comparison of means for key variables between these samples. For Senegal, the children in the panel had slightly lower second-grade test scores on average than the children not in the panel, and they also came from households with slightly lower asset scores. For Madagascar, the children interviewed in second grade, and as adults, came from households with slightly less wealth. These individuals are also slightly younger than the overall sample. In Madagascar, however, we see no systematic differences in test scores. We find that the differences arise from the fact that an attempt was not made to reach all communities in the follow-up, rather than arising from attrition within a community (Tables C2 and C3). To alleviate concerns related to attrition and sample selection, we conducted a robustness check of our results by estimating inverse probability weighted regressions, where the weights are calculated based on the estimated probability of being in a community that was included in our follow-up surveys. This check is based on different characteristics in the baseline data. This is discussed in detail in Section 6. The results from this exercise show that the results are robust to the attrition and sample selection-related adjustment.

Despite the checks intended to alleviate concerns over attrition and sample selection for follow-up, we want to emphasize that we do not make any claims regarding our cohort being representative of the entire population in the age group of the cohorts in the two countries. 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 note, however, 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, as measured by test scores, 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 sample 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 the cognitive production function, and then, present the empirical framework that 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 Singh (2017). We also draw on literature, studying the relationship between height and later-life outcomes, which for the most part, finds a strong association between height and cognitive skills

---

[18] We should note that other 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)

in adulthood (Case and Paxson 2008; LaFave and Thomas 2017).

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

$$Y_2 = f(\beta_1 A_1(\mu_0) + \beta_2 P_1 + \beta_3 H_2(n_1, \mu_o) + \beta_4 S_1), \tag{1a}$$

where the grade attainment Y_2 in Period 2 is a function of cognitive ability A_1, and height H_2 in Period 2, which is largely determined by cumulative health/nutritional endowments and socioeconomic factors (particularly, in the first few years of life) denoted by n_1 (Martorell and Habicht 1986). Also, both ability and height 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.

If expressed in the form of skill accumulation, the model is

$$A_2 = g(\gamma_1 A_1(\mu_0) + \gamma_2 P_1 + \gamma_3 H_2(n_1, \mu_o) + \gamma_4 S_1), \tag{1b}$$

in which we explain the stock of skills in Period 2, A_2, using the skill 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 (worse) performing children, which would then potentially lead the children to perform even better (or not as well) in the next period (Glick and Sahn 2009, 2010; Akresh et al. 2012a, 2012b). This is relevant in resource-constrained environments, such as Madagascar and Senegal, where child labor is prominent and the opportunity cost of schooling is high. Parents, who are assumed to be maximizing their lifetime utility, must therefore choose between short-term gains of their children working versus the potential long-term benefits of education. In families with several children, as is most often the case in Senegal and Madagascar, the parents might be inclined to invest in the schooling of the best performing child, but this may not necessarily always be the case.

4.2. Empirical framework

The simplest empirical counterpart of equation (1a) is a reduced form model, which can be estimated using an OLS model:

$$Y_{i,2012} = \beta_o + \beta_1 A_{i,1996} + \beta_2 Height_{i,2012} + \beta_3 HH_i + \beta_5 X_i + \gamma_j + \varepsilon_i \qquad \text{(2a)}$$

In this regression, $Y_{i,2012}$ stands for the highest grade attained by the cohort member in 2012, and $A_{i,1996}$ stands for a measure of childhood skills, which in our case is measured using math and French scores at the beginning and end of second grade (called pretest and posttest, respectively). The time index used in equation 2a is 1996, which is the year corresponding to the Senegal data, while in the Madagascar data it is 1998. $Height_{i,2012}$ refers to height measured in early adulthood in 2012, which is a function of both health inputs received over the life course, particularly, *in utero* and in early childhood, as well as genetics (Martorell and Habicht 1986). We include it in our model, as evidence suggests that adult height is strongly related to outcomes in adulthood; thus, omitting height from the model could potentially lead to inflated coefficient estimates for other covariates in the model (Case and Paxson 2008; LaFave and Thomas 2017). HH_i is a vector of household-level (time-invariant) inputs; γ_j are school fixed effects, corresponding to school j; and X_i denotes time-invariant control variables.

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

$$A_{i,2012} = \beta_o + \beta_1 A_{i,1996} + \beta_2 Height_{i,2012} + \beta_3 HH_i + \beta_4 X_i + \gamma_j + \varepsilon_i \tag{2b}$$

Our dependent variables $A_{i,2012}$ are performances on French and math tests in 2012. We model these test score outcomes individually, as well as a composite score.

This setup is analogous to a value-added (VA) specification in which current test scores are regressed on earlier period outcomes and other determinants. Although value-added models have primarily been used to analyze skill acquisition from one grade to another, often focusing on estimating teacher and school characteristics and quality of learning, our paper differs in an important way: we are interested in explaining skills in early adulthood—a time during which the cohort is no longer in school using skills from a previous period (second grade). [19] Since our

[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.

empirical specification includes lagged inputs and lagged achievement, it can therefore be thought of as a "combination of the 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] Although 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, 15–17 years.

Our model takes school inputs into account through the inclusion of school fixed effects. Each individual is assigned to the school that he/she 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 also control for time-invariant, community-level factors, due to the one-to-one correspondence between schools and communities. Consequently, our empirical specification compares children who attended the same school (and class) when in second grade, after controlling for other household and individual covariates. Hence, it is likely that the children were exposed to roughly the same socioeconomic and environmental factors in their childhood, thus making the comparisons even more relevant. We include in the models the asset index of the household where the young adult lived when in the second grade. The coefficient can then be interpreted the effect of wealth in early childhood on later-life outcomes. We also use height in early adulthood, a proxy for the

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

lifetime cumulative health status (but predominantly influenced by the period from conception to 24 months of age) on young adult test scores. Additionally, we control for some individual-specific attributes, such as parents' education, which further reduces concerns regarding omitted variables in this specification.

We measure childhood academic ability of the individual using second-grade math and French test scores. We obtain information on scores of pretests that were administered to students at the start of second grade (1995 in Senegal and 1997 in Madagascar), and posttests that were administered at the end of second grade (1996 in Senegal and 1998 in Madagascar). In addition to capturing the role of cognitive ability and genetic factors that contribute to test performance in the second grade, these early-life test scores are a function of household and school inputs that the children received from the time of conception until the second-grade test was conducted. Although we have a choice of using scores from tests conducted at the start and end of the school year, we use the latter in our specifications, because the tests are comparable across the two countries. We also show models with composite scores (using both the pretests and posttests) during second grade as a robustness check (Table 9).

We also estimate a model with only lagged inputs, as well as a model that excludes 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 for each round of survey in each country—math, French, and composite scores. In latter specifications, we explore whether math and French test scores obtained during the second grade are equally strong predictors for adult skills, or if, as found 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 a one-point-in-time performance of students on an administered test, which could be impacted by many factors related 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 issue by

[21] Another potential specification for studying the effect of lagged inputs on skills in early adulthood is to employ a fixed effects framework, as in 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); but more important, this approach is not feasible due to the fact that we do not have time-varying inputs in our regressions.

using an instrumental variable (IV) approach. Since we have test score data at the beginning (pretest) and at the end (posttest) of the second grade, we use the second-grade pretest scores to instrument 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:

$$TS_{i,1996}^{post} = \alpha_o + \alpha_1 TS_{i,1996}^{pre} + \alpha_2 Height_{i,2012} + \alpha_3 HH_i + \alpha_4 X_i + \gamma_j + \tau_i \tag{3a}$$

$$Y_{i,2012} = \delta_o + \delta_1 TS_{i,1996}^{post} + \delta_2 Height_{i,2012} + \delta_3 HH_i + \delta_4 X_i + \gamma_j + \theta_i \tag{3b}$$

where posttest and pretest scores are denoted by $TS_{i,1996}^{post}$ and $TS_{i,1996}^{pre}$, 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, 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 childhood 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, similar to other papers that have looked at childhood ability and how it affects outcomes in adult life, we rely on an important set of controls to at least mitigate endogeneity concerns. While we acknowledge the possibility of endogeneity in our specification, we also note that several recent papers, which have compared value-added estimates of the type explored here and estimates from experimental or quasi-experimental analyses, have mostly concluded that the nonexperimental estimates are unbiased, when compared with estimates from experiments (Angrist, Pathak, and Walters 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, and which could only be done if there was some sort of experimental design implemented during the original time period—in our case, the mid 1990s. To further assuage concerns related to this issue, we conduct a variety of robustness checks to test the sensitivity of our results.

5. Results

5.1 Highest grade attained

First, we turn our attention to the models in Tables 1.a and 1.b, in which we show the relationship between second-grade test scores and the highest grade attained by young adults in Senegal and Madagascar, respectively. It should be noted that the highest grade attained might be different from the number of years of schooling. This is because repetition of grades is quite common in the two countries in our sample, as it is the case in most African countries that follow the French educational model. The first column of Tables 1.a and 1.b display the results from OLS regressions using a single covariate, the composite French and math score from the second-grade posttest. 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 second-grade composite test score one standard deviation above the mean is associated with an increase in the highest grade attained by around 1.64 years. In Madagascar, the corresponding coefficient is 0.99 (Table 1b, column 1). Both of these coefficients are significant at the one percent level.

In columns 2 through 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. As noted earlier, since each community had one school, the school fixed effects can also be thought of as community-level fixed effects. The coefficients in column (2) change little relative to column (1), remaining significant at the one per cent level in both countries.

In columns (3) and (4), we add a series of household and individual covariates. They do not lead to noteworthy changes in the coefficient of the second-grade test scores in either country and the test score coefficient remains strongly statistically significant (at 1 percent level) in these specifications. The father's education level has a positive relationship with grade attainment in Madagascar, with the mother's education having a modest additional effect. In Senegal, the average level of parents' education is low, so we use dummies for whether each parent has any education, instead of using a continuous measure.[22] The results for Senegal indicate that parents' education has a positive, albeit statistically insignificant, relationship with 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 significant effects of assets in early childhood. This might be because of the lower overall level of assets in households in Madagascar, as compared to those in Senegal.[23] It could also be that the coefficient estimate of the asset index is insignificant, because the regressions already control for parental education, which is an important determinant of living standards of the household.[24] We also tried adding interaction terms of the second-grade scores with assets and parents' education—these variables were not significant and therefore 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), height is a proxy measure of childhood health and nutritional status, particularly, as affected by *in utero* and early

---

[22] In Senegal, mother's education is 1.3 years and father's 2.7 years, 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 the asset index is significant when we remove the parental education variable.

childhood inputs. Results indicate that, in both countries, the coefficient on second-grade test scores is largely unaffected by the inclusion of height. In Senegal, height has a significant positive relationship with highest grade attained, whereas in Madagascar the coefficient albeit positive, is much smaller in magnitude and not significant. Our results indicate that being 1 cm taller is associated with an increase of 0.04 years of schooling in Senegal. The fact that we find that the relationship of early childhood and adult test scores is not affected by the inclusion of the height variable shows that early-life health and human capital (measured by test scores) have independent effects on adult outcomes.[25] This is largely consistent with the current literature, which found a statistically significant effect of height on human capital formation (Perisco, Postlewaite, and Silverman 2004; Case and Paxson 2008, 2010; Spears 2012).

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 composite test score taken at the end of second grade with the score on the test administered at the beginning of 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 weak instruments.

[25] In the case of Madagascar, we have also run the model controlling for ethnicity, which should be correlated with height, given that there is a mix of ethnic groups that are both Asian and African in origin. The results remain similar, when ethnicity is controlled for. Results are available from the authors by request.

The magnitudes of the IV coefficients of the impact of composite test scores on grade attainment are similar in both countries, 1.38 and 1.29 for Senegal and Madagascar, respectively. Thus, the IV results portray a consistent narrative of a significant positive relationship between second-grade test scores and educational achievement later in life. It is not clear, however, why the idiosyncratic measurement error correction matters more in Madagascar than in Senegal. This may reflect the fact that the measurement error correction seems to work better with the pretest conducted in Madagascar than it does with that in Senegal, or that there might have been greater measurement 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 pretests (used as the instrument) differed across the two countries.

5.2 Test scores

In Tables 2.a and 2.b, we estimate the relationship between second-grade test scores and adult composite French and math test scores (columns 1 and 2), as well as math (columns 3 and 4) and French separately (columns 5 and 6). The findings in these tables are consistent with the results discussed previously in terms of grade attainment: second-grade cognitive ability has a strong and persistent association with later-life skills. More specifically, columns 1 and 2 show evidence of a robust positive and statistically significant relationship between second-grade skills 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). The results in the IV model in column 2 of Tables 2.a and 2.b show that a 1 standard deviation increase in composite scores in second grade is associated with higher adult composite scores by 0.27 and 0.32 standard deviation in Senegal and Madagascar, respectively. The results for Senegal are statistically significant at the 1 percent level, whereas the Madagascar results are significant at the 5 percent level.

As expected, results in Table 2.a suggest that, in Senegal, the assets of the household when the cohort member was in the second grade is positively and significantly associated with later-life cognition, even after controlling for parents' education. A 1 standard deviation increase in the asset index is associated with an increase in the composite test score of 0.14 standard deviation. In Madagascar, although the asset index coefficient 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 through 6 in Tables 2.a and 2.b, in which the individual scores on 2012 math and French tests are modeled separately. Childhood skills have a statistically significant positive association with both adult math and adult French scores in Senegal and Madagascar. However, the coefficient estimate is far stronger in the case of math than for French.[26] Overall, the results describe a situation in which childhood test scores are

[26] 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.

strongly and persistently associated with later-life human capital outcomes. These relationships hold even after the addition 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 human capital outcomes.

Figure 4 summarizes the findings on the highest grade attained and the test score analysis (Sections 5.1 and 5.2). The coefficients plotted are from the model with highest grade attained as the outcome variable (Tables 1.a for Senegal and 1.b for Madagascar, column 4). The coefficients for the models with test score variables as outcome variables are from Table 2a. (Senegal) and 2.b (Madagascar), columns 1, 3, and 5 for composite, math, and French, respectively. Figure 4 shows how the results are consistently stronger in Senegal than in Madagascar in all of the outcome variables.

5.3 Heterogeneity tests

5.3.1 Differential results of French and math scores

In order to explore another dimension of the relationships discussed above, we replicate the regressions using a slightly modified empirical strategy. Instead of using the composite math and French scores in childhood, 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 taken at the end of second grade.[27]

We are motivated to do so because math and French tests potentially capture different types of abilities. Previous research has found that math skills in childhood are stronger predictors of later-life skills than language skills, although this evidence is from predominantly English-speaking countries (Duncan et al. 2007; Duncan and Magnuson 2011). Our 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, a 1 standard deviation increase in the second-grade math score is associated with an increase in highest grade attained by 1.4 years, whereas the corresponding coefficient estimate in Madagascar is 1.18 years (column 2 of Tables 3a and 3b, respectively).

In the first two columns of Tables 4.a and 4.b, we present similar evidence on the relationship between second-grade French scores and later-life grade attainment. The relationship between a 1 standard deviation increase in the second-grade French test score and 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 coefficient estimates are similar to the results that use the composite test score (Tables 1.a and 1.b).

[27] The results are qualitatively similar if we were to use the pretest as the independent variable and the posttest as the instrument. The results are available from the authors by request.

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 scores on the composite, math, and French tests in the second grade, respectively. In Senegal, the French score has a statistically significant association with all 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 suggest that childhood math scores are stronger predictors of later-life math scores of later-life French scores, particularly in Senegal. Additionally, childhood math scores predict later-life French scores better than childhood French scores do, in the case of Madagascar. For Senegal, adult French scores are equally well predicted by both childhood French and math scores. In sum, there is some evidence that the math scores are driving the strong relationship between composite scores (math and French) and later-life outcomes in Madagascar (Table 1.b). We also note that the importance of other background characteristics is similar in the models when math, French, and composite scores from early childhood are used as covariates in the model.

5.3.2. Gender differences

We also explore whether there are any gender differences in the relationship between childhood skills and later-life outcomes by running separate models for boys and girls. The results in Tables 5.a and 5.b indicate that the test score coefficient differs in magnitude between girls and boys in both countries. Across all outcomes in both countries, the coefficient for the childhood test score is consistently higher for girls than for boys. This gender difference is especially pronounced in Senegal. We conduct a t-test to check for the equality of the test score coefficients in the male and female regressions and reject the null of equality of coefficients in one case in Madagascar and in two cases in Senegal.[28] The evidence that childhood performance is potentially more persistent in its impact on later-life cognitive ability for girls 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 in both Madagascar and Senegal.

5.3.3. Differences in height

We next divide the sample into two groups based on whether the cohort member's height falls above or below the median gender-specific height in each country (Tables 6.a and 6.b). In Senegal, the second-grade test score coefficient in the grade attainment models for the below-median group (relatively shorter) is greater than the coefficient in the above-median group (relatively taller). These differences, however, are not statistically significant. In Madagascar, the patterns are similar, but, again, we do not find statistically significant differences in the coefficient on test scores of the two groups of relatively shorter/taller cohort members. Taken together, these results provide some suggestive evidence that there is greater persistence in test scores from childhood to adulthood among shorter individuals. To the extent that shorter and less healthy cohort members are not only more vulnerable in childhood, but also have a higher

[28] 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 may be 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.

persistence in their poor performance over time, the result suggests early deficits are unlikely to be overcome unless concerted investment/effort is expended to correct them.[29]

5.3.4 Differences in household assets

Finally, we check whether differences in household assets in the second grade matter for the persistence in the relationship between childhood scores and later-life outcomes. To do so we divide the sample into two groups based on whether household assets were above or below the (country-specific) mean assets in second grade. The results in Tables 7.a and 7.b suggest that having a higher level of assets in childhood is associated with a larger persistence between second-grade test scores in both Madagascar and Senegal. This 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 education. Another interpretation is that, among children from economically disadvantaged households, there is lower persistence in the relationship between early- and later-life test scores, which could imply that the children might be able to overcome their early disadvantages in test scores. However, the fact that the t-test of difference in the coefficients is significant in only one case at the 5 percent level in Madagascar suggests the need for caution in drawing firm conclusions.

6. Robustness Checks

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

6.1 Accounting for attrition and sample selection

The attrition rates and sample selection 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 and sample selection for the follow-up. Recall from our discussion above that only a subset of the communities was randomly selected for follow-up, but this selection process does not necessarily ensure that they are representative of the original communities. First, in Table C.1 we test whether there are systematic differences between the sample of observations in the panel and the full sample of students at baseline. In the balance test, we include a number of school-level covariates, available from the PASEC surveys, to check whether the school environments differ across the full baseline sample and the panel sample. We only find modest differences, mostly in the Senegalese sample. To control for these differences, we run school fixed effects models, which account for *all* time-invariant, school-specific characteristics.

In Tables C.2 and C.3, we compare other subsamples. Table C.2 compares the means for observations in clusters chosen for follow-up with the full sample of students at baseline. We find that, for both countries, the results in Table C.2. are similar to the ones that we found in Table C.1, which are accounted for by the school fixed effects. However, we find no systematic mean differences within the clusters that were chosen for follow-up (Table C.3). That is, individuals reached and not reached within the communities that were chosen for the follow-up were very similar at baseline. To conclude, the balance checks presented in Tables C.1–C.3 show that, insofar as there are differences between the baseline PASEC sample and the panel subsample, they are driven by the geographical differences arising from the fact that only a subset of PASEC communities were included in the follow-up, and *not* due to differences between individuals that were reached and not reached within the selected communities. This finding applies for both countries.

Second, we estimate Inverse Probability Weighted (IPW) regressions, to account for these differences in the panel subsample and the full sample at baseline. These weights are obtained from a logistic regression and use a dummy variable denoting the probability of being in the panel sample as the dependent variable. This model contains a variety of household- and individual-level covariates from the full sample of the first round of data as covariates.[30] This specification is run using the baseline data, and the predicted probabilities are used as weights in the main regression to check their robustness to this adjustment. Tables C.4.a and C.4.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. A comparison of Tables 1.a and C.4.a shows that the results for the highest grade obtained in Senegal are consistent in sign, significance, and value, even after the aforementioned attrition adjustment. A comparison of Tables 1.b and C.4.b shows that the magnitudes are very similar in the case of Madagascar as well, and that most of the statistical significance levels also remain the same. The pattern of the results is similar for the test score outcome variables (comparing Tables 2a and 2b with C.4.a and

[30] Namely, the test scores of the second grade, gender, asset index, a school-level infrastructure index constructed with factor analysis, and the education level of the teacher. Observations with a missing weight have been given the average IPW weight.

C.4.b, columns 6–8). The fact that the results do not change considerably when adjustments are made for attrition and sample selection demonstrates the robustness of this relationship across the two countries, despite small differences in the samples between the full original sample from the PASEC surveys in the mid-1990s, and the long panel of cohort members that we were able to track over the 17-year interval in Senegal.

We do a similar analysis to study attrition from within the clusters chosen for follow-up. More specifically, we run the IPW regressions (described above) based on the weights from a logistic model, which estimates the probability of being in the panel sample, conditional on being in a community that was chosen for the follow-up. The results are presented in Tables C.5.a and C.5.b for Senegal and Madagascar, respectively. A comparison with Tables 1.a and 1.b shows that the results are robust to attrition in both countries—the coefficient estimates of the grade attained are very similar in both magnitude and significance. Finally, columns 6-8 in Tables C.5.a and C.5.b confirm also that the coefficient estimates of the test score variables are similar to those in Tables 2.a and 2.b. They show a similar pattern of math scores being more persistent than French scores in both countries. Overall, we can conclude that even though the selection of only a subset of the communities for follow-up introduced some differences across the panel and the full PASEC sample at baseline, we find that our results are robust to this sample selection and also to accounting for the fact that the follow-up only included a subset of the children in the communities that were visited again.

6.2 Lewbel (2012) corrections

In another robustness check, we complement our main IV strategy that is correcting for measurement error with a novel methodological approach. Lewbel (2012) described an empirical framework in which the IV strategy exploits heteroscedasticity, 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 to be able to apply this model: the presence of at least one 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 in which heteroscedasticity has been used as a source of identification (King, Sentana, and Wadhwani 1994; Heckman and Vytlacil 1998; Sentana and Fiorentini 2001; among others).

In our case, we present results using the pretest and the generated instruments as instrumental variables in our model.[31] The inclusion of an extra instrument allows us to conduct the Sargan-Hansen overidentification test. Under the null that the overidentifying 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 the Lewbel (2012) method allows us to conduct this test as the generated instruments make the model overidentified. These results can be

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

compared to the IV regression results in Tables 1 and 2, which use only the pretest as an instrument.

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 coefficient estimate of the test score on all the outcomes remains relatively stable (as compared to Tables 1.a and 2.a) and statistically significant at the 1 percent level. The results for Madagascar lose a little bit of statistical significance but still retain the correct sign and are of a 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 overidentifying restrictions is valid for all outcomes across both countries. Therefore, we conclude that our main IV specification, employed to correct for measurement error, is robust to the Lewbel (2012) instrumental variables strategy.

7. Conclusions

We find persuasive evidence of a strong association of childhood academic skills with those measured in early adult life in two francophone sub-Saharan African countries, Senegal and Madagascar. Using a production function framework for human capital, we find that composite math and French test scores, measured in the second grade, have large and significant positive associations with the highest grade attained, as well as math and French test scores in young adulthood in both countries. This enduring relationship is stronger in the case of Senegal, as compared to Madagascar; we also find that childhood math scores are stronger predictors of later-life cognitive outcomes, as compared to childhood 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 lifetime cumulative health, measured using adult height, is significantly associated with adult human capital, and whether its inclusion in the models affects the strength of the relationship between second-grade test scores and adult cognition. We only find statistically significant coefficient estimates of height in Senegal, although in Madagascar, the sign and magnitude of the coefficient is quite similar. Despite the inclusion of height, the aforementioned relationships between childhood test scores and later-life schooling and skills are persistent and found to operate 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 member was in the second grade, as well as school fixed effects. Parental inputs have an independent relationship with early adulthood outcomes in both countries. Household assets measured in second grade have a significant positive association with adulthood outcomes, even controlling for early test scores and other variables in Senegal and 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 to imply that children from relatively richer households are better able to sustain their better performance in second grade later into life.

Additionally, we discuss challenges that arose, due to the ambitions of examining test scores over a span of more than 15 years, including issues of attrition, as well the potential for measurement error. By employing techniques, such as estimating inverse probability weighted regressions, and employing the Lewbel (2012) instrumental variable method, we show that our results are robust to these potential issues.

While we do not directly address policies to improve cognitive outcomes of young adults, our results imply that childhood academic skills are a powerful predictor of young adulthood human capital outcomes. In turn, this implies that policies should target preschool-aged children who are lagging behind other children in terms of their skills and health status, and that such interventions are particularly important for young girls (and shorter individuals) who seem less able to catch up from early academic disadvantage.

References

Akresh, Richard, Emilie Bagby, Damien De Walque, and Harounan Kazianga. 2012a. "Child Ability and Household Human Capital Investment Decisions in Burkina Faso." *Economic Development and Cultural Change* 61 (1): 157–86.

Akresh, Richard, Emilie Bagby, Damien de Walque, and Harounan Kazianga. 2012b. *Child Labor, Schooling, and Child Ability (Presentation)*. Mathematica Policy Research.

Alderman, H., J. Behrman, H.-P. Kohler, J. A. Maluccio, and S. Watkins. 2001. "Attrition in Longitudinal Household Survey Data: Some Tests for Three Developing-Country Samples." *Demographic Research* 5: 79–124.

Alderman, H., J. Hoddinott, and B. Kinsey. 2006. "Long Term Consequences of Early Childhood Malnutrition." *Oxford Economic Papers* 58 (3): 450–74.

Andrabi, Tahir, Jishnu Das, Asim Ijaz Khwaja, and Tristan Zajonc. 2011. "Do Value-Added Estimates Add Value? Accounting for Dynamics." *American Economic Journal: Applied Economics* 3, no. 3 (2011): 29-54.

Angrist, J. D., P. A. Pathak, and C. R. Walters. 2013. Explaining Charter School Effectiveness. *American Economic Journal: Applied Economics* 5 (4): 1–27.

Aubery, F., and D. E. Sahn. 2014. "Cognitive Achievement Production in Madagascar: A Value-Added Model Approach." Technical report, Cornell University.

Azomahou, T. T., and E. A. Yitbarek. 2016. "Intergenerational Education Mobility in Africa: Has Progress Been Inclusive?" World Bank Policy Research Working Paper 7843, World Bank Group, Washington, DC.

Behrman, J. R., J. Hoddinott, J. A. Maluccio, E. Soler-Hampejsek, E. L. Behrman, R. Martorell,

M. Ramírez-Zea, and A. D. Stein. 2014. "What Determines Adult Cognitive Skills? Influences of Pre-School, School, And Post-School Experiences in Guatemala." *Latin American Economic Review* 23 (1), e4.

Behrman, Jere R., Whitney Schott, Subha Mani, Benjamin T. Crookston, Kirk Dearden, Le Thuc Duc, Lia CH Fernald, and Aryeh D. Stein. 2017. "Intergenerational Transmission of Poverty And Inequality: Parental Resources and Schooling Attainment and Children's Human Capital in Ethiopia, India, Peru, and Vietnam." *Economic Development and Cultural Change* 65 (4): 657–97.

Birnbaum, A. 1968. "Some Latent Trait Models and Their Use in Inferring an Examinee's Ability." In *Statistical Theories of Mental Test Scores*, edited by F. M. Lord, and M. R. Novick, 397–479. Reading, MA: Addison-Wesley.

Bossuroy, T., and D. Cogneau. 2013. "Social Mobility in Five African Countries." *Review of Income and Wealth* 59 (S1): S84–S110.

Bourne, V. J., H. C. Fox, I. J. Deary, and L. J. Whalley. 2007. "Does Childhood Intelligence Predict Variation in Cognitive Change in Later Life?" *Personality and Individual Differences* 42 (8): 1551–9.

Case, A., and C. Paxson. 2008. "Stature and Status: Height, Ability, and Labor Market Outcomes." *Journal of Political Economy* 116 (3): 499–532.

Case, A., and C. Paxson. 2010. "Causes and Consequences of Early-Life Health." *Demography* 47(1): S65–85.

Cunha, F., and J. Heckman. 2007. "The Technology of Skill Formation." *American Economic Review* 97 (2): 31–47.

Cunha, F., and J. J. Heckman. 2008. "Formulating, Identifying and Estimating the Technology of

Cognitive and Noncognitive Skill Formation.” *Journal of Human Resources* 43 (4): 738–82.

Cunha, F., J. J. Heckman, and S. M. Schennach. 2010. “Estimating the Technology of Cognitive and Noncognitive Skill Formation.” *Econometrica* 78 (3): 883–931.

Cunningham, A. E., and K. E. Stanovich. 1997. “Early Reading Acquisition and Its Relation to Reading Experience and Ability 10 Years Later.” *Developmental Psychology* 33 (6): 934–45.

Currie, Janet, and Tom Vogl. 2013. “Early-life Health and Adult Circumstance in Developing Countries.” *Annual Review of Economics.* 5 (1): 1–36.

Das, J., and T. Zajonc. 2010. “India Shining and Bharat Drowning: Comparing Two Indian States to the Worldwide Distribution in Mathematics Achievement.” *Journal of Development Economics* 92 (2): 175–87.

Deming, D. J. 2014. “Using School Choice Lotteries to Test Measures of School Effectiveness.” *American Economic Review* 104 (5): 406–11.

Deming, D. J., J. S. Hastings, T. J. Kane, and D. O. Staiger. 2014. “School Choice, School Quality, and Postsecondary Attainment.” *American Economic Review* 104 (3): 991–1013.

Dumas, C., and S. Lambert. 2011. “Educational Achievement and Socio-Economic Background: Causality and Mechanisms in Senegal.” *Journal of African Economies* 20 (1): 1–26.

Duncan, G. J., C. J. Dowsett, A. Claessens, K. Magnuson, A. C. Huston, P. Klebanov, L. S. Pagani, L. Feinstein, M. Engel, J. Brooks-Gunn, H. Sexton, K. Duckworth, and C. Japel. 2007. “School Readiness and Later Achievement.” *Developmental Psychology* 43 (6): 1428–46.

Duncan, G. J., and K. Magnuson. 2011. “The Nature and Impact of Early Achievement Skills, Attention Skills, and Behavior Problems." In *Whither Opportunity*, ed. G. J. Duncan, and Richard J. Murnane, 47–70. New York: Russell Sage Foundation.

Feinstein, L. 2003. "Inequality in the Early Cognitive Development of British Children in the 1970 Cohort." *Economica* 70 (277): 73–97.

Fiorini, M., and M. P. Keane. 2014. "How the Allocation of Children's Time Affects Cognitive and Noncognitive Development." *Journal of Labor Economics* 32 (4): 787–836.

Glewwe, Paul, Sofya Krutikova, and Caine Rolleston 2017. "Do Schools Reinforce or Reduce Learning Gaps between Advantaged and Disadvantaged Students? Evidence from Vietnam and Peru." *Economic Development and Cultural Change* 65 (4): 699–739.

Glick, P., J. C. Randrianarisoa, and D. E. Sahn. 2011. "Family Background, School Characteristics, and Children's Cognitive Achievement in Madagascar." *Education Economics* 19 (4): 363–96.

Glick, P., and D. E. Sahn. 2009. "Cognitive Skills among Children in Senegal: Disentangling the Roles of Schooling and Family Background." *Economics of Education Review* 28 (2): 178–88.

Glick, P., and D. E. Sahn. 2010. "Early Academic Performance, Grade Repetition, and School Attainment in Senegal: A Panel Data Analysis." *World Bank Economic Review* 24 (1): 93–120.

Grajeda, R., J. R. Behrman, R. Flores, J. A. Maluccio, R. Martorell, and A. D. Stein. 2005. "The Human Capital Study 2002–04: Tracking, Data Collection, Coverage, and Attrition." *Food and Nutrition Bulletin* 26 (2 Suppl. 1): S15–S24.

Hanushek, E. A. 2013. "Economic Growth in Developing Countries: The Role of Human Capital." *Economics of Education Review* 37: 204–212.

Hanushek, E. A., and L. Woessmann. 2008. “The Role of Cognitive Skills in Economic Development.” *Journal of Economic Literature* 46 (3): 607–68.

Hanushek, E. A., and L. Woessmann. 2012. “Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation.” *Journal of Economic Growth* 17 (4): 267–321.

Heckman, J. J., and S. Mosso. 2014. “The Economics of Human Development and Social Mobility.” *Annual Review of Economics* 6 (1): 689–733.

Heckman, J. J., J. Stixrud, and S. Urzua. 2006. “The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior.” *Journal of Labor Economics* 24 (3): 411–82.

Heckman, James, and Edward Vytlacil. 1998. “Instrumental Variables Methods for the Correlated Random Coefficient Model: Estimating the Average Rate of Return to Schooling When the Return is Correlated with Schooling.” *Journal of Human Resources* 33 (4): 974–87.

Helmers, C., and M. Patnam. 2011. “The Formation and Evolution of Childhood Skill Acquisition: Evidence from India.” *Journal of Development Economics* 95 (2): 252–66.

Jones, S., Y. Schipper, S. Ruto, and R. Rajani. 2014. “Can Your Child Read and Count? Measuring Learning Outcomes in East Africa.” *Journal of African Economies* 23 (5): 643–72.

Kane, T. J., D. F. McCaffrey, T. Miller, and D. O. Staiger. 2013. “Have We Identified Effective Teachers? Validating Measures of Effective Teaching Using Random Assignment.” Measures of Effective Teaching (MET) Project Research Paper, Bill and Melinda Gates Foundation.

King, Mervyn, Enrique Sentana, and Sushil Wadhwani. 1994. "Volatility and Links between National Stock Markets." *Econometrica: Journal of the Econometric Society* 62 (4): 901–33.

Ladd, Helen F., and Randall P. Walsh. 2002."Implementing Value-Added Measures of School Effectiveness: Getting the Incentives Right." *Economics of Education Review* 21 (1): 1–17.

LaFave, D., and D. Thomas. 2017. "Height and Cognition at Work: Labor Market Productivity in a Low Income Setting." *Economics and Human Biology* 25: 52–64.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business & Economic Statistics* 30 (1): 67–80.

Lundborg, Petter, Paul Nystedt, and Dan-Olof Rooth. 2014. "Height and Earnings: The Role of Cognitive and Noncognitive Skills." *Journal of Human Resources* 49 (1): 141–66.

Marchetta, Francesca, and Sahn, David E. 2016. "The Role of Education and Family Background in Marriage, Childbearing, and Labor Market Participation in Senegal." *Economic Development and Cultural Change* 64 (2): 369–403.

Martorell, R. and J.-P. Habicht. 1986. "Growth in Early Childhood in Developing Countries." In *Human Growth: A Comprehensive Treatise*, Vol. 3: *Methodology. Ecological, Genetic, and Nutritional Effects on Growth*, 2nd ed., ed. F. Falkner, and J.M. Tanner, 241–62. New York: Plenum Press.

Michaelowa, K. 2001. "Primary Education Quality in Francophone Sub-Saharan Africa: Determinants of Learning Achievement and Efficiency Considerations." *World Development* 29 (10): 1699–716.

PASEC. 2016. Programme d'analyse des systèmes éducatifs de la Confemen. http://www.pasec.confemen.org/

Persico, Nicola, Andrew Postlewaite, and Dan Silverman. 2004. "The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height." *Journal of Political Economy* 112 (5): 1019–53.

Schady, Norbert, Jere Behrman, Maria Caridad Araujo, Rodrigo Azuero, Raquel Bernal, David Bravo, Florencia Lopez-Boo, Karen Macours, Daniela Marshall, Christina Paxson , and Renos Vakis. 2015. "Wealth Gradients in Early Childhood Cognitive Development in Five Latin American Countries." *Journal of Human Resources* 50 (2): 446–63.

Sentana, Enrique, and Gabriele Fiorentini. 2001. "Identification, Estimation and Testing of Conditionally Heteroskedastic Factor Models." *Journal of Econometrics* 102 (2): 143–64.

Singh, A. 2017. "Learning More with Every Year: School Year Productivity and International Learning Divergence." Presented at the Institute for International Economic Studies, Stockholm University, Stockholm. https://pp-prod-admin.it.su.se/polopoly_fs/1.316990.1485330058!/menu/standard/file/JMP_IntLearningGaps.pdf

Singh, R., and P. Mukherjee. 2016. "Determinants of Successful Completion of Secondary Education: Evidence from Young Lives, Andra Pradesh." Young Lives Working Paper. No. 143, Young Lives, Oxford Department of International Development (ODID), University of Oxford, Oxford.

Sohn, Kitae. 2015. "The Height Premium in Indonesia." *Economics and Human Biology* 16: 1–15.

Spears, D. 2012. "Height and Cognitive Achievement among Indian Children." *Economics and*

Human Biology 10 (2): 210–19.

Strauss, Richard S. 1997 "Effects of the Intrauterine Environment on Childhood Growth." *British Medical Bulletin* 53 (1): 81–95.

Tanner, J. M. 1979. "A Concise History of Growth Studies from Buffon to Boas." In *Human Growth*, Vol. 3 Neurobiology and Nutrition, ed. Frank Falkner and J. M. Tanner, 515–93. Boston: Springer.

Todd, P. E., and K. I. Wolpin. 2003. "On the Specification and Estimation of the Production Function for Cognitive Achievement." *The Economic Journal* 113 (485): F3–F33.

Todd, P. E., and K. I. Wolpin. 2007. "The Production of Cognitive Achievement in Children: Home, School, and Racial Test Score Gaps." *Journal of Human Capital* 1 (1): 91–136.

Vogl, T. S. 2014. "Height, Skills, and Labor Market Outcomes in Mexico." *Journal of Development Economics* 107: 84–96.

World Bank. 2016. World Bank database. www.databank.worldbank.org

Tables

Table 1: Highest grade completed as a function of childhood composite French and math scores

a. Senegal

	(1)	(2)	(3)	(4)	(5)
	No School FE	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS	IV
Second-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 second 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

	(1)	(2)	(3)	(4)	(5)
	No school FE	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS	IV
Second-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 second 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: Adult test scores as a function of childhood composite French and math scores

a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)
	Math and French	Math and French	Math	Math	French	French
VARIABLES	OLS	IV	OLS	IV	OLS	IV
Second-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 second 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

	(1)	(2)	(3)	(4)	(5)	(6)
	Math and French	Math and French	Math	Math	French	French
VARIABLES	OLS	IV	OLS	IV	OLS	IV
Second-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 second 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: Adult outcomes as a function of childhood math scores

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
Second-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 second 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Grade	Grade	Composite	Composite	Math	Math	French	French
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Second-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: Adult outcomes as a function of childhood French scores

a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Grade	Grade	Composite	Composite	Math	Math	French	French
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Second-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 second 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Grade	Grade	Composite	Composite	Math	Math	French	French
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Second-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 second 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 Education		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
Second-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 Education		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
Second-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	IV	IV	IV	IV	IV	IV	IV
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Second-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	IV	IV	IV	IV	IV	IV	IV
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Second-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	IV	IV	IV	IV	IV	IV	IV
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Second-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	IV	IV	IV	IV	IV	IV	IV
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Second-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
Second-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.

Table 9: Robustness Check—Using average of second-grade pretest and posttest scores as an independent variable

a. Senegal

VARIABLES	(1) Highest Grade School FE OLS	(2) Composite Score School FE OLS	(3) Math Score School FE OLS	(4) French Score School FE OLS
Second-grade composite score, pretest and posttest average	1.612***	0.328***	0.608***	0.271***
	(0.237)	(0.058)	(0.093)	(0.055)
Height 2012	0.048**	0.008	0.014*	0.007
	(0.023)	(0.006)	(0.008)	(0.006)
Assets 2nd grade	0.484	0.136*	0.225**	0.148**
	(0.311)	(0.074)	(0.113)	(0.072)
Age 2012	-0.525***	-0.066***	-0.116***	-0.062***
	(0.082)	(0.021)	(0.030)	(0.020)
Female	0.384	0.092	-0.024	0.117
	(0.416)	(0.109)	(0.156)	(0.105)
Mother's education (Dummy)	0.482	-0.057	-0.064	-0.006
	(0.611)	(0.148)	(0.216)	(0.139)
Father's education (Dummy)	0.299	0.025	0.032	0.053

	(0.529)	(0.130)	(0.182)	(0.129)
Observations	447	381	447	381
R-squared	0.390	0.321	0.302	0.316

b. Madagascar

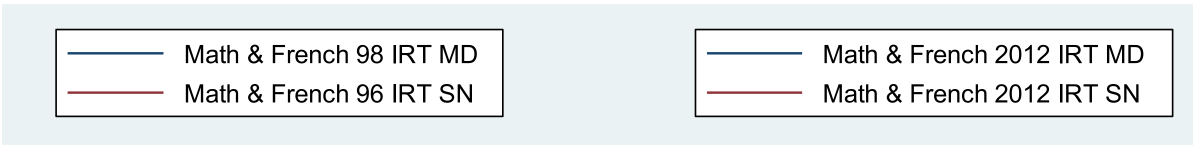
	(1)	(2)	(3)	(4)
	Highest Grade	Composite Score	Math Score	French Score
	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS
Second-grade composite score, pretest and posttest average	0.885***	0.206***	0.221***	0.175**
	(0.283)	(0.079)	(0.082)	(0.084)
Height 2012	0.018	0.004	-0.002	0.004
	(0.020)	(0.006)	(0.006)	(0.006)
Assets 2nd grade	-0.063	0.061	0.085	0.017
	(0.244)	(0.068)	(0.066)	(0.081)
Mother's education	0.083	0.024*	0.022	0.029**
	(0.053)	(0.014)	(0.016)	(0.014)
Father's education	0.137***	0.017	-0.003	0.035***

	(0.049)	(0.012)	(0.014)	(0.012)
Age 2012	-0.724***	-0.134***	-0.123***	-0.103***
	(0.121)	(0.036)	(0.037)	(0.038)
Female	-0.118	-0.035	-0.155	0.064
	(0.329)	(0.101)	(0.102)	(0.107)
Observations	333	310	318	312
R-squared	0.502	0.494	0.382	0.531

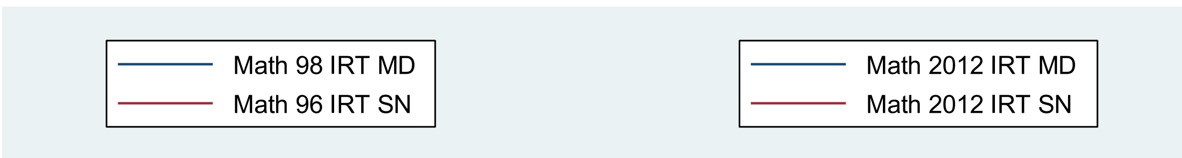
Notes: The main independent variable of interest is the second-grade average of pretest and posttests. Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. All the specifications include school-level fixed effects. All test scores are constructed using country-specific IRT. 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. Heteroscedasticity-robust standard errors in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Figure legends

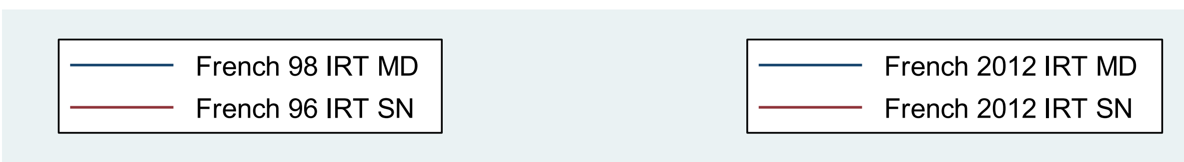
Legend Figure 1a: Cumulative distribution functions of composite scores



Legend Figure 1b: Cumulative distribution functions of math



Legend 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

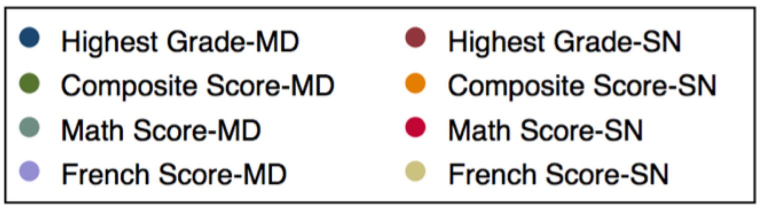
Notes: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round. Kernel: epanechnikov, degree=0, bandwidth=0.2, pwidth=0.65

Figure 3: Height and composite test scores in 2012

a. Madagascar

Notes: Kernel: epanechnikov, degree=0, bandwidth=0.03, pwidth=1

Figure 4: Coefficient estimate comparison across countries



Notes: Point estimates with 95 per cent coefficient interval. All coefficient estimates are for the posttest variable in the full OLS model. The coefficient for the model with highest grade attained as the outcome variable are from Table 1.a (Senegal) and 1.b (Madagascar), column 4. The coefficients for the models with test score variables as outcome variables are from Table 2a. (Senegal) and 2.b (Madagascar) columns 1, 3, and 5 for composite, math, and French, respectively.

Figures

Figure 1a: Cumulative distribution functions of composite scores

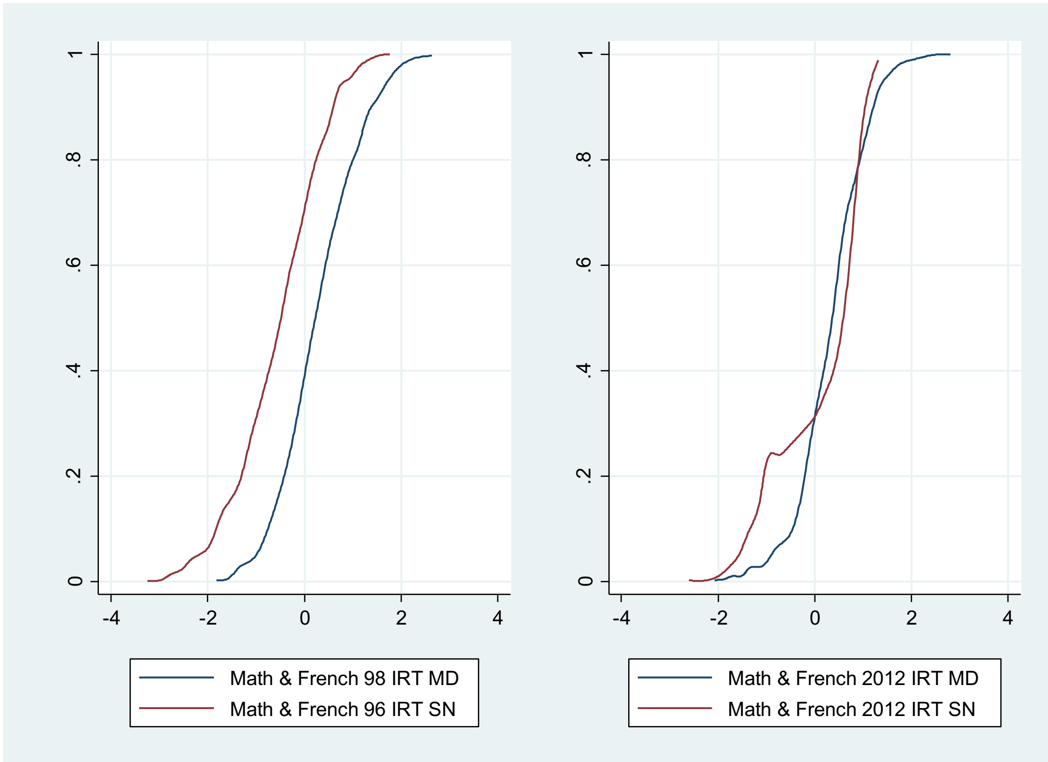


Figure 1b: Cumulative distribution functions of math

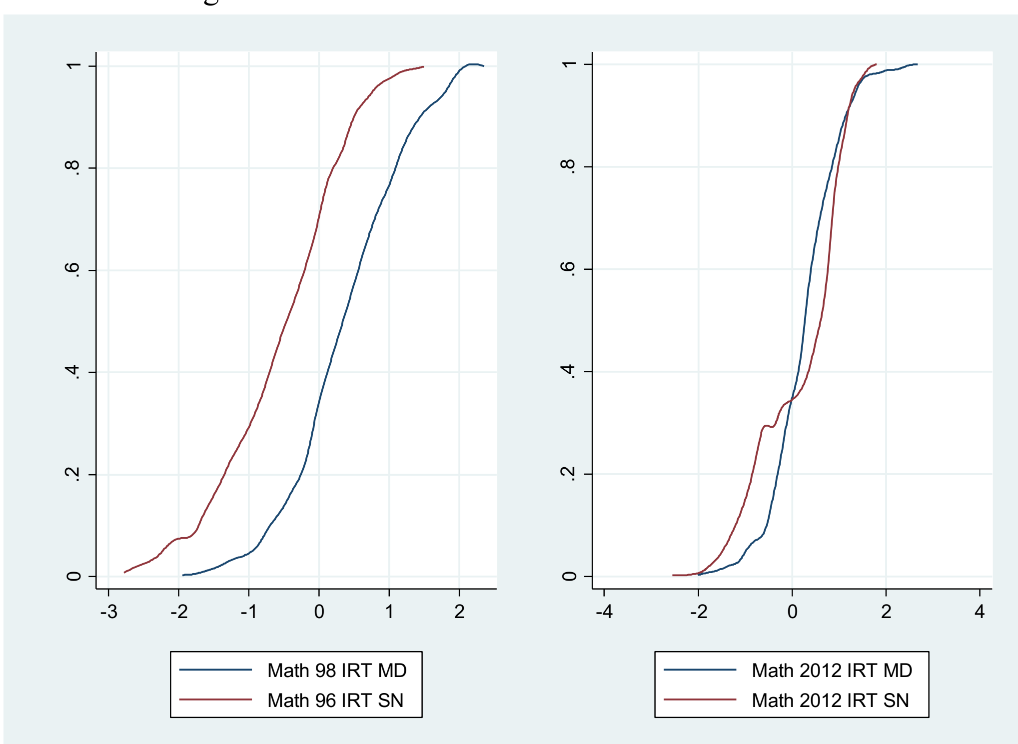
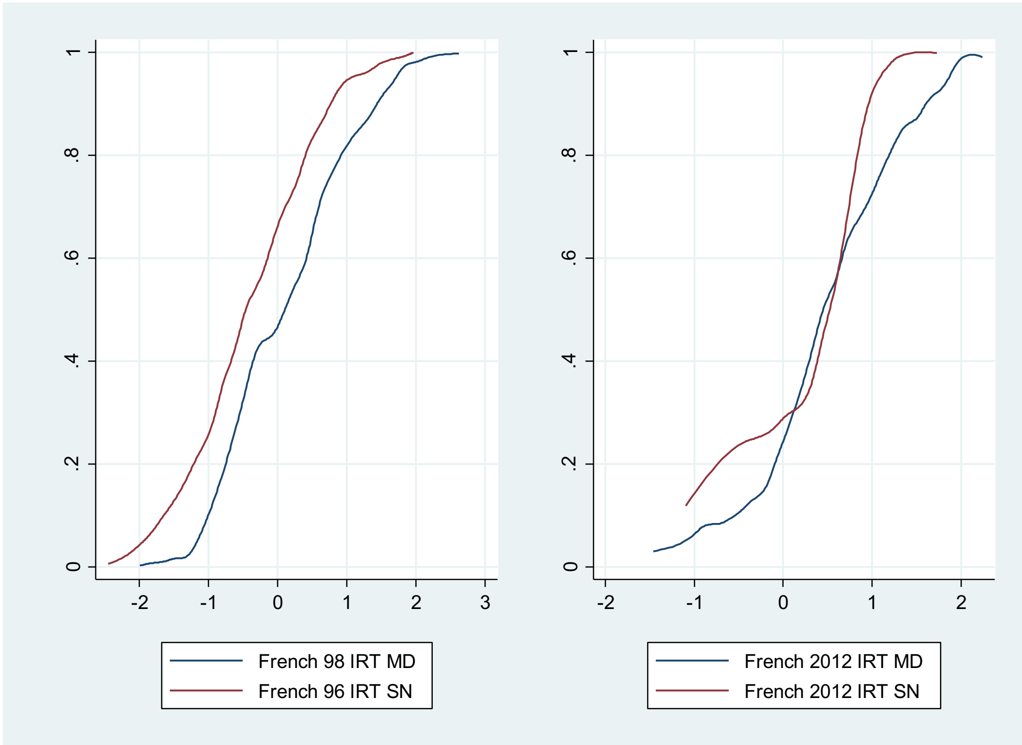
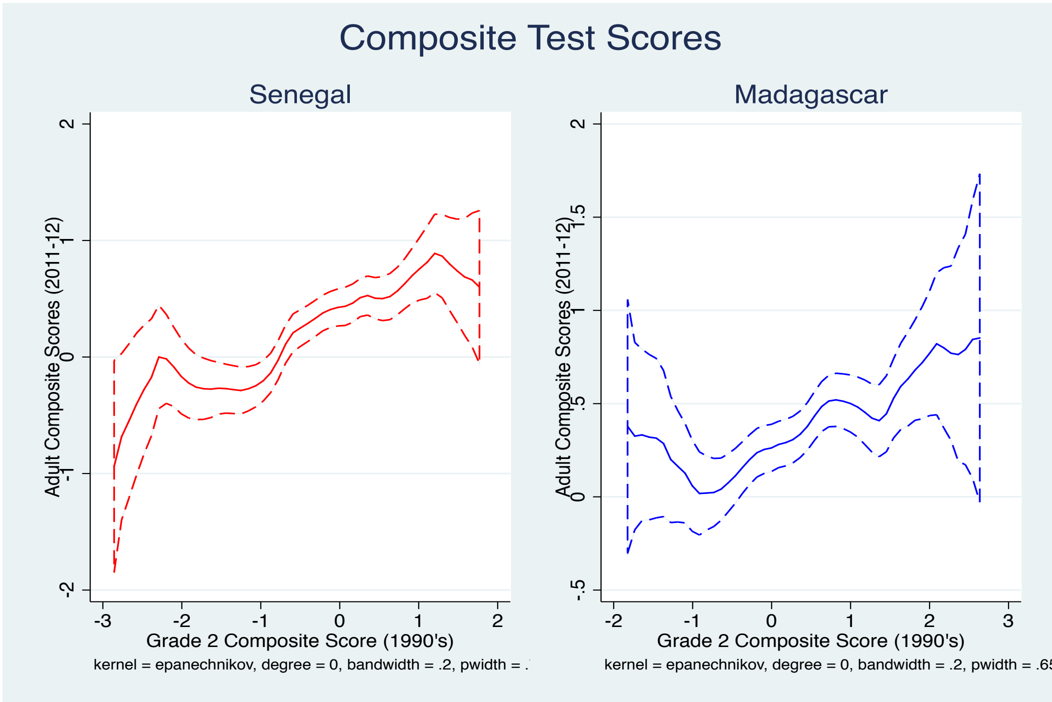


Figure 1c: Cumulative distribution functions of French



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

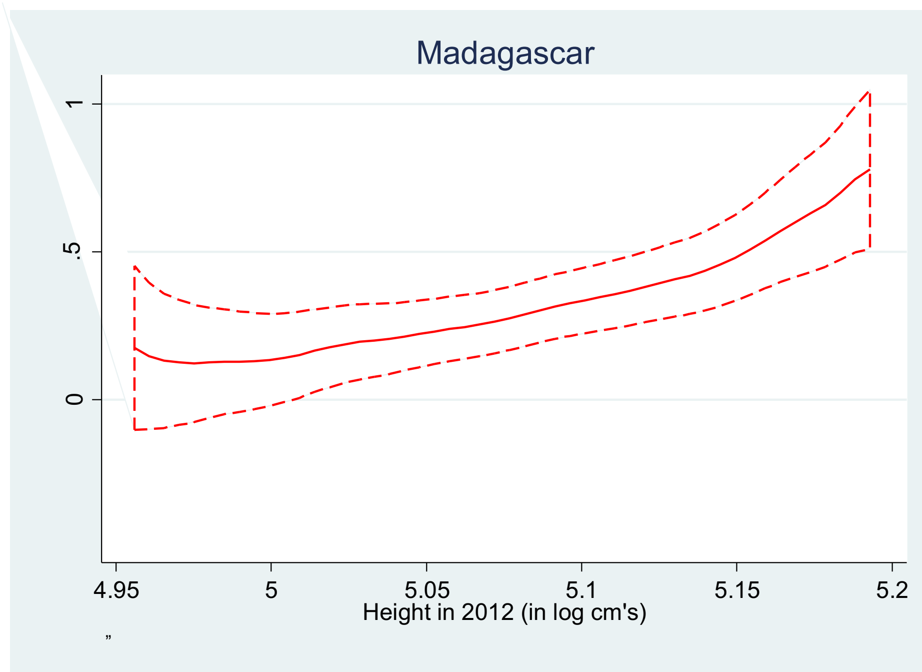
Figure 2: Learning progress curves composite scores



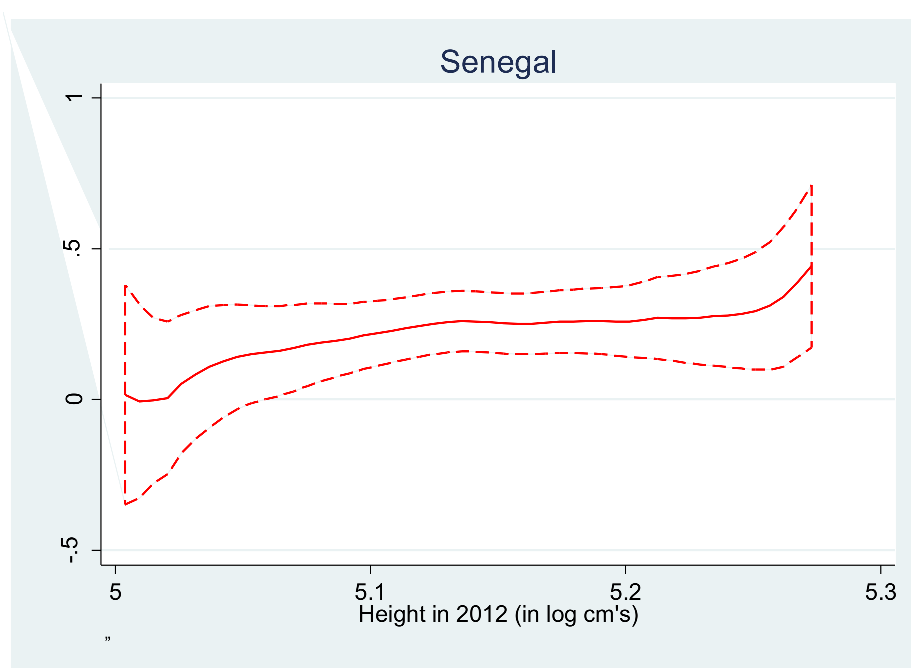
Notes: Test scores used are jointly estimated for each round for both countries using IRT. They are comparable across countries within each round. Kernel: epanechnikov, degree=0, bandwidth=0.2, pwidth=0.65

Figure 3: Height and composite test scores in 2012

b. Madagascar

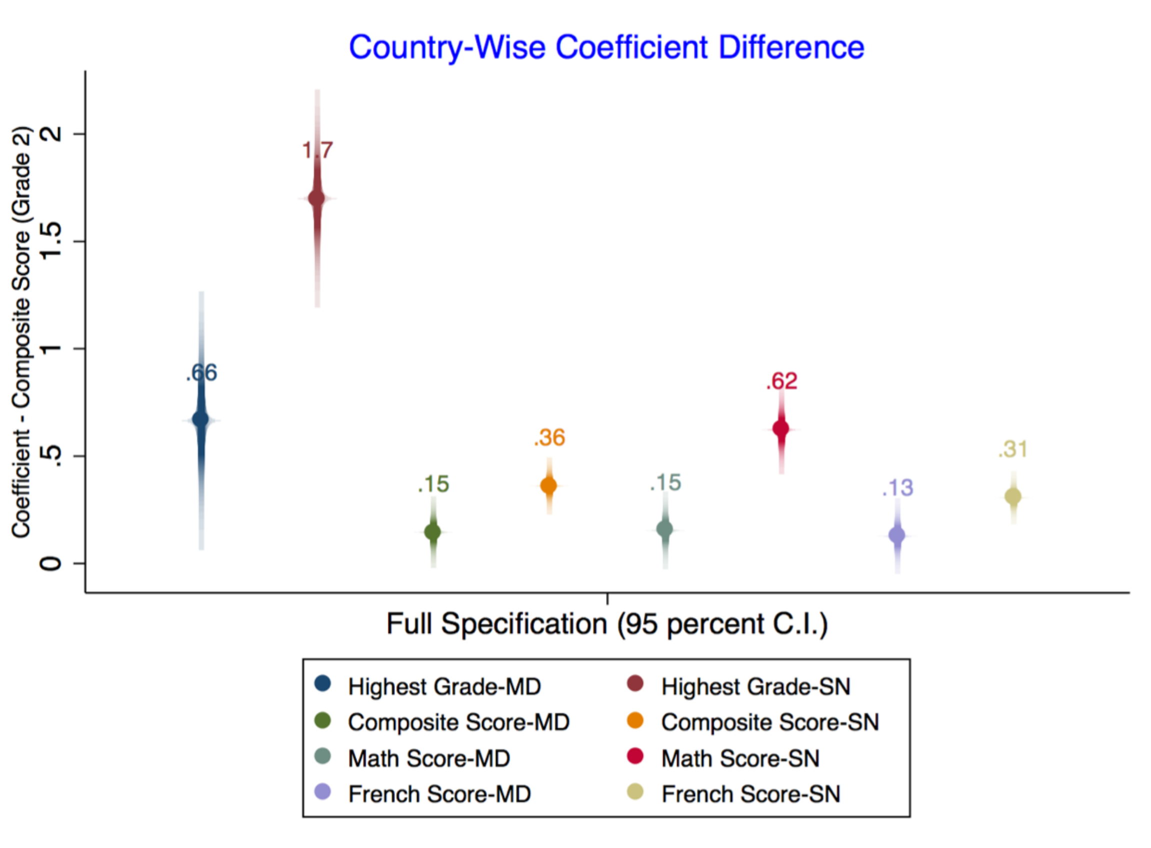


c. Senegal



Notes: Kernel: epanechnikov, degree=0, bandwidth=0.03, pwidth=1

Figure 4: Coefficient estimate comparison across countries



Notes: Point estimates with 95 per cent coefficient interval. All coefficient estimates are for the posttest variable in the full OLS model. The coefficient for the model with highest grade attained as the outcome variable are from Table 1.a (Senegal) and 1.b (Madagascar), column 4. The coefficients for the models with test score variables as outcome variables are from Table 2a. (Senegal) and 2.b (Madagascar) columns 1, 3, and 5 for composite, math, and French, respectively.

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 Programme for International Student Assessment (PISA), Trends in International Mathematics and Science Study (TIMMS), and Graduate Record Examination (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); and 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:

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

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 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 1995–6 and in Madagascar in 1997–8 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 “pretest” and “posttest,” 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.

Table A.1 below reports which data sets are similar across space and time. In the regressions we use IRT scores that are calculated for each country; 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). Table A.1 below explains what the similarities are in different tests across time and space. Notice that tests administered in the second grade are different from those administered in 2012.

Table A.1. Comparison of tests' questions

		Madagascar (MD)		Senegal (SN)	
		Math	*French*	*Math*	*French*
Children	*Second grade pretest*	No overlap with other tests	No overlap with other tests	Partially same as posttest in SN and posttest in MD.	Same as post-test in SN and posttest in MD.
	Second grade posttest	Partially same as pre-test in SN, same as posttest in SN	Same as posttest and pretests in SN	Partially same as pretest in SN, same as posttest in MD	Same as pretest in SN and posttest in MD
Adults	*2012*	Partially same in test as 2012 SN	Partially same test as 2012 SN	Partially same test as 2012 MD	Partially same test as in 2012 MD

Notes: The rows indicate the timing of the test and the columns the country of the test and whether the test is math or French. Each cell includes an explanation of whether any test of the same discipline in the other country was fully the same (exactly the same test questions), partially same (some overlap in the test questions), or completely different (such that no overlap in test questions between countries).

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 second grade (pre)	405	-0.09	0.84	-1.47	1.89
French second grade (post)	405	-0.12	0.86	-2.14	2.19
Math second grade (pre)	405	-0.09	0.92	-1.69	2.60
Math second grade (post)	405	-0.08	0.93	-2.59	2.22
Math and French second grade (post)	405	-0.11	0.88	-2.65	2.16
Math and French second 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’s education (dummy)	405	0.09	0.28	0.00	1.00
Father’s education (dummy)	405	0.18	0.38	0.00	1.00
Assets second 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 second grade (pre)	333	0.10	1.00	-2.11	2.70
French second grade (post)	333	-0.09	0.99	-2.36	2.51
Math second grade (pre)	333	0.06	0.96	-2.79	1.80
Math second grade (post)	333	0.01	0.89	-2.42	2.15
Math and French second grade (post)	333	-0.04	0.94	-2.43	2.54
Math and French second 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 second 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 measured in 2012. Household asset index is constructed using factor analysis.

C. Sample and attrition

Sample

In Madagascar, the *Programme d'Analyse des Systemes Educatifs de la CONFEMEN* conducted a school-based testing program of 20 second graders in 119 randomly selected schools from 119 communities (PASEC 2016).[32] In 2003, and again in 2012, a subset of schools, consisting of 44 of the original 119 schools, were randomly selected[33] to be resurveyed. Within those 44 schools, we randomly selected 15 of the original second-grade test-takers to be included in the follow-up surveys. Thus, we targeted data collection for 660 individuals in 2012. We were only able to locate 333 of those individuals. This yields an attrition rate of just under 50 percent between 1997–2012.

Analogous to Madagascar, in the 2003 and 2012 surveys in Senegal, a subset of 57 schools (out of a total of 94 surveyed in the previous round) were chosen to be surveyed. In each of these schools, 15 students were chosen to be a part of the sample. This led to a total target sample of 855 observations, of which we have data on 447, which implies an attrition of approximately 48 percent.

---

[32] All except one of the schools had 20 students chosen for the test from the 2nd grade; one school had only 17 children taking the test, resulting in a total sample size of 2,377 individuals.

[33] In 2003 we originally targeted sampling 47 schools in Madagascar, but political insurgency precluded us from visiting 3 of those schools in 2012.

Tests for sample selection and attrition

We run three balance checks for sample selection of communities and of attrition in Tables C.1–C.3. In Table C.1 we present mean comparisons between the individuals in the full PASEC survey conducted in the mid-1990s with those that we successfully found in 2012. There are some differences across the two groups in both countries, which arise for two potential reasons. The first is that only a subset of the initial sample schools were selected, as discussed previously. And even though they were chosen randomly, the fact that less than half the original schools were selected to be resurveyed would be expected to contribute to sample differences. The second reason is attrition of individuals among the sample schools selected. Below we probe these differences further and check whether they are driven by the communities selected for follow-up (Table C.2) or by systematic attrition within these communities (Table C.3).

In Table C.2, we check for systematic differences arising from the selection of communities for follow-up. We compare the baseline characteristics of all the cohort members in the 47 Malagasy and 57 Senegalese communities that were selected for the follow-up with the characteristics of the students that were in the communities that were not chosen for the follow-up.

Next, in Table C.3 we look for attrition-induced differences in baseline characteristics by checking for balance *within* the 47 (57) communities that were chosen for follow-up in

Madagascar (Senegal); that is, we compare the people that were followed within those clusters in 2012 with those that were in the clusters, but were not surveyed in 2012. In other words, we split the sample into two parts: one is comprised of the persons that were part of the cohort found in 2012 (333 in Madagascar and 447 in Senegal), and second, those that were not (607 in Madagascar and 686 in Senegal).

Results in tables C.2 and C.3 suggest that although there are systematic differences between the clusters chosen for follow-up and those that were not, there are limited differences in the attrited and non-attrited samples within these clusters. Since our paper makes limited claims regarding the representativeness of the sample under consideration, attrition does not seem to have a major impact on the analysis. Even so, we conduct Inverse Probability Weighted regressions (IPW) to correct for any attrition bias in our study, which we next discuss.

Robustness checks of the main results for sample selection and attrition

To check for sample selection and attrition-related biases in our analysis, we estimate two sets of Inverse Probability Weighted regressions. In the first version, we use all observations in the subset of 47 (57) communities in Madagascar (Senegal) that were chosen for follow-up to calculate the weights assigned to each observation (Tables C.4a and C.4b). Another approach we employ involves using all observations in the baseline (1995 Senegal, 1997 Madagascar) data set to estimate the observations' weights. These results are presented in Tables C.5.a and C.5.b. These checks essentially confirm that our findings are robust to both attrition and sample selection. This holds even when comparing the full PASEC sample with the 2012 sample, regardless of the fact that only a subset of communities was targeted for followed-up in our study.

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

a. Senegal 1996–97

	Not panel		Panel		
	mean	*n*	mean	*n*	Difference
French second grade (pre)	0.02	1424	-0.07	448	0.09^{*}
French second grade (post)	0.02	1424	-0.08	448	0.11^{**}
Math second grade (pre)	0.02	1424	-0.08	448	0.11^{**}
Math second grade (post)	0.01	1424	-0.07	448	0.08
Math and French second grade (pre)	0.02	1424	-0.05	448	0.07
Math and French second grade (post)	0.02	1424	-0.08	448	0.10^{**}
Assets second grade	0.09	1427	-0.29	448	0.38^{***}
Female	0.46	1425	0.41	448	0.05^{*}
Age second grade	8.28	1407	8.33	444	-0.05
Teacher education index	-0.06	1335	0.08	400	-0.14^{*}
Teacher experience (yrs)	12.70	1420	13.48	435	-0.78
Director experience (yrs)	11.59	1397	11.08	418	0.51

b. Madagascar 1997–98

	Not panel		Panel		
	mean	*n*	mean	*n*	Difference
French second grade (pre)	-0.01	2044	0.10	333	-0.11*
French second grade (post)	0.02	2044	-0.09	333	0.11*
Math second grade (pre)	-0.01	2044	0.06	333	-0.06
Math second grade (post)	0.01	2044	0.01	333	-0.00
Math and French second grade (pre)	-0.01	2044	0.07	333	-0.08
Math and French second grade (post)	0.01	2044	-0.04	333	0.06
Female	0.51	2005	0.53	331	-0.03
Age second grade	8.74	1919	8.21	324	0.53***
Assets second grade	0.02	2044	-0.08	333	0.10**
Teacher education index	-0.04	1881	0.02	316	-0.06
Teacher experience (yrs)	14.44	1970	13.65	327	0.79
Director experience (yrs)	12.30	1954	13.12	323	-0.82

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. Mother's and father's education were not measured at baseline, but in 2012; hence, they are not reported in this table. Household asset index is constructed using factor analysis. Teacher education index is constructed using factor analysis. The variable consists of variables denoting the education level of the teacher, whether they have formal teaching training, and whether they have done any internships. Teacher's and director's experience variables denote the years of experience they have been a teacher and a school director, respectively.

TABLE C.2. Mean comparison across clusters chosen for follow-up and full sample of students at baseline

a. Senegal

	Clusters not in follow-up	*n*	Clusters in follow-up	*n*	Difference
French 2nd grade (pre)	0.07	738	-0.04	1134	0.11***
French 2nd grade (post)	0.15	738	-0.10	1134	0.25***
Math 2nd grade (pre)	0.12	738	-0.08	1134	0.21***
Math 2nd grade (post)	0.14	738	-0.10	1134	0.23***
French–math 2nd grade (post)	0.16	738	-0.11	1134	0.27***
French–math 2nd grade (pre)	0.12	738	-0.08	1134	0.20***
Teacher's education	12.72	718	12.92	1077	-0.20*
School infrastructure 2nd grade	0.28	738	-0.13	1097	0.41***
Assets 2nd grade	0.45	738	-0.29	1137	0.74***
Female 1995–96	0.49	738	0.42	1135	0.07***
Age 2nd grade	8.29	720	8.30	1131	-0.01
Teacher education (PCA)	-0.25	698	0.12	1037	-0.38***

Teacher experience (yrs)	14.22	738	12.01	1117	2.21^{***}
Director experience (yrs)	12.96	738	10.45	1077	2.52^{***}

b. Madagascar

	Clusters not in follow-up	n	Follow-up clusters	n	Difference
French 2nd grade (pre)	-0.02	1437	0.03	940	-0.04
French 2nd grade (post)	0.07	1437	-0.10	940	0.17***
Math 2nd grade (pre)	-0.03	1437	0.06	940	-0.09**
Math 2nd grade (post)	0.02	1437	-0.02	940	0.04
Math–French 2nd grade (pre)	-0.02	1437	0.04	940	-0.06
Math–French 2nd grade (post)	0.06	1437	-0.08	940	0.14***
Female	0.49	1409	0.55	927	-0.06***
Age second grade	8.61	1349	8.75	894	-0.14*
Assets 2nd grade	0.03	1437	-0.03	940	0.06
Teacher education index	-0.04	1317	-0.02	880	-0.02
Teacher experience (yrs)	14.60	1377	13.91	920	0.68*
Director experience (yrs)	12.29	1377	12.60	900	-0.31

Notes: Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. The sample consists of all the individuals in the 199 communities in Senegal and 47 in Madagascar that were chosen for the follow-up study, splitting between those in the panel and not in the panel. All test scores are constructed using country-specific IRT. Mother's and father's education were not measured at baseline, but in 2012; hence, they are not reported in this table. Household asset index is constructed using factor analysis. Teacher education index is constructed using factor analysis. The variable consists of variables denoting the education level of the teacher, whether they have formal teaching training, and whether they have done any internships. Teacher's and director's experience variables denote the years of experience they have been a teacher or a school director, respectively.

Table C.3 Mean comparison within clusters that were chosen for follow-up: individuals reached (panel) and not reached (not in panel) at baseline

a. Senegal

	Not in panel	*n*	Panel	*n*	Difference
French 2nd grade pre	-0.03	686	-0.07	448	0.04
French 2nd grade post	-0.11	686	-0.08	448	-0.03
Math 2nd grade pre	-0.08	686	-0.08	448	-0.00
Math 2nd grade post	-0.12	686	-0.07	448	-0.05
French–Math 2nd grade post	-0.13	686	-0.08	448	-0.05
French–Math 2nd grade pre	-0.09	686	-0.05	448	-0.04
Teacher's education	12.99	657	12.80	420	0.18
School infrastructure 2nd grade	-0.11	676	-0.15	421	0.04
Assets 2nd grade	-0.29	689	-0.29	448	-0.00
Female 1995–96	0.43	687	0.41	448	0.02
Age 2nd grade	8.28	687	8.33	444	-0.06
Teacher education index	0.15	637	0.08	400	0.08
Teacher experience (yrs)	11.07	682	13.48	435	-2.41^{***}
Director experience (yrs)	10.05	659	11.08	418	-1.02^{**}

b. Madagascar

	Not in panel	*n*	Panel	*n*	Difference
French 2nd grade (pre)	-0.01	607	0.10	333	-0.10
French 2nd grade (post)	-0.10	607	-0.09	333	-0.01
Math 2nd grade (pre)	0.06	607	0.06	333	-0.00
Math 2nd grade (post)	-0.03	607	0.01	333	-0.04
Math–French 2nd grade (pre)	0.02	607	0.07	333	-0.05
Math–French 2nd grade (post)	-0.09	607	-0.04	333	-0.05
Female	0.55	596	0.53	331	0.02
Age second grade	9.05	570	8.21	324	0.84^{***}
Assets 2nd grade	-0.00	607	-0.08	333	0.08
Teacher education index	-0.05	564	0.02	316	-0.07
Teacher experience (yrs)	14.06	593	13.65	327	0.41
Director experience (yrs)	12.31	577	13.12	323	-0.81

Notes: Second grade children were surveyed in 1995–96 in the case of Senegal and 1997–98 in Madagascar. All test scores are constructed using country-specific IRT. Mother's and father's education were not measured at baseline, but in 2012; hence, they are not reported in this table. Household asset index is constructed using factor analysis. Teacher education index is constructed using factor analysis. The variable consists of variables denoting the education level of the teacher, whether they have formal teaching training, and whether they have done any internships. Teacher's and director's experience variables denote the years of experience they have been a teacher or a school director, respectively.

Table C.4: Grade completed and test scores in 2012 as a function of second- grade composite French and math scores: Inverse Probability Weights using the full PASEC baseline sample

a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade	Grade	Grade	Grade	Grade	Composite	Math	French
	No School FE	School FE	School FE	School FE	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Math and French 2nd grade (post)	1.801***	2.006***	1.927***	1.886***	1.639***	0.284***	0.599***	0.227***
	(0.194)	(0.213)	(0.196)	(0.197)	(0.328)	(0.070)	(0.118)	(0.069)
Height 2012				0.038	0.041*	0.007	0.014*	0.007
				(0.023)	(0.022)	(0.005)	(0.008)	(0.005)
Assets 2nd grade			0.412	0.407	0.465	0.150**	0.205*	0.162***
			(0.310)	(0.309)	(0.296)	(0.064)	(0.106)	(0.063)
Mother’s education (dummy)			0.644	0.484	0.490	-0.014	0.013	0.033
			(0.632)	(0.658)	(0.611)	(0.121)	(0.189)	(0.121)

Father's education (dummy)			0.186	0.149	0.140	-0.017	-0.026	0.018
			(0.551)	(0.551)	(0.514)	(0.108)	(0.164)	(0.111)
Age 2012			-0.472***	-0.477***	-0.480***	-0.058***	-0.113***	-0.056***
			(0.083)	(0.083)	(0.076)	(0.018)	(0.028)	(0.018)
Female			0.099	0.471	0.439	0.101	0.019	0.127
			(0.372)	(0.421)	(0.395)	(0.091)	(0.142)	(0.089)
Observations	447	447	447	447	447	381	447	381
R-squared	0.168	0.377	0.430	0.435	0.259	0.189	0.218	0.165
F					10.86	4.696	8.911	3.781
widstat					204.7	194.7	204.7	194.7

b. Madagascar

VARIABLES	(1) Grade No School FE OLS	(2) Grade School FE OLS	(3) Grade School FE OLS	(4) Grade School FE OLS	(5) Grade School FE IV	(6) Composite School FE IV	(7) Math School FE IV	(8) French School FE IV
Math and French 2nd grade (post)	0.951***	0.385	0.417	0.422	1.311**	0.352**	0.416***	0.243
	(0.244)	(0.318)	(0.277)	(0.277)	(0.541)	(0.148)	(0.161)	(0.153)
Height in 2012				0.027	0.028	0.003	-0.004	0.007
				(0.027)	(0.024)	(0.007)	(0.006)	(0.008)
Assets 2nd grade			-0.020	-0.009	-0.020	0.037	0.094	-0.029
			(0.316)	(0.317)	(0.319)	(0.083)	(0.073)	(0.103)
2012 age (in years)			-0.726***	-0.729***	-0.766***	-0.137***	-0.108***	-0.120***
			(0.163)	(0.160)	(0.150)	(0.042)	(0.041)	(0.046)

Female (=1)			-0.448	-0.218	-0.186	-0.086	-0.210**	0.086
			(0.360)	(0.402)	(0.365)	(0.106)	(0.105)	(0.122)
Mother’s education			0.103*	0.097*	0.078	0.019	0.018	0.028*
			(0.057)	(0.057)	(0.055)	(0.015)	(0.017)	(0.014)
Father’s education			0.093	0.087	0.088	0.020	0.003	0.032**
			(0.061)	(0.061)	(0.058)	(0.014)	(0.016)	(0.014)
Observations	333	333	333	333	333	310	318	312
R-squared	0.083	0.411	0.514	0.516	0.144	0.048	-0.006	0.095
F					7.047	3.758	2.915	3.824
widstat					65.80	43.28	44.24	42.84

Notes: All regressions weighted with inverse probability weights using the full PASEC sample. Second grade denotes 1995–96 in the case of Senegal and 1997–98 in Madagascar. The sample sizes for the inverse probability weights are 1875 in Senegal, and 2,377 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 C.5: Grade completed and test scores in 2012 as a function of second-grade composite French and math scores: Inverse Probability Weights using the subset of communities chosen for follow-up

a. Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade	Grade	Grade	Grade	Grade	Composite	Math	French
	No School FE	School FE	School FE	School FE	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Math and French 2nd grade (post)	1.671***	1.842***	1.788***	1.754***	1.465***	0.279***	0.568***	0.223***
	(0.188)	(0.206)	(0.195)	(0.197)	(0.309)	(0.068)	(0.116)	(0.066)
Height 2012				0.041*	0.044**	0.007	0.011	0.006
				(0.023)	(0.022)	(0.005)	(0.008)	(0.005)
Assets 2nd grade			0.448	0.441	0.505*	0.157**	0.236**	0.167***
			(0.312)	(0.311)	(0.297)	(0.066)	(0.107)	(0.064)

Mother's education (dummy)			0.724	0.572	0.561	-0.025	0.004	0.026
			(0.604)	(0.617)	(0.579)	(0.132)	(0.201)	(0.125)
Father's education (dummy)			0.311	0.252	0.255	0.022	0.027	0.051
			(0.527)	(0.523)	(0.488)	(0.116)	(0.166)	(0.116)
			-	-	-		-	-
Age 2012			0.470***	0.474***	0.474***	-0.058***	0.105***	0.054***
			(0.083)	(0.083)	(0.077)	(0.019)	(0.028)	(0.019)
Female			-0.124	0.274	0.239	0.073	-0.070	0.098
			(0.334)	(0.405)	(0.380)	(0.096)	(0.141)	(0.094)
Observations	447	447	447	447	447	381	447	381
R-squared	0.151	0.363	0.420	0.425	0.239	0.172	0.199	0.148
F					10.54	4.773	8.346	3.902
widstat					245.4	232.1	245.4	232.1

b. Madagascar

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade	Grade	Grade	Grade	Grade	Composite	Math	French
	No School FE	School FE	School FE	School FE	School FE	School FE	School FE	School FE
VARIABLES	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Math and French 2nd grade (post)	0.982***	0.618*	0.589**	0.595**	1.483***	0.374**	0.446***	0.281*
	(0.226)	(0.318)	(0.267)	(0.267)	(0.501)	(0.153)	(0.166)	(0.155)
Height in 2012				0.028	0.030	0.005	-0.002	0.007
				(0.024)	(0.022)	(0.006)	(0.006)	(0.007)
Assets 2nd grade			-0.084	-0.073	-0.135	0.029	0.069	-0.031
			(0.294)	(0.295)	(0.298)	(0.080)	(0.071)	(0.102)
2012 age (in years)			-0.754***	-0.757***	-0.776***	-0.131***	-0.115***	-0.106***
			(0.138)	(0.137)	(0.126)	(0.037)	(0.039)	(0.041)

Female (=1)			-0.444	-0.213	-0.192	-0.087	-0.214**	0.062
			(0.336)	(0.365)	(0.333)	(0.102)	(0.104)	(0.111)
Mother's education			0.085	0.079	0.065	0.020	0.019	0.029**
			(0.055)	(0.054)	(0.052)	(0.014)	(0.016)	(0.013)
Father's education			0.131**	0.125**	0.123**	0.024*	0.003	0.039***
			(0.054)	(0.054)	(0.051)	(0.013)	(0.015)	(0.012)
Observations	333	333	333	333	333	310	318	312
R-squared	0.082	0.387	0.505	0.508	0.175	0.077	0.024	0.111
F					11.12	5.146	3.654	5.338
widstat					81.98	51.55	53.66	51.04

Notes: 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.