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Cognitive Skills and Intra-Household Allocation of Schooling

Jorge García Hombrados
University of Sussex
j.garcia-hombrados@sussex.ac.uk

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JEL classification: D13, I21

Key words: cognitive skills; investments in education; intra-household allocation of resources

Cognitive Skills and Intra-Household Allocation of Schooling

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Abstract

Using household data from two districts in northern Ghana, this study examines how cognitive skills affect the allocation of schooling across the children of a household. The analysis reveals that relative to the rest of the siblings in the household, an increase of one standard deviation in the score of cognitive tests increases by 0.128-0.178 the number of years of schooling attended in the following three years, depending on the cognitive test used. These results are interpreted as empirical evidence for the main prediction of the theoretical model for intra-household allocation of resources developed in the seminal paper Becker (1981): parents reinforce cognitive differences between siblings through allocating more human capital resources to the more able siblings. The study also explores whether the effect of cognitive skills on the allocation of schooling across siblings depends on the gender of the child or on household level characteristics. On the one hand, I find weak evidence suggesting that the effect of cognitive skills on schooling investments seems larger for boys than for girls although the results are not conclusive. On the other hand, the analysis suggests that polygyny, household size and household wealth do not affect relevantly the magnitude of this effect.

1 Introduction

Understanding how households allocate resources among their members has been an inquiry of primary interest for economists for decades (Chiappori and Meghir, 2014), with important implications for the intergenerational transmission of human capital (Datar et al., 2010). One key aspect of the intra-household allocation of resources is the role of cognitive skills in the distribution of school investments across the children of a household. Do parents allocate more schooling to more able children or do they try to compensate less skilled children with more schooling? Answering this question is of crucial importance for the design of effective policies that pursue improvements in education for all the population. For example, if parents focus their school investments in their most endowed children, supply-side schooling interventions such as reductions in class size or schools construction may benefit mostly the most able children while demand-side schooling interventions that target the less able children such as conditional cash transfers could be more effective in promoting universal schooling (Akresh et al., 2012).

The winner of the 1992 Nobel Prize in Economics Gary Becker proposes in his seminal book *A Treatise on the Family* (Becker, 1981) a theoretical model that conceptualizes the intra-household

*PhD student University of Sussex

allocation of human and nonhuman capital investments across siblings. One of the main predictions of the model is that siblings with higher returns to human capital receive larger human capital investments. Assuming that returns to human capital investments are larger the higher the cognitive ability (Appleton, 2000; Becker, 1981), the model predicts that parents reinforce genetic differences in cognitive skills through allocating more human capital investments to more able siblings and compensate less endowed siblings with more nonhuman capital investments.

Using longitudinal data from rural Ghana, this study builds in the existing literature and tests one of the predictions of Becker's model: Do parents allocate investments in education reinforcing cognitive differences between siblings? More specifically, the study assesses whether in a context in which the intra-household variation in school attendance across siblings in compulsory and post-compulsory school age is large, better cognitive skills relative to the rest of the siblings in the household affect the probability of attending school. This chapter makes three contributions. First, the study adds evidence to the thin literature that examines whether cognitive skills affect the intra-household allocation of school investments. Second, to achieve this objective, the study uses 4 rounds of a panel dataset from rural Ghana. The empirical strategy relies on the use of cognitive tests applied in the first round of the survey as *treatment* variables to proxy for cognitive skills, and school attendance the subsequent years as dependent variable in the specification. Variables aiming to capture human capital investments before the implementation of the cognitive tests are included as control variables in the specification to address endogeneity concerns. Although this empirical strategy is not without its limitations, I show that it represents an advantage relative to previous papers investigating the same question. Finally, this is the first study testing whether the effect of cognitive skills on the allocation of schooling across siblings depends on the gender of the child, household wealth, household size or on whether the household is polygynous.

I find suggestive evidence that parents reinforce cognitive skills differences through allocating more schooling to those children that score better in cognitive skills tests. These results are aligned with previous papers that assess empirically the role played by cognitive skills in the intra-household allocation of investments in education (Kim, 2005; Akresh et al., 2012; Ayalew, 2005) and provide support for the main prediction of Becker's model. Furthermore, the effect of cognitive skills on the allocation of schooling across siblings seems larger for boys than for girls although the evidence is not conclusive. On the other hand, the results also suggest that the magnitude of this effect does not depend on the household characteristics analysed.

The paper is structured as follows. Section 2 presents the conceptual framework. Then, section 3 summarizes the literature that investigates the role played by child endowments in the allocation of resources across siblings. Section 4 introduces some relevant aspects of the educational system in Ghana. Section 5 describes the data. Section 6 presents the empirical strategy and section 7 discusses the main results of the study. Then, section 8 examines whether the effect of cognitive skills on the allocation of schooling across siblings varies across different types of households and depends on the gender of the child. Section 9 concludes.

2 Conceptual framework: Becker (1981)

This section summarizes the theoretical model developed in Becker (1981)[1]. This model aims to formalize the intra-household allocation of human and nonhuman capital across the siblings of a household. In it, parents maximize a utility function that depends on their own current consumption and on the future wealth of their children:

$$U = U(c, I_1, .., I_n) \tag{2.1}$$

where c is the consumption of the parents in the present and I_i indicates the future wealth of child i. The future wealth of a child is described as a function of the human capital and nonhuman capital investments received by this child:

$$I_i = R_i^h(h_i, a_i)h_i + R^m m_i \tag{2.2}$$

where h_i and m_i indicate the level of human and nonhuman capital resources that parents allocate to child i. R_i^h is the rate of return on human capital for child i, a_i indicates the cognitive skills of the same child, and R^m is the market rate of return on nonhuman capital. The model assumes that while the rate of return on human capital function is concave in the investment level and higher the larger the innate cognitive skills, the rate of return on nonhuman capital is constant in the investment level and independent of innate cognitive skills implying that it is the same across siblings. Formally, if $R_i^h(h_i, a_i)$ and R_i^m are the functions of marginal returns on human and nonhuman capital, Becker's model assumes that $\delta R_i^h/\delta h_i < 0$, $\delta R_i^h/\delta a_i > 0$, $\delta R_i^m/\delta m_i = 0$ and $\delta R_i^m/\delta a_i = 0$. The assumption made in Becker's model of a larger marginal rate of return on human capital for better endowed siblings has some empirical support in the literature (Appleton, 2000).

Parents maximize their utility function through allocating human and nonhuman capital resources until the marginal rate of return on human capital is equal across siblings and also equal to the rate of return on nonhuman capital. Formally, the latter condition can be expressed as follows: $R_1^h = R_2^h = ... = R_n^h = R^m$.

The model yields two main predictions. First, because they have higher returns on human capital, more able siblings receive larger levels of human capital investments than less cognitively endowed siblings. In consequence, with their human capital investments, parents reinforce cognitive differences between siblings. This prediction is straightforward in the model: if under optimal levels of investment across siblings $R_1^h(h_1, a_1) = ... = R_n^h(h_n, a_n) = R^m$, $\delta R_i^h/\delta h_i < 0$, $\delta R_i^h/\delta a_i > 0$ and for the following two siblings we assume $a_1 > a_2$, then $h_1 > h_2$. More generally, the model implies that $\delta h/\delta a > 0$.

The second prediction of the model is that parents compensate siblings with lower returns on human capital through allocating them larger bequests or other nonhuman capital resources (e.g. inter-vivos transfers unrelated with education or health). The implication of this prediction is that less able siblings receive larger nonhuman capital investments. To see how the model leads to this conclusion, I use as example a household with two siblings where $a_1 > a_2$. In this household,

[1]The notation used is based on Kim (2005).

parents maximize their utility when $\frac{\delta U}{\delta I_1} \Big/ \frac{\delta U}{\delta I_2} = \frac{R_2}{R_1}$, where R_i is the rate of return from additional investments in child i. Because in the optimal level of investments $R_1 = R_2 = R^m$, the former condition can only be satisfied when $I_1 = I_2$. Thus, if $a_1 > a_2$ and $h_1 > h_2$, the condition $I_1 = I_2$ can only be achieved if $m_1 < m_2$.

Using a sample of Ghanaian children, the core of this study focuses on testing the first prediction of the model using years of schooling as a measure of human capital investments and the scores in different cognitive tests as proxies for cognitive skills. Furthermore, using the conceptual framework described above as a departing point, section 8 examines whether the magnitude of the effect of cognitive skills on the allocation of schooling across siblings depends on the gender of the child and on household level characteristics such as household size, polygyny status or household wealth. Unfortunately, the lack of information on the intra-household allocation of nonhuman capital resources precludes the empirical assessment of the second prediction of the model.

3 Related Literature

Several studies assess empirically the effects of child endowments on the allocation of human and nonhuman capital resources across siblings, testing the predictions of the Becker's model presented in section 2. Most of these studies focus on examining the effect of health endowments such as birthweight or body mass index (BMI) on the intra-household allocation of health, schooling and other inter-vivos transfers. The evidence is mixed and while some of these studies find that children with better health seem to receive larger levels of health (Behrman et al., 1994; Pitt et al., 1990) and educational investments (Behrman et al., 1994; Miller et al., 1995), other studies suggest that parents favour less endowed children with more education (Frijters et al., 2010; Griliches, 1979; Behrman et al., 1982; Ermisch and Francesconi, 2000; Leight, 2014) and health investments (Datar et al., 2010; Ayalew, 2005). The evidence is also inconclusive on whether children with worse health receive more nonhuman capital transfers, including inter-vivos transfers unrelated with health or education (McGarry and Schoeni, 1995; Dunn and Phillips, 1997; Hochguertel and Ohlsson, 2009; Wolff, 2006) .

Although plenty of studies assess whether child endowments affect the intra-household allocation of human capital investments, only a few of them investigate the specific role of cognitive endowments. Indeed, there are only three studies that use data on cognitive tests to explore empirically the role of cognitive endowments in the allocation of human capital investments across the children of the household. The main methodological challenge in these studies is the potential endogeneity in the link between the results in cognitive tests such as IQ, Raven or Digit Span tests obtained by the child and the human capital investments that this child has received.

The first study that addressed empirically this research question was Kim (2005). Using data from high schools in the state of Wisconsin, in the US, the author shows that conditional on a wide set of household and individual level controls, higher scores in IQ tests are associated not only with receiving larger human capital investments but also with receiving larger inter-vivos transfers unrelated with education. This finding provides evidence in favour of the first prediction of Becker's model but against the second. Nonetheless, we cannot rule out the possibility that the statistical association between IQ and investments received is partially driven by reverse causality.

Using cross-sectional data from Ethiopia, Ayalew (2005) finds that while parents allocate more health investments to children with worse cognitive abilities, they also tend to reinforce cognitive differences through allocating more educational investments to those children that have better cognitive skills. To measure these skills, the author constructs a proxy variable for innate cognitive ability as follows. First, the score obtained in the Raven cognitive test is regressed against individual characteristics of the child including age, gender and years of schooling. Then, the residuals in the latter regression are used as a proxy for innate cognitive ability in a main specification that includes school attendance as dependent variable and the residuals of the Raven score regression as the treatment variable. The main problem of this empirical strategy is that, in order to overcome the endogeneity in the link between years of schooling and the Raven score in the first regression, years of schooling are instrumented with land and livestock owned. This solution would violate the instrumental variables exclusion restriction if land or livestock owned affect the performance in the Raven test through any mechanism other than through years of schooling. If so, the estimated effect of innate ability on school attendance in the main regression would also be biased.

The most recent paper that investigates the effect of cognitive skills on the allocation of schooling investments across siblings is Akresh et al. (2012). Relying on panel data from Burkina Faso, the authors show that higher scores in cognitive tests and better parents' expectations regarding future earnings relative to the rest of the siblings in the household, increase significantly school attendance. The study uses the results of Raven, Forward Digit Span and Backward Digit Span tests as direct measures of cognitive skills. Then, to test whether the results are driven by reverse causality, the authors exploit the panel data dimension of the data restricting the analysis to (a) children aged 5 to 7 years old and therefore, not yet enrolled in school at the time of the collection of the first wave of surveys, and to (b) children in grades 1 and 2, for whom the authors argue that the score in the cognitive tests is not significantly affected by school attendance.

Remarkably, the results of these three studies in terms of the effect of cognitive skills on the allocation of investments in education across siblings are in line with the first prediction of Becker (1981). On the other hand, both Kim (2005) and Ayalew (2005) fail to find any evidence of reinforcing mechanisms in terms of other human capital investments (e.g. health investments) or compensatory behaviour using nonhuman capital transfers. In the light of the existing evidence, some studies suggest that differences in parental investments across their children might not be primarily caused by larger returns on investments in some of the children in the household (Kim, 2005; Mechoulan and Wolff, 2015). For example, Kim (2005) suggests that the allocation of human and nonhuman capital resources across siblings could be mainly driven by parental differences in affection for their children.

4 Education in Ghana

When Ghana achieved its independence in 1957, the vast majority of its citizens lacked access to education (MacBeath, 2010). The post-colonial government implemented different programmes with the objective of increasing access to primary and secondary education across the country and although the process faced important challenges such as the lack of qualified teachers, the enrolment rates raised dramatically in all the country (MacBeath, 2010; Addy, 2013). Over the following decades, a free and compulsory educational system was consolidated in Ghana, with average levels of enrolment and gender parity above the average for Sub-Saharan countries (UNESCO, 2014; USAID, 2009). World Bank data from 2013 show that while the average net enrolment rates in primary and secondary education in sub-Saharan Africa were 77% and 33%, the net enrolment rates in primary and secondary education in Ghana were 87% and 52%. Furthermore, and unlike other Sub-Saharan countries, the net enrolment rates in primary and secondary education in Ghana are not significantly different for boys and girls (GSS, 2015).

However, despite achieving relatively large average enrolment rates and gender parity, the education system in Ghana is facing important challenges. An analysis of some of them is provided in UNESCO (2014). Together with the lack of infrastructure and delayed attendance, two threats gather the attention from policy makers and international organizations working in West Africa. First, different reports highlight that the quality of primary and secondary education is deficient in many schools in both urban and rural areas[2]. Indeed, Ghana took last position in the 2015 OECD Global Education ranking in the category *Math and Science*. This report ranked internationally the quality of education for different subjects in 76 countries[3]. Second, Addy (2013) shows that school attendance remains low in the less-developed areas of the country, particularly in the north of Ghana, where average enrolment rates in primary and secondary education are significantly lower than national averages. For example, according to the 2014 Ghana Demographic and Health Survey, the net enrolment rates in primary and secondary school in the regions where the villages sampled are located were 68.1 and 30.0 in the Northern Region and 73.1 and 30.4 in the Upper East Region (GSS, 2015). Interestingly, girls in these regions are slightly more likely to be attending primary school than boys.

After the 2009 reform, formal education in Ghana is structured in three different parts. The basic education starts at age 4 and finishes at 15, and it is free and compulsory. During the basic education cycle, the students follow 2 years of pre-school education, 6 years of primary education and 3 years of junior secondary school. In this education cycle, grade promotion is automatic if the child attends school regularly during the year. At the end of the third year of the junior secondary school, the students are eligible to take the Basic Education Certificate Examination (BECE). Passing the latter exam gives students access to senior secondary education or vocational education in Ghana. Both the senior secondary education and vocational education last for three years and the state provides them for free in public schools. However they are not compulsory and promotion at the end of the year is based on school performance. At the end of secondary school, the students are eligible to take the West African Senior School Certificate Examination, which is required to access tertiary education. Although the duration of tertiary education depends on the academic degree undertaken, bachelor degrees in public universities typically last for four years and most students face small tuition fees.

[2]See for example the UNICEF country report available at:http://www.unicef.org/about/annualreport/files/Ghana_COAR_2010.pdf

[3]see http://www.bbc.co.uk/news/business-32608772

5 Data

The analysis conducted in this study relies on four rounds of a household panel survey conducted annually between 2012 and 2015 for the impact evaluation of the Millennium Villages Project in the districts of Builsa and West Mamprusi in northern Ghana. The survey targets every year the same 2250 households in 103 villages in the districts of Builsa and West Mamprusi. During this period, a total of 2,080 households were successfully interviewed every year.

With the first round of the survey, implemented in 2012, the enumerators applied three widely used cognitive tests aiming to measure cognitive skills of every person aged 5-19 in the sample regardless of whether this person ever attended school: the Raven's Progressive Matrices, the Digit Span Forward (DSF) and the Digit Span Backward (DSB) tests. The Raven's Progressive Matrices is a nonverbal test developed by John C. Raven in 1936 that measures abstract reasoning and has been used to measure fluid intelligence. The test administered includes 12 questions and the score ranges between 0 and 12. In these questions, the children have to identify the missing element that completes patterns of increasing difficulty until they get an answer wrong[4]. The test was designed to be unambiguously interpretable and easy to administer (Raven, 1994). Although the test was constructed to be affected as little as possible by education and experience, some studies suggest that these two features may influence test performance. For example, Ayalew (2005) and Alderman (1995) show that boys in rural areas in Pakistan and Ethiopia obtain significantly higher scores in the Raven test than girls, casting doubts on whether the score is influenced by human capital investments.

The DSF and DSB tests are components of the Wechsler memory scales (WMS) and the Wechsler intelligence scales for adults and children (Woods et al., 2011). In these tests, the children have to repeat different strings of numbers both in the order stated by the enumerator (forward test) or in reverse order (backward test). The strings of numbers increase in length as the child answers correctly up to a total of 8 digits and the score ranges between 0 and 16. These tests measure working memory and ability to concentrate[5]. Following Akresh et al. (2012), I compute age-adjusted z-scores[6] for each of these cognitive tests so that the mean and the standard deviation of the score in each test for children of the same age in completed years are 0 and 1.

A crucial stage of the study is the construction of variables that measure investments in education. Given that the study is set in deprived areas of a low-income country with large intra-household variation in terms of school attendance, I follow Akresh et al. (2012) and use school attendance as a measure of school investments. Information on school attendance is collected yearly at the individual level in the survey during the period 2012-2015. The survey includes two different questions aiming to record school attendance. First, enumerators collect information on the number of years of schooling of every child equal or older than 3 years old. Using this information, I construct a measure of school attendance between 2013 and 2015 as the difference in years of schooling reported in 2015 and in 2012. Second, the survey also asks whether children equal or

[4]An example of a question in the Raven Matrices test is provided in appendix A.

[5]Examples of questions in the Digit Span Forward and Backward tests are provided in appendix A.

[6]Age-adjusted z-score are computed through subtracting to every cognitive test score the mean score of the same test for the children with the same age in completed years and then dividing by the standard deviation of the score for these children.

older than 3 years old attend school at any point during the last 12 months. I use this information to construct a variable that ranges between 0 and 3 and measures how many years during the period 2013-2015 the individual has attended school at least once during the last 12 months.

The main concern with the second attendance measure is that it might not truly capture *relevant* attendance because children that for example attend school for just one week during the year might be categorized as attending school using this criteria. Indeed, the percentage of children aged 5-18 that attended school at least once during the last twelve months remains above 70% for children aged 5-18 and over 60% for individuals aged between 19-21. Furthermore, since only 27% of the households with more than 1 child in school age present between-siblings variation in terms of school attendance at some point in the last 12 months, this measure of school attendance is not ideal to conduct the analysis proposed. On the other hand, the main concern with the first attendance measure is that it is constructed using years of schooling rather than attendance, which might not be driven only by school attendance but also by the ability of the individual to promote to the next school grade. Although this concern could be relevant for children undertaking senior secondary school, tertiary education or vocational education where access and grade promotion at the end of the school year is not automatic, the share of children in the sample attending any of these educational levels at baseline is below 2%.

In the light of these facts and given the intermittent school attendance of most children in the sample[7], the school attendance variable based on the difference in years of schooling reported in 2012 and in 2015 seems to be more adequate to measure investments in education than the school attendance variable based on whether a child attended school at least once in the last 12 months. Nonetheless, and although the main analysis uses the measure of school attendance based on the difference between years of schooling reported in 2015 and in 2012 as the main dependent variable, I also test the robustness of the results to the use of the alternative school attendance measure mentioned above.

The sample of primary interest for the analysis are those children aged 5-18 that are sons or daughters of the household head and live in a household interviewed every year over the period 2012-2015 with at least two siblings aged 5-18 when the first round of the survey was implemented in 2012. In total, 4,003 children from 1,468 households fulfil these conditions. However, and despite all these children were eligible for the cognitive tests, only 2,489 of these children from 1,010 households took at least one of the three cognitive tests. The majority of children that did not take any cognitive test were not at home at the time of the interview, accounting for 62-71% of the eligible children that did not take the test, depending on the cognitive test examined. The rest of these children were at home but decided not to take any cognitive test.

Table 1 provides descriptive statistics on child level characteristics for the sample of interest. The statistics are presented separately for children that took the cognitive tests and for children that did not. The average number of correct answers in the sample of children that took the cognitive tests was 4.09 for the Raven Matrices test, 4.42 for the DSF test and 1.75 for the DSB test. The share of girls in this sample is 0.46 and the mean age of these children is 10.29 years.

[7]The prevalence of intermittent school attendance is discussed at the end of paragraph 10 in section 5.

Table 1: Summary statistics: Individual characteristics of children aged 5-18 in 2012.

	Took cognitive test		Did not take cognitive test		
	Mean	Standard deviation	Mean	Standard deviation	Difference
Individual level characteristics					
Age	10.29	3.74	11.53	4.30	-1.23***
Female	0.46	0.50	0.47	0.50	-0.02
Sibling rank	3.41	2.20	3.67	2.65	-0.26**
Health insurance scheme	0.72	0.45	0.65	0.48	0.07***
Ever attend. school	0.85	0.36	0.74	0.44	0.11***
Attendance 2012	0.81	0.39	0.67	0.47	0.14***
N years attended 2013-2015	2.47	1.00	2.01	1.26	0.47***
Years of school 2012	3.59	2.89	3.77	3.63	-0.18
Years of school 2015-2012	1.51	1.20	1.36	1.26	0.16***
Paid work	0.20	0.40	0.30	0.46	-0.10***
Raven test results (1-12)	4.09	2.14			
Raven age-adjusted z-score	-0.01	1.00			
Digit span forward results (1-16)	4.42	3.00			
DSF age-adjusted z-score	0.00	1.00			
Digit span backward results (1-16)	1.75	1.91			
DSB age-adjusted z-score	0.01	1.01			
N of households	1,010		765		
N of children	2,489		1,514		

Note: Values of individual level characteristics based on the first round of the survey (2012).***p<0.01;**p<0.05;*p<0.1.

The data reveal that 85% of the children aged 5-18 in 2012 that took the cognitive tests ever attended school and that 81% of these children attended school at least once in the last 12 months. Consistently, the table shows that the average number of years during the period 2013-2015 that these children attended school at least once is 2.47. The corresponding net attendance rate to primary and secondary school among this sub-sample of children in the data is 53% and 23.4%[8]. The net enrolment rates found in the sample are smaller than the net enrolment rates reported in GSS (2015) for the Northern and the Upper East regions for primary (68.1% and 73.1%) and secondary education (30.0% and 30.4%). When attendance during the same period is measured using the difference between years of schooling in 2015 and 2013, the average number of years of schooling completed during the relevant period for the sample of children that took at least one of the cognitive tests is 1.51.

[8]Primary education includes the 6 years of primary education, excluding the 2 years of pre-primary education. The group of reference for the calculation of the net enrolment rate in primary education are children aged 6 to 12 years old. The secondary education includes the 3 years of junior secondary school and the 3 years of senior secondary school. The group of reference are the children aged 13 to 18 years old.

Figure 1: School attendance by age (year 2012)

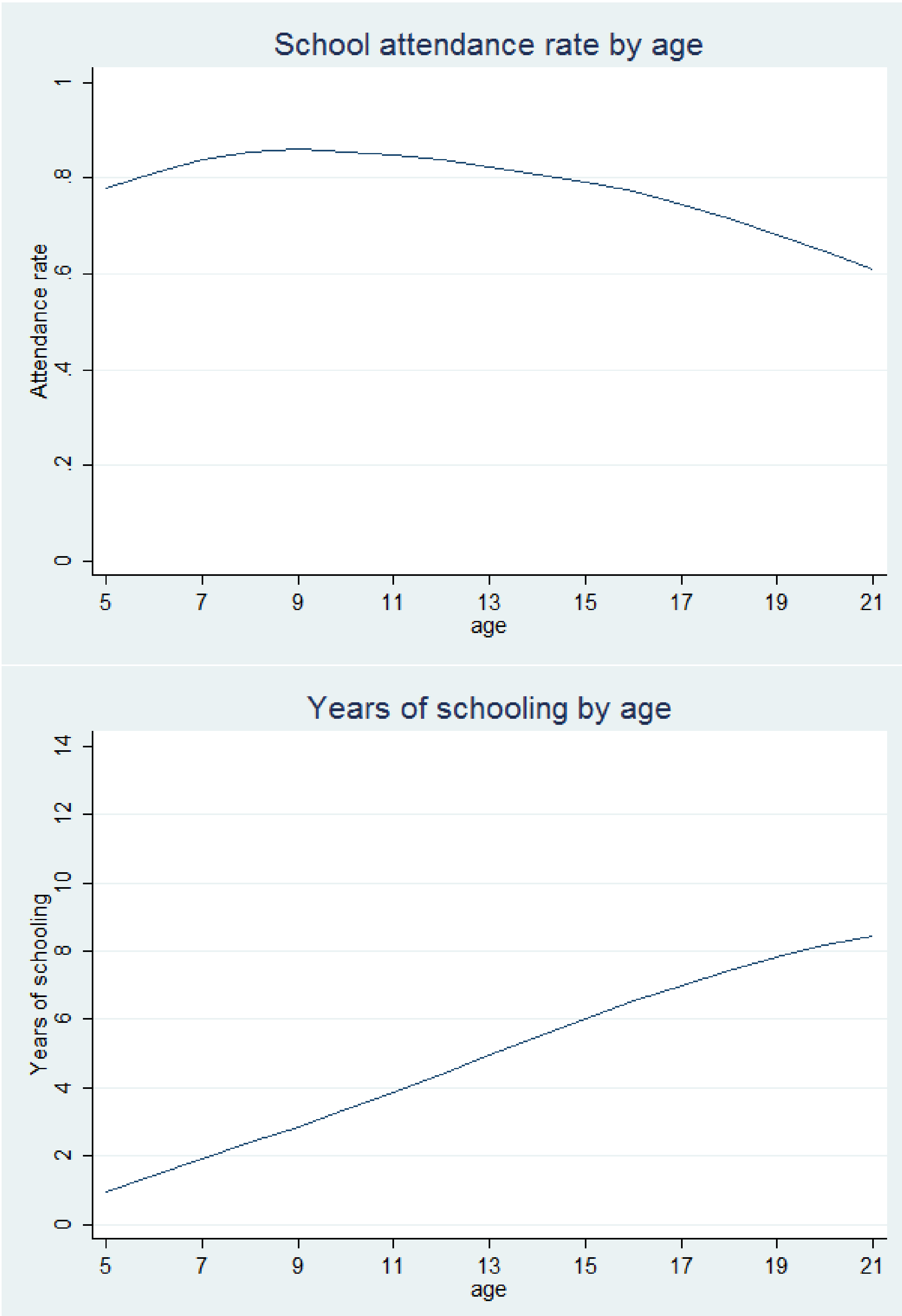

Table 2: Summary statistics: Household characteristics of children aged 5-18 years in 2012.

	HH took cognitive tests		HH did not take cognitive tests		
	Mean	Standard deviation	Mean	Standard deviation	Difference
Household level characteristics					
P/c expenditure (cedis)	742.37	654.74	723.25	618.73	19.12
Poor	0.88	0.33	0.90	0.30	-0.02
Economic shock index (0-5)	3.46	1.31	3.47	1.37	-0.01
MVP area	0.34	0.47	0.35	0.48	-0.01
Polyg. household	0.31	0.46	0.32	0.47	-0.02
Monog. household	0.59	0.49	0.57	0.50	0.02
One-parent household	0.10	0.30	0.10	0.30	-0.00
Years school of HH	1.24	3.14	1.12	3.21	0.12
HH female	0.09	0.28	0.10	0.29	-0.01
HH age	46.97	12.93	48.54	12.48	-1.57**
N of hh members	8.18	3.08	8.96	4.05	-0.78***
N of children hh members	4.64	2.12	5.13	2.78	-0.49***
Ratio female members over total hh members	0.51	0.16	0.49	0.16	0.02**
Ratio female children over total children	0.48	0.26	0.47	0.26	0.02
N of households	1,010		458		

Note: Values of household level characteristics based on the first round of the survey (2012). First sample is formed by those household with at least one child aged 5-18 undertaking one cogntive test. Second sample is formed by those households with eligible children in which none of the them took any cognitive test.***p<0.01;**p<0.05;*p<0.1.

Figure 1 provides further insights into school attendance and years of schooling by age for the sample of children that took at least one of the cognitive tests. The figure reveals that the share of individuals aged 5-21 that attended school at some point in the last twelve months remains over 70% until the age of 18 and over 60% at the age of 21. Interestingly, the share of children attending school decreases slightly but constantly from the age of 10. Besides, the figure shows that the slope of the LOWESS regression that displays the relation between the age and the years of schooling is well below 1 during all the period of interest. Combined with the fact that the percentage of children that reports having attended school at least once in the last 12 months remains above the 80% for children younger than 16 years old, the small slope in every point of the function suggests that despite attending school at some point during the year, many of these children might not be attending school regularly during the year.

Worth to mention, table 1 also shows that children that did not take the cognitive tests are on average 14 percentage points less likely to have attended school at least once during the last 12 months, 1.2 years older, 10 percentage points more likely to have a job, 7 percentage points less likely to have a health insurance and have a higher sibling rank. On the other hand, there is not any significant difference between children that did and did not take cognitive tests in terms of gender, years of schooling at baseline and years of schooling completed between 2012 and 2015.

Table 2 presents descriptive statistics on household characteristics collected in the first round of the survey (2012) for the sample of households surveyed every year that have at least 2 children that were eligible to undertake the cognitive tests. The information is provided separately for those households in which at least one child took one or more cognitive tests and for those in which despite having eligible children, none of them took any of the cognitive tests. The descriptive statistics reveal that 88% of the households in the sample with at least one child that took the cognitive tests live on a level of per capita consumption below the national poverty line, 31% of them are polygynous and only 9% of them are female headed. The average household size in the sample of interest is 8.18 and the average number of household members aged below 18 is 4.64.

6 Empirical Strategy

This section introduces the empirical strategy for the estimation of the effect of cognitive skills on the allocation of school attendance across siblings using four rounds of data collected for the evaluation of the Millennium Villages Project in northern Ghana. The main challenge for the identification of this effect arises from the fact that the link between cognitive skills and school attendance is likely affected by reverse causality or unobservable factors such as parental preferences. Indeed, although the cognitive tests used to measure cognitive skills are designed with the intention of being unaffected by schooling, culture and family background (see for example Raven (1994)), it is not possible to rule out the possibility that these measures are themselves affected by schooling or by any other differential treatment that some children within the household may receive (Ayalew, 2005; Glewwe, 1999; Akresh et al., 2012).

An additional challenge when estimating the effect of cognitive skills on years of schooling arises from the fact that approximately the 38% of the eligible children in the sample did not take any of the cognitive tests. The restriction of the sample used in the analysis to only the children that took the cognitive tests could lead to a problem of sample selection bias. In line with this hypothesis, table 1 shows that those children that took at least one cognitive test are different from those that did not in terms of key characteristics such as labour force participation, sibling rank or school attendance.

To overcome these challenges, I follow Cueto et al. (2014) and propose the two steps procedure developed in Heckman (1979). In the first stage, I estimate equation 6.1 using a Probit model:

$$TakeCogTest_{i,h} = \omega_1 X_{i,h} + \omega_2 Z_h + u_{i,h} \tag{6.1}$$

where $TakeCogTest_{i,h}$ is a dummy variable that is equal to 1 if child i in household h took the cognitive test and X is a vector of child-level variables that are likely to affect the probability of taking the cognitive tests. This vector of variables includes school attendance, labour force participation, years of schooling, gender of the child, a proxy for health investments, sibling rank, labour force participation and a vector of dummies indicating the age in completed years of the child. Z_h is a vector of household level characteristics that could affect the probability of taking the cognitive tests. The vector of household level variables includes per capita expenditure, an index of exposure to economic shocks, polygamy status, education and gender of the household head, household size, the number of children in the household, the number of male household members under 18 years and enumerator, village and time at survey fixed effects[9]. Both the individual and the household level characteristics included in the regression as right-hand side variables are measured in the first round of the survey (2012).

Once equation 6.1 is estimated, the next step is the calculation of the Inverse Mills Ratio (IMR), also known as selectivity correction term. The latter is calculated for every child as the coefficient of the standard normal density function of the predicted probability of taking cognitive test for every child divided by the standard normal cumulative distribution function of the predicted probability of taking the cognitive test for the same child.

In the second stage, I estimate using OLS the following equation:

$$YearsSchool_{i,h} = \omega_1 CognitiveSkills_{i,h} + \omega_2 X_{i,h} + \delta_h + u_{i,h} \tag{6.2}$$

where $YearsSchool_{i,h}$ is the number of years that the child i in household h went to school between the years 2013 and 2015, $CognitiveSkills_{i,h}$ indicates the age-adjusted z-score in the cognitive test taken in 2012 for child i and $X_{i,h}$ is a vector of child level characteristics in 2012 that includes gender, a proxy for health investments, sibling rank, a set of dummy variables for age, the IMR, years of schooling and school attendance. The specification also includes a dummy for every specific household surveyed. This vector of household fixed effects dummies account for differences in all the factors that are constant within a household. $u_{i,h}$ is the error term in the regression. The parameter of interest is ω_1. Since household fixed effects are included in the regression, ω_1 yields the average effect on the number of years that the child attended school between 2013 and 2015 of an increase in one standard deviation in the cognitive test score of the child relative to the mean score of his siblings. Note that since the values of the variable $CognitiveSkills$ (measured in 2012) are not affected by school attendance between 2013 and 2015 and because the specification is already accounting for years of education and school attendance in 2012, the parameter ω_1 is not affected by the reverse causality problem. Furthermore, sample selection bias in equation 6.2 is addressed through the inclusion of the Inverse Mills Ratio (Heckman, 1979) as a control variable.

A potential limitation of the identification strategy presented in equation 6.2 is that in addition to innate cognitive ability and school investments, the cognitive skills measured in 2012 might be affected by other human capital investments. The household fixed effects may account for this problem if the investments are equal across siblings. As described in Akresh et al. (2012), the problem would arise if for example parents allocate more health investments to those siblings that have worse cognitive skills. If this is the case and the specification does not account adequately for health investments, the parameter that measures the effect of cognitive skills on schooling would be biased downwards. The best way I can cope with this problem is through including in the regression a dummy variable that takes the value of 1 if the child is registered with the National

[9] The term fixed effects in this context implies that a dummy variable is included in the specification for every specific value found in the data for the variable of interest. For example, village fixed effects implies that a dummy is included in the specification for every village surveyed. The time at survey fixed effects is a vector of dummies for the hour of the day in which the enumerators started surveying the household.

Health Insurance Scheme (NHIS) and 0 otherwise. The NHIS is a health insurance provided by the state. Registration with the NHIS is at the individual level and it is subject to a yearly fee that varies depending on the socioeconomic situation of the household. In this context, I use this variable to account for within household variation in the health investments received by the children.

7 Results

Table 3 presents the results of the first stage regression. The table shows that the child-level determinants of cognitive tests uptake are the same for the three tests examined. Being male, school attendance and lower age are factors positively associated with the uptake of cognitive tests. In the specifications with household fixed effects, the health insurance variable is also positive and statistically significant. Among the household level determinants, per capita expenditure, the number of male household members aged below 18 and whether the household head is male for the DSB test are negatively associated with the probability of children undertaking the cognitive tests.

Table 4 reports the estimates for equation 6.2 using the three different measures of cognitive skills collected in 2012: the score in Raven, DSF and DSB tests. The dependent variable in the analysis is the number of years that a child attended school between 2013 and 2015, calculated as the difference in years of schooling reported in 2015 and in 2012. Columns 1 to 3 of the table show the results for the three cognitive skills tests when equation 6.2 is estimated without accounting for non-random uptake of the cognitive tests. The results suggest that the effect of cognitive skills is positive and statistically significant at the 1%: an increase of one standard deviation in the score in cognitive tests relative to the average score of the rest of the siblings in the household is associated with 0.126-0.178 more years of schooling between 2013 and 2015, depending on the cognitive measure used. When the IMR is included as a control variable to account for sample selection bias, the estimates displayed in columns 4 to 6 are very similar, with the effect of one standard deviation increase in the score of the cognitive tests relative to the average score of the rest of the siblings ranging between 0.128-0.178 years of schooling. Interestingly, the IMR is not statistically significant in these equations suggesting that at least in these estimates, the observed non-random uptake of the cognitive tests does not bias the estimation of the effect of cognitive skills on the allocation of schooling across siblings.

A potential critique to the analysis reported in table 4 is that the dependent variable measures school progression, which may not only be driven by school attendance but also by the cognitive skills of the child, which may directly influence his school marks and promotion to the next school year. Although grade promotion is automatic until senior secondary school and only less than 2% of the sample is currently or ever enrolled in post-junior secondary school educational levels[10], it might be possible that the effects found are driven by the most able children passing the BECE exam and accessing senior secondary school.

[10] The educational system in Ghana is discussed in section 4.

Table 3: First stage (Probit coefficients): Participation of children in cognitive skills tests (children 5-18 in 2012).

	(1) Take Raven Test	(2) Take Raven Test	(3) Take DSF test	(4) Take DSF test	(5) Take DSB test	(6) Take DSB test
Female	-0.130***	-0.151**	-0.127***	-0.139*	-0.117**	-0.141*
	(0.049)	(0.076)	(0.049)	(0.075)	(0.048)	(0.074)
Years of school 2012	-0.014	-0.010	-0.016	-0.017	-0.017	-0.022
	(0.011)	(0.019)	(0.011)	(0.019)	(0.011)	(0.019)
Attendance 2012	0.438***	0.570***	0.411***	0.564***	0.426***	0.543***
	(0.070)	(0.126)	(0.071)	(0.128)	(0.070)	(0.126)
Health insurance scheme	0.085	0.506***	0.051	0.501***	0.033	0.450***
	(0.064)	(0.142)	(0.065)	(0.146)	(0.064)	(0.137)
Paid work	0.005	-0.102	-0.074	-0.141	-0.046	-0.131
	(0.068)	(0.129)	(0.067)	(0.123)	(0.067)	(0.124)
Sibling rank	-0.011	-0.007	-0.021*	-0.017	-0.011	-0.005
	(0.013)	(0.020)	(0.013)	(0.020)	(0.013)	(0.020)
Age	-0.040***	-0.053***	-0.040***	-0.054***	-0.040***	-0.050***
	(0.009)	(0.015)	(0.009)	(0.015)	(0.009)	(0.015)
Ln P/c expenditure	-0.103**		-0.129***		-0.122**	
	(0.047)		(0.049)		(0.049)	
Economic shock index (0-5)	0.019		0.039		0.025	
	(0.027)		(0.026)		(0.027)	
Polyg. household	0.022		0.036		-0.005	
	(0.066)		(0.070)		(0.068)	
N of children hh members	-0.010		-0.031		-0.018	
	(0.025)		(0.025)		(0.025)	
N of children-boys hh members	-0.040*		-0.049**		-0.046*	
	(0.024)		(0.024)		(0.024)	
N of hh members	-0.017		-0.001		0.001	
	(0.017)		(0.017)		(0.017)	
Years school of HH	0.000		-0.001		0.003	
	(0.008)		(0.008)		(0.008)	
HH female	0.171		0.147		0.194*	
	(0.106)		(0.104)		(0.106)	
HH age	-0.000		0.000		-0.000	
	(0.002)		(0.002)		(0.002)	
Enumerator FE	Yes	No	Yes	No	Yes	No
Time at survey FE	Yes	No	Yes	No	Yes	No
Household FE	No	Yes	No	Yes	No	Yes
Village FE	Yes	No	Yes	No	Yes	No
Observations	3,939	2,655	3,931	2,605	3,946	2,663

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

To explore this possibility, I conduct the following two analyses. First, I re-estimate equation 6.2 using only the sample of children aged 12 or below in 2012. During the period studied, these children were only eligible for pre-school, primary or junior secondary education, where there is automatic course promotion at the end of the school course. The results of this analysis are reported in table 5. The coefficients of the cognitive tests are positive, statistically significant at conventional confidence levels and similar in terms of magnitude to those reported for the whole sample in table 4, suggesting that the effect of cognitive skills on years of schooling during the period 2013-2015 identified in table 4 is not driven by less able children being unable to achieve grade promotion at the end of the school year. Second, I re-estimate equation 6.2 using as dependent variable the sum between 2013, 2014 and 2015 of a dummy variable collected yearly that is equal to 1 if the child attended school at least once during the last 12 months. The estimates for this analysis are reported in table 9 in appendix A and show consistent results. The effect of an increase in one standard deviation in the score obtained in cognitive tests relative to the rest of the siblings in the household is positive and overall, statistically significant at 10%. The magnitude of this effect ranges between 0.046 and 0.060 additional years of school attendance during the period 2013-2015, depending on the cognitive test used and on whether the selectivity correction term is included as an additional control variable.

Table 4: Child cognitive skills and years of schooling 2012-2015 (children 5-18 in 2012).

	(1) Years of school 2015-2012	(2) Years of school 2015-2012	(3) Years of school 2015-2012	(4) Years of school 2015-2012	(5) Years of school 2015-2012	(6) Years of school 2015-2012
Female	0.054	0.115	0.087	0.010	0.071	0.079
	(0.070)	(0.072)	(0.071)	(0.121)	(0.114)	(0.113)
Attendance 2012	0.667***	0.657***	0.665***	0.813**	0.823**	0.717*
	(0.142)	(0.147)	(0.148)	(0.403)	(0.374)	(0.414)
Years of school 2012	-0.114***	-0.119***	-0.123***	-0.119***	-0.128***	-0.125***
	(0.025)	(0.025)	(0.024)	(0.027)	(0.028)	(0.029)
Health insurance scheme	0.380***	0.348**	0.409***	0.429***	0.389***	0.415***
	(0.141)	(0.148)	(0.139)	(0.158)	(0.150)	(0.141)
Sibling rank	0.002	-0.003	-0.004	-0.000	-0.009	-0.005
	(0.025)	(0.024)	(0.025)	(0.026)	(0.028)	(0.026)
Raven age-adjusted z-score	0.126***			0.128***		
	(0.041)			(0.041)		
DSF age-adjusted z-score		0.167***			0.176***	
		(0.046)			(0.046)	
DSB age-adjusted z-score			0.178***			0.178***
			(0.042)			(0.043)
IMR				0.559	0.639	0.201
				(1.592)	(1.427)	(1.540)
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,147	2,061	2,073	2,125	2,034	2,058
R-squared	0.576	0.573	0.580	0.576	0.575	0.579

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

The results presented in this section are consistent with the main prediction of Becker's model: parents reinforce cognitive differences with their human capital investments. In a rural context where households have more than one child in school age and do not send all of them to school, parents are *ceteris paribus* more likely to concentrate school investments in the most able children in the household. This finding is also consistent with the results of previous studies that assess empirically the role of cognitive skills in the intra-household allocation of educational investments in Burkina Faso (Akresh et al., 2012), Ethiopia (Ayalew, 2005) and the US (Kim, 2005).

Table 5: Child cognitive skills and years of schooling 2012-2015 (Children 5-12 in 2012).

	(1) Years of school 2015-2012	(2) Years of school 2015-2012	(3) Years of school 2015-2012
Female	0.048	0.102	0.097
	(0.204)	(0.181)	(0.182)
Attendance 2012	0.656	0.587	0.567
	(0.715)	(0.581)	(0.668)
Years of school 2012	-0.154***	-0.153***	-0.153***
	(0.044)	(0.047)	(0.046)
Sibling rank	0.025	0.028	0.017
	(0.038)	(0.043)	(0.036)
Health insurance scheme	0.368*	0.281	0.354**
	(0.217)	(0.183)	(0.167)
IMR	-0.122	-0.266	-0.684
	(2.971)	(2.351)	(2.623)
Raven age-adjusted z-score	0.116**		
	(0.055)		
DSF age-adjusted z-score		0.174***	
		(0.064)	
DSB age-adjusted z-score			0.211***
			(0.065)
Age fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Observations	1,342	1,284	1,304
R-squared	0.630	0.634	0.635

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

8 Heterogeneous Effects

This section examines whether the effect of cognitive skills on the allocation of schooling across siblings in a household depends on the gender of the child or on different household level characteristics. First, I test whether in a context with larger rates of school attendance among girls than among boys, the cognitive skills reinforcing mechanism operates differently across gender. Second, I investigate whether the strength of this reinforcing mechanism varies across polygynous and non-polygynous, larger and smaller and wealthier and poorer households.

8.1 Gender

In the sample, school attendance is more widespread and the average number of years of schooling is larger for girls (84% and 3.9) than for boys (77% and 3.5). GSS (2015) shows that the larger rates of attendance to primary school among girls than among boys observed in the data is a well-established pattern in the Northern Region and in the Upper-East Region, the areas where the districts sampled are located. At the national level, Ghana has no gender differences in terms of net enrolment rates in primary education. One possible explanation for this could be the launch in the late 1990's and early 2000's of The Ghana Education Trust Fund (GETFUND) and the Compulsory Universal Basic Education (FCUBE) programme promoting school attendance in Ghana, particularly among girls and children from poor households (GSS, 2015).

The conceptual framework described in section 2 would predict a differential effect of cognitive skills on school investments in boys and in girls if the degree in which the returns to school for the child or for the parents depend on cognitive skills is different for boys and girls. The latter premise would be consistent with low levels of labour force participation for women. If returns to school depend more strongly on cognitive skills for boys, the model would predict that the allocation of investments in education across siblings reinforces more strongly cognitive differences between boys than between girls.

At this point, it is important to remark that a stronger effect of cognitive skills on school investments for boys would not imply that returns to education are lower for women than for men or that households find more profitable to allocate educational investments to boys than to girls. Rather, I am testing whether cognitive skills play a different role in understanding the intra-household allocation of schooling depending on the gender of the sibling. Thus, a weaker effect of cognitive skills on school investments in women would not be incompatible with the larger rate of school attendance for girls observed in the sample, particularly when considering that the economic returns to education for girls and their parents are not only limited to the labour market[11].

To test whether the effect of cognitive skills on the allocation of school investments across siblings is different for boys and girls, I propose two different tests. First, I estimate the following specification:

$$YearsSchool_{i,h} = \omega_1 CognitiveSkills_{i,h} + \omega_2 CognitiveSkills_{i,h} * Female_{i,h} + \omega_3 X_{i,h} + \delta_h + u_{i,h} \quad (8.1)$$

where $CognitiveSkills_{i,h} * Female_{i,h}$ is an interaction term of the score in the cognitive tests with a dummy variable that is equal to 1 if the child is a girl. X is a vector of child level variables that includes among others, a dummy variable that indicates the gender of the child and the IMR. In equation 8.1, the parameter ω_1 indicates the effect on school attendance for boys of increasing in one standard deviation the score in the cognitive test relative to the rest of the siblings. The effect for girls is yielded by the sum of the parameters $\omega_1 + \omega_2$. The parameter of interest in the equation would be ω_2. If the latter parameter is larger (lower) than 0, the effect of cognitive skills on years

[11]For example, using data from Zimbabwe, Ashraf et al. (2016) show that education has large and positive effect in the bride price in the marriage market.

of schooling would be larger (lower) for girls than for boys.

Table 6: Effect by gender: child cognitive skills and years of schooling 2012-2015 (children 5-18 in 2012).

	(1) Years of school 2012-2015	(2) Years of school 2012-2015	(3) Years of school 2012-2015	(4) Years of school 2012-2015	(5) Years of school 2012-2015	(6) Years of school 2012-2015
Female	0.007	0.066	0.081			
	(0.121)	(0.115)	(0.113)			
Attendance 2012	0.821**	0.833**	0.721*	1.511*	1.559*	1.512
	(0.402)	(0.376)	(0.415)	(0.892)	(0.888)	(0.968)
Years of school 2012	-0.122***	-0.128***	-0.126***	-0.062	-0.114	-0.103
	(0.027)	(0.028)	(0.029)	(0.065)	(0.076)	(0.084)
Health insurance scheme	0.428***	0.390***	0.410***	-0.244	-0.409	-0.310
	(0.156)	(0.151)	(0.142)	(0.412)	(0.462)	(0.462)
Sibling rank	-0.002	-0.010	-0.006	0.016	-0.008	0.054
	(0.026)	(0.028)	(0.026)	(0.124)	(0.127)	(0.125)
IMR	0.633	0.712	0.216	3.886	4.325	3.627
	(1.590)	(1.437)	(1.546)	(3.445)	(3.132)	(3.439)
Raven age-adjusted z-score	0.201***			0.230*		
	(0.052)			(0.137)		
Female × Raven	-0.155**			-0.042		
	(0.069)			(0.196)		
DSF age-adjusted z-score		0.210***			0.026	
		(0.059)			(0.259)	
Female × DSF		-0.078			0.257	
		(0.074)			(0.340)	
DSB age-adjusted z-score			0.209***			0.162
			(0.056)			(0.188)
Female × DSB			-0.067			0.086
			(0.074)			(0.363)
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,125	2,034	2,058	252	249	234
R-squared	0.579	0.575	0.579	0.723	0.693	0.712

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

Second, I estimate equation 8.1 restricting the analysis to those households with all the household individuals aged 5-18 years either all girls or all boys. In this estimation, the variable $CognitiveSkills_{i,h} * Female_h$ is an interaction term of cognitive skills with a dummy variable defined at the household level that is equal to 1 if all the children aged 5-18 in the household are girls and 0 if all the children 5-18 are boys. In this case, ω_1 indicates the effect on school attendance of increasing in one standard deviation the score in the cognitive test relative to the rest of the siblings in households where all the children are boys. The effect in households where all the children are girls is yielded by the sum of the parameters $\omega_1 + \omega_2$.

The estimates for these two analyses are reported in table 6 and show mixed results. On the one hand, the interaction term $Female \times CognitiveSkills$ in columns 1 to 3 is consistently negative suggesting that the effect of cognitive skills on the allocation of schooling across siblings is larger for boys than for girls although this coefficient is only statistically significant at conventional confidence levels for the Raven test. On the other hand, the estimations reported in columns 4 to 6 yield mixed results. While the interaction term is negative for the Raven test, it is positive for the digit span tests although in none of the cases is statistically significant at conventional confidence levels. In any case, the sample size used in this second analysis is small and thus, the results should not be taken as conclusive.

8.2 Polygyny

Defined as the marital life of one men and more than one women, the practice of polygyny is widespread in West Africa. Although polygamy is not as high in Ghana as it is in other West African countries such as Guinea Conakry or Senegal, the 31% of the households in the data used in this study are polygynous

One assumption behind the predictions of Becker's model is the alignment of incentives across the parents of the children. However, polygyny could break the alignment of incentives across parents if every mother prefer her own children to be more educated than the children of the other women in the household regardless of their cognitive skills. To examine whether the misalignment of incentives across parents in polygynous household affects the role of cognitive skills in the allocation of schooling investments across siblings, I estimate the following equation:

$$YearsSchool_{i,h} = \omega_1 CognitiveSkills_{i,h} + \omega_2 CognitiveSkills_{i,h} * Polyg_h + \omega_3 X_{i,h} + \delta_h + u_{i,h} \quad (8.2)$$

where $CognitiveSkills_{i,h} * Polyg_h$ is an interaction term of the score in the Raven test with a dummy variable defined at the household level that is equal to 1 if the child lives in a polygynous household and 0 otherwise. In equation 8.2, the parameter ω_1 indicates the effect on school attendance of increasing in one standard deviation the cognitive test score in non-polygynous households. The effect in polygynous households is yielded by the sum of the parameters $\omega_1 + \omega_2$. The key parameter is ω_2. If this parameter is larger (lower) than 0, the effect of cognitive skills on school attendance in polygynous households would be larger (lower) than in non-polygynous households.

Column 1 of table 7 shows the estimates for equation 8.2. The coefficient for ω_2 is positive suggesting that cognitive ability relative to siblings is a stronger determinant of educational investments received in polygynous household. However, although the magnitude of the coefficient is non-negligible, it is also statistically indistinguishable from 0 at conventional confidence levels. The results suggest that the misalignment of incentives across parents arguably existent in polygynous households does not seem to weaken the role of cognitive skills in the allocation of schooling across siblings. Two potential explanations for this could be that more cognitively able wives (that may have children with better innate cognitive skills) achieve higher educational investments for their children or that fathers in polygynous households decide alone on the allocation of schooling investments across siblings.

Table 7: Effect by household characteristics: child cognitive skills and years of schooling 2012-2015 (children 5-18 in 2012).

	(1) Years of school 2012-2015	(2) Years of school 2012-2015	(3) Years of school 2012-2015
Female	0.104	0.108	0.113
	(0.115)	(0.115)	(0.115)
Attendance 2012	0.491	0.492	0.476
	(0.377)	(0.378)	(0.378)
Years of school 2012	-0.108***	-0.108***	-0.108***
	(0.027)	(0.027)	(0.027)
Sibling rank	0.003	0.004	0.004
	(0.027)	(0.027)	(0.027)
IMR	-0.880	-0.902	-0.946
	(1.465)	(1.471)	(1.470)
Raven age-adjusted z-score	0.096*	0.139*	0.203**
	(0.054)	(0.077)	(0.092)
Polygamous hh × Raven score	0.082		
	(0.083)		
HH<4 children × Raven score		-0.021	
		(0.118)	
HH 4-6 children × Raven score		-0.012	
		(0.096)	
P/c Consump(Terc. 1)× Raven score			-0.114
			(0.110)
P/c Consump(Terc. 2)× Raven score			-0.071
			(0.112)
Age fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Observations	2,125	2,125	2,125
R-squared	0.573	0.573	0.573

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

Although the survey collects information on the nature of the relation of every household member with the household head, the survey does not collect sufficient information to identify confidently the mother of most of the children in polygynous households. This fact hinders the possibility of providing a deeper insight into the role played by mother characteristics or wife rank in the intra-household allocation of school investments in polygynous households.

8.3 Household Size

Children with a lot of siblings in school age may benefit from economies of scale in school costs (e.g. books, uniforms) or in household chores. On the other hand, more siblings can increase competition for scarce resources. In order to determine whether the effect of cognitive skills on the allocation of schooling investments across siblings depends on the number of children in the household, I estimate equation 8.3:

$$YearsSchool_{i,h} = \omega_1 CognitiveSkills_{i,h} + \omega_2 CognitiveSkills_{i,h} * HhSize_h + \omega_3 X_{i,h} + \delta_h + u_{i,h} \quad (8.3)$$

where $CognitiveSkills_{i,h} * HhSize_h$ is a vector of interaction terms of the score in the Raven test with a set of dummy variables defined at the household level that indicate whether less than 4 children[12], between 4 and 6 children or more than 6 children live in household h. The thresholds used to define the three household size dummies resulted in a division of the sample of households in three equal parts. In equation 8.3, the parameter ω_1 indicates the effect of cognitive skills on the allocation of school attendance across siblings in the reference group, that is formed by those households with more than 6 children. On the other hand, the vector of parameters ω_2 measures the differential effect of cognitive skills on school attendance in households with 4 to 6 children and in households with less than 4 children relative to the reference group. If these parameters are larger (lower) than 0, the effect of cognitive skills on school attendance in these groups of households would be larger (lower) than in the reference group.

The results of this analysis are reported in column 2 of table 7. The coefficients show that on average, the larger the household size, the larger the effect of Raven score on years of schooling. For example, the estimated effect of an increase in one standard deviation in the Raven test score on years of schooling between 2012 and 2015 is 0.139 in households with more than 6 children. This coefficient is statistically significant at the 10%. The estimates provided show that the effect is 0.127 (0.139-0.012) in households with 4 to 6 children and 0.118 (0.139-0.021) in households with less than 6 children. However, it is important to remark that none of the coefficients that measure the differential effect of cognitive skills on the allocation of schooling in smaller and larger households is statistically significant at conventional confidence levels. Therefore, in the light of the results, it is not possible to reject the hypothesis that the magnitude of the effect of cognitive skills on the allocation of schooling across siblings does not depend on household size.

8.4 Household Consumption

An additional prediction of Becker's model is that the reinforcing pattern in the allocation of human capital investments would be weaker (if any) in poor households because nonhuman capital resources are limited in these households and therefore, disadvantaged households would not be able to compensate less able children with larger nonhuman capital transfers. At this point, the reinforcing mechanism in households that cannot make nonhuman capital investments would depend on the degree of parents' aversion towards sibling inequality: the stronger the aversion for sibling

[12] A child is defined as a household member aged below 18 years.

inequality, the smaller the difference in schooling investments received by more and less able siblings, and the larger the differential effect of cognitive skills on the allocation of schooling across siblings in poorer and wealthier families. To test this hypothesis, I estimate the following specification:

$$YearsSchool_{i,h} = \omega_1 CognitiveSkills_{i,h} + \omega_2 CognitiveSkills_{i,h} * Consum_{i,h} + \omega_3 X_{i,h} + \delta_h + u_{i,h} \tag{8.4}$$

where $CognitiveSkills_{i,h} * Consum_h$ is an interaction term of cognitive skills with a set of dummy variables defined at the household level that capture whether the household is in the first, second or third tercile in the distribution of per capita household consumption. In equation 8.4, the parameter ω_1 yields the effect of cognitive skills on the allocation of schooling across siblings in households in the top tercile of the per capita consumption distribution. The vector of parameters ω_2 are the estimates of first importance in this analysis. If the latter parameters are larger (lower) than 0, the effect of cognitive skills on schooling in these households would be larger (lower) than in the households in the richest tercile.

The results of this analysis are reported in column 3 of table 7. The effect of cognitive skills on school investments in the richest tercile of households is statistically significant at the 5%. The parameters that measure the differential effect in households in the first and second tercile are negative indicating that on average, the lower the per capita consumption in the household, the smaller the effect of cognitive skills on the allocation of schooling across siblings. Although the sign of the coefficients for the interaction terms is in line with the prediction of Becker's model under some degree of aversion for sibling inequality, none of these coefficients is statistically significant at conventional confidence levels.

9 Conclusions

This study examines empirically a prediction of the model of intra-household allocation of resources developed in the seminal paper Becker (1981): with their investment in schooling, parents reinforce cognitive differences between siblings. Relying on 4 rounds of a household panel survey conducted in 103 villages of the north of Ghana, I find evidence that cognitive skills strongly determine the allocation of schooling across siblings. In the preferred set of specifications, an increase of one standard deviation in the score of cognitive tests relative to the rest of the siblings in the household, raises the number of years of schooling attended in the following three years by 0.128-0.178, depending on the cognitive measure used. These results are consistent with the main prediction of Becker's model and are in line with the results found in previous studies.

The evidence suggests that policies aiming to increase school attendance in northern Ghana should take into account that parents target their educational investments towards the most capable children rather than spreading these investments equally among all the children in the household. In this context, demand-side educational interventions such as conditional cash transfers that promote school attendance among less able siblings would probably be more effective in promoting universal schooling than supply side interventions such as reductions in class size (Akresh et al., 2012).

The study also investigates whether the magnitude of the effect of cognitive skills on the allocation of schooling across siblings depends on the gender of the child or on different household characteristics. On the one hand, the analysis suggests that the effect of cognitive skills on schooling is larger for boys although the results should only be interpreted as suggestive and they are not unambiguous. On the other hand, I do not find any evidence that the effect of cognitive skills on the allocation of schooling across siblings is significantly different in richer and poorer, polygynous and non-polygynous, and larger and smaller households.

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A Appendix

Table 8: First stage (Probit coefficients): Participation of children 5-18 in 2012 in cognitive skills tests (school attendance).

	(1) Take Raven Test	(2) Take Raven Test	(3) Take DSF test	(4) Take DSF test	(5) Take DSB test	(6) Take DSB test
Female	-0.133***	-0.150*	-0.138***	-0.154**	-0.124**	-0.150**
	(0.049)	(0.077)	(0.049)	(0.076)	(0.048)	(0.076)
Years of school 2012	-0.009	-0.003	-0.012	-0.009	-0.012	-0.015
	(0.012)	(0.020)	(0.012)	(0.020)	(0.011)	(0.020)
Attendance 2012	0.400***	0.539***	0.378***	0.529***	0.394***	0.509***
	(0.071)	(0.129)	(0.073)	(0.130)	(0.071)	(0.127)
Health insurance scheme	0.095	0.490***	0.054	0.468***	0.032	0.411***
	(0.064)	(0.143)	(0.064)	(0.146)	(0.063)	(0.139)
Paid work	-0.009	-0.088	-0.082	-0.131	-0.054	-0.118
	(0.069)	(0.132)	(0.068)	(0.125)	(0.068)	(0.126)
Sibling rank	-0.012	-0.005	-0.022*	-0.014	-0.011	-0.001
	(0.013)	(0.020)	(0.013)	(0.020)	(0.013)	(0.020)
Age	-0.042***	-0.057***	-0.042***	-0.056***	-0.041***	-0.052***
	(0.009)	(0.015)	(0.009)	(0.015)	(0.009)	(0.015)
Ln P/c expenditure	-0.100**		-0.119**		-0.118**	
	(0.047)		(0.049)		(0.049)	
Economic shock index (0-5)	0.012		0.034		0.020	
	(0.028)		(0.027)		(0.028)	
Polyg. household	0.027		0.044		0.005	
	(0.067)		(0.071)		(0.069)	
N of children hh members	-0.011		-0.030		-0.017	
	(0.025)		(0.025)		(0.025)	
N of children-boys hh members	-0.044*		-0.056**		-0.051**	
	(0.025)		(0.025)		(0.024)	
N of hh members	-0.015		-0.001		0.001	
	(0.017)		(0.017)		(0.017)	
Years school of HH	0.001		0.000		0.004	
	(0.008)		(0.008)		(0.008)	
HH age	-0.000		0.000		-0.000	
	(0.002)		(0.002)		(0.002)	
HH female	0.206*		0.162		0.224**	
	(0.108)		(0.106)		(0.109)	
Enumerator FE	Yes	No	Yes	No	Yes	No
Time at survey FE	Yes	No	Yes	No	Yes	No
Household FE	No	Yes	No	Yes	No	Yes
Village FE	Yes	No	Yes	No	Yes	No
Observations	3,875	2,584	3,867	2,528	3,882	2,588

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.

Table 9: Child cognitive skills and school attendance 2013-15 (children 5-18).

	(1) N years attended school 2013-2015	(2) N years attended school 2013-2015	(3) N years attended school 2013-2015	(4) N years attended school 2013-2015	(5) N years attended school 2013-2015	(6) N years attended school 2013-2015
Female	0.042	0.062	0.051	0.067	0.111	0.151**
	(0.044)	(0.045)	(0.043)	(0.091)	(0.079)	(0.073)
Attendance 2012	1.236***	1.271***	1.280***	1.147***	1.105***	0.941***
	(0.121)	(0.125)	(0.121)	(0.289)	(0.250)	(0.261)
Years of school 2012	0.047***	0.037**	0.040**	0.049***	0.041**	0.049***
	(0.016)	(0.017)	(0.016)	(0.017)	(0.019)	(0.017)
Sibling rank	0.020	0.021	0.024	0.022	0.028	0.030*
	(0.016)	(0.017)	(0.016)	(0.018)	(0.020)	(0.016)
Health insurance scheme	0.385***	0.387***	0.378***	0.361***	0.364***	0.341***
	(0.106)	(0.108)	(0.108)	(0.129)	(0.114)	(0.112)
Raven age-adjusted z-score	0.046*			0.047*		
	(0.025)			(0.025)		
DSF age-adjusted z-score		0.052*			0.050	
		(0.031)			(0.031)	
DSB age-adjusted z-score			0.060**			0.056*
			(0.028)			(0.029)
IMR				-0.443	-0.789	-1.538
				(1.253)	(0.928)	(0.960)
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,132	2,046	2,057	2,110	2,019	2,042
R-squared	0.745	0.750	0.758	0.745	0.751	0.759

Note: Standard errors clustered at the household level are reported in parentheses.***p<0.01;**p<0.05;*p<0.1.