# Formation of Children's Human Capital in Kenya: The Role of Teachers, Private Schools and the Family



By

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# Declaration

I declare that this thesis is my original work. Where other people's work is used, acknowledgements have been made. I declare that it has not been previously submitted for the award of a degree at any university.

Fredrick Masinde Wamalwa

# Dedication

I dedicate this work to my father, Mwalimu Dismas Wamalwa Wanami who passed away nearly a year before its completion.

# Acknowledgments

I will forever remain grateful for the support and guidance I received from my Supervisor, Professor Justine Burns while writing this dissertation. Right from the beginning, she was very confident in me and perhaps that is what kept me going. She always found time to read my work despite her busy teaching and administrative roles. Again, I will forever remain very grateful for this support.

I am indebted to my wife Anne Wangalachi for taking care of the family while I was away. She also paid for my upkeep when the African Economic Research Consortium (AERC) scholarship came to an end. Our children Jude and Nadine never understood why I was always away from home but remained quite patient. I am grateful to my entire family, my dear brothers and sisters, for their moral support.

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Any errors remain entirely mine.

# Abstract

In this thesis, we investigate the role of teachers, private schools and the family in the formation of children's human capital in Kenya. We focus on Kenya due to the declining learning outcomes the country is experiencing, in the wake of increasing public spending in the education sector. The first essay examines the effect of teacher subject knowledge, pedagogical skill, teacher effective instruction time and teacher classroom practices on grade 4 language and maths test scores. Our results show that a one standard deviation increase in the teacher's knowledge in language (maths) increases student test scores by 0.075 (0.126) of a standard deviation in language (maths). An additional hour of teacher effective instruction time increases student achievement by 0.051 and 0.059 score standard deviations in language and maths, respectively.

The second essay estimates the size of the effect of private school attendance on literacy (language) and numeracy (maths) skill acquisition among children drawn from lower primary grades (grades 2-4) in Kenya. Using a household survey data, we apply different estimation techniques (OLS, fixed effects and propensity score matching) to deal with the potential endogeneity of school choice. We find positive and significant effects of private school attendance on both language and maths achievements across all the estimation techniques. For instance, the household fixed effects yield a private school premium of 0.13 to 0.21 score standard deviation in maths and language, respectively.

The third essay examines the effect of the gender and order of birth of a child on intra-household investments in, and educational outcomes of, children in Kenya. We measure the intra-household education investment in children by the household's decision to enrol a child in a private school. We define educational outcomes by two variables: completed years of education and relative grade progression. We control for the potential endogeneity of child's gender, birth order, family size and household level unobservables using household fixed effects model. We find no female advantage in terms of private school enrolment. However, there is a consistent female advantage in terms of completed years of education and relative grade progression. We find significant negative birth order effects on private school enrolment, completed years of education and relative grade progression.

# Abbreviations and Acronyms

EAC: East Africa Community

AERC: African Economic Research Consortium

AfDB: African Development Bank

ASER: Annual Status of Education Report

ATT: Average Treatment on the Treated

CM: Confluence Model

DHS: Demographic and Health Survey

EFA: Education for All

FPE: Free Primary Education

GCSE: General Certicate of Secondary Education

GDP: Gross Domestic Product

GER: Gross enrolment Rate

GPI: Gender Parity Index

HLM: Hierarchical Linear Modeling

IEA: Institute of Economic Affairs

IQ: Intelligence Quotient

IV: Instrumental Variable

KIPPRA: Kenya Institute for Public Policy Research and Analysis

KNBS: Kenya National Bureau of Statistics

LPM: Linear Probability Model

MoEHRD: Ministry of Education and Human Resource Development

NARC: National Rainbow Coalition

ND: Not Dated

OLS: Ordinary Least Squares

PCA: principal components analysis

PISA: Programme for International Student Assessment

PSM: Propensity Score Matching

RDH: Resource Dilution Hypothesis

SAPs: Structural Adjustment Programs

SB: Standardized Bias

SDG: Sustainable Development Goals

SDI: Service Delivery Indicators survey

TIMSS: Trends in International Mathematics and Science Study

UN: United Nations

UNCRC: United Nations Convention on the Rights of the Child

UNESCO: United Nations Educational, Scientific and Cultural Organization

USA: United States of America

USAID: United States Agency for International Development

USD: United States Dollar

WB: World Bank

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# Chapter 1

# Background and Motivation of the Study

## 1.1 Introduction

Evidence gathered over the past 40 years demonstrates that education is important, both at the micro and macro level. From the seminal work of Mincer (1970, 1974) on school attainment and individual earnings, estimates of the return to schooling for a majority of countries now exists (Psacharopoulos and Patrinos, 2004). Education has been associated with increase in workers' productivity (Mincer, 1974; Psacharopoulos and Patrinos, 2004), higher economic growth (Hanushek and Woessmann, 2008), improved health status and reduced crime (Lochner, 2011) among other non-monetary outcomes.

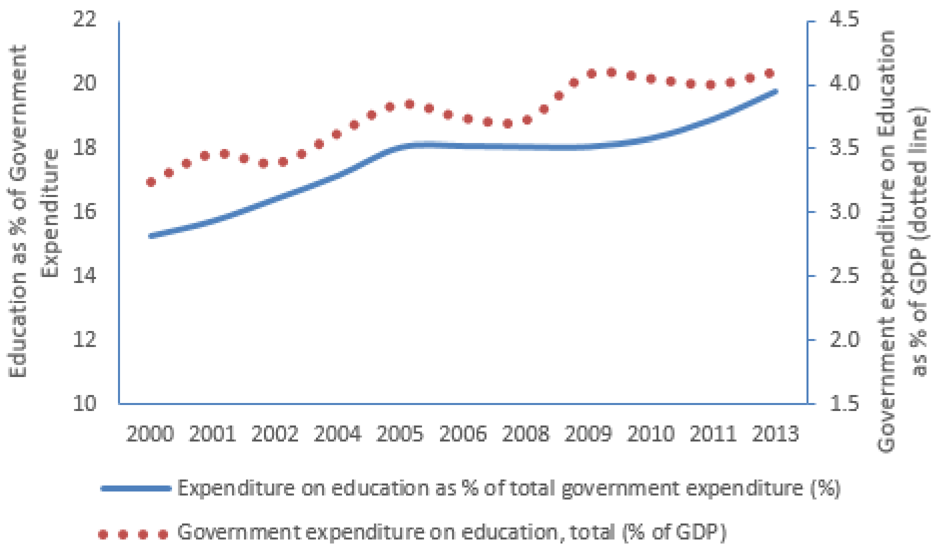
As observed by Glewwe et al. (2011), policymakers in developing countries have generally been convinced that education is important for growth. As a result, efforts at national and global levels over the past decade were devoted to ensuring that by 2015, *all children, boys and girls alike, have access to primary education that is free, compulsory and of good quality.* At the global level, the *Dakar Framework for Action on Education for All* (UNESCO, 2000)[1] and the *United Nations Millennium Development Goals* provided overarching political commitments that guided the achievement of this goal. A number of countries in sub-Saharan Africa responded by implementing ambitious and wide-ranging reforms to achieve this goal. For instance, overwhelming evidence that user-fees were a major barrier to access (Riddell, 2003; Bruns and Rakotomalala, 2003) provided the basis for the key reform of making public primary education free (World-Bank, 2009).[2]

[1] United Nations Educational, Scientific and Cultural Organization
[2] World Bank

Kenya enacted the policy in 2003 while other sub-Saharan African countries did the same between 1994-2005. These include Ethiopia and Malawi (1994), Uganda (1997), Lesotho (2000), Mozambique (2004) and Ghana (2005) (Bold et al., 2013b; World-Bank, 2009).

Currently, across the developing world, education takes the largest proportion of public spending. In Brazil, education accounts for 5.9 percent of Gross Domestic Product (GDP) while it is 6.3 percent in Vietnam. In Kenya and Ghana, education accounts for around 6 percent of gross domestic product (World-Bank, 2016). As shown in figure 1.1, average expenditure on education in sub-Saharan Africa, both as percent of total government expenditure (continuous line) and as percent of gross domestic product (GDP) (dotted line) has been on the rise from early 2000 when most countries enacted the free primary education policy. Evidence further suggests that much of this increased education spending took the form of improving school infrastructure and instructional inputs all aimed at improving enrolments (Glewwe et al., 2011). Recent reviews show that primary school completion in developing countries is no longer limited primarily by access as distance to the nearest school has greatly been shortened (Pritchet and Banerji, 2013; Glewwe et al., 2011).

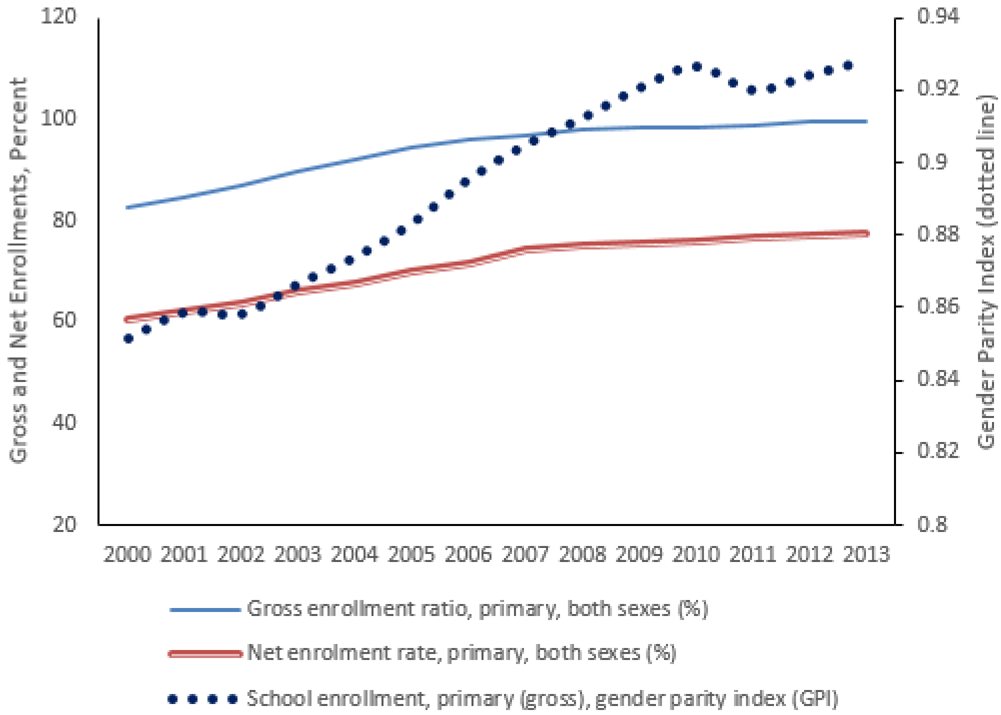
Figure 1.1: Trends in Average Spending on Education in sub-Saharan Africa




*Source:* World Bank (World Development Indicators, 2016)

Increased spending in the sector appears to have paid off. Although there is still room for progress, there is evidence across the developing world that more children are going to and staying in school (UN, 2015). Figure 1.2 shows that average gross primary enrolment [3] in sub-Saharan Africa increased from 83 percent to 100 percent between 2002 and 2013 while net primary enrolment[4] rose from 58 percent to 78 percent during the same period (World-Bank, 2016). Efforts to get more girls into schools are also bearing fruits. Figure 1.2 further shows that the gender parity index (GPI)[5] in primary school enrolment in sub-Saharan Africa increased from 0.84 in 2000 to about 0.94 in 2013.

Figure 1.2: Gross enrolment, Net enrolment and Gender Parity Index at Primary level in sub-Saharan Africa




*Source*: World Bank (World Development Indicators, 2016)

Despite increased access to education opportunities in sub-Saharan Africa and the developing world in general, evidence from national and regional student assessments show that learning achievement remains quite low. The status of learning in developing countries is detailed in a recent synthesis by the Center for Global Development (Pritchet and Banerji, 2013). Drawing on evidence from different countries such as Kenya, Uganda, Tanzania, Bangladesh and India, this review reports that many children in developing

[3]Gross primary enrolment is defined as total primary enrolment within a country regardless of age, expressed as a percent of the total population of children of official primary school age.

[4]Net primary enrolment is the ratio of the number of children of official primary school age who are enrolled in primary education to the total population of children of official primary school age, expressed as a percentage.

[5]Gender parity index is the ratio of females to males enrolled in a given stage of education (primary, secondary, etc.)

countries who complete primary school are unable to read a simple passage, perform simple addition, use a ruler to measure the length of a pencil or even tell the time on a clock - skills that are supposed to be mastered at the end of the second year of primary.

The Uwezo annual literacy and numeracy assessments of school age children[6] shed light on the depth and nature of the problem in East Africa. According to this survey, a majority of grade 3 children (81 percent in Uganda and 89 percent in Tanzania) cannot read a grade 2 English level text (Uwezo, 2015, 2012). In Kenya, results from the Service Delivery Indicators survey, described in detail in the next chapter, show that even after 3 years of schooling, 11 percent of the children cannot identify 3 out of 9 simple words and 84 percent cannot correctly read all the 58 words in a paragraph. In India, the Annual Status of Education Report (ASER) of 2014 shows that 75 percent of grade 3 learners and 25 percent of grade 8 learners cannot read a grade 2 English text fluently (ASER, 2014).[7]

Such low quality of learning has implication at micro and macro levels. At a micro level, low level of skill acquisition at basic primary school level is likely to negatively affect the individual's knowledge acquisition in later grades. At a macro level, the opportunity cost of time spent in school that is not adequately compensated represents potential dead weight loss to the economy (Jones et al., 2014). According to Hanushek and Woessmann (2012), it is what workers know, not the amount of time they spent in school that makes them more productive and their economies more prosperous.

The weak learning outcomes, particularly in public schools, coming in the wake of increasing public spending on education inputs raises an important research question as to whether school inputs matter for student achievements and if they do, which inputs matter. Recent literature suggests that the challenges of learning in developing countries goes beyond school funding, especially infrastructure and instructional inputs financing (Hanushek, 2008; Pritchet and Banerji, 2013; Glewwe et al., 2011). According to this literature, investments in inputs (infrastructure) in front-line service provider units (such as hospitals and schools) in developing countries have merely led to marginal improvements in outcomes because of deficiencies in the incentive structures in those front-line facilities (Spence and Lewis, 2009; Swanson et al., 2012; Hanushek, 2008; Pritchet and Banerji, 2013; Glewwe et al., 2011).

[6]The Uwezo initiative implements large-scale household surveys that assesses literacy and numeracy competencies of school age children across East Africa. An explanation of how the Uwezo surveys are administered is presented in Chapter 2.

[7]In the Annual Status of Education Report (ASER) assessment, reading fluency is based on a task that involves asking the learner to read a grade 2 level story comprising of 8 to 10 sentences and approximately 60 words. For more details about Annual Status of Education Report (ASER) assessment please see: http://www.asercentre.org/

In education, this literature stresses on the importance of teacher input and more so, the importance of teacher competence (knowledge) and behavior in the delivery of education services. Schools inputs (infrastructure) are crucial for student learning but teachers, as key service providers in the production of education, need to be present, motivated and able to instruct. In other words, conditional on teachers being appropriately skilled and exerting the necessary effort, the provision of school resources and infrastructure has important effects on student achievements. Despite this, the linkage between teacher knowledge and effort and outcomes has not been fully explored in the context of sub-Sahara Africa largely due to lack of data.

Education in most countries is provided by the public and private sectors.[8] In a number of sub-Saharan African countries, evidence shows that the elimination of user fees in public primary schools was followed by dramatic increases in private schools (Dixon and Tooley, 2012; Dixon, 2012; Tooley and Dixon, 2005; Tooley et al., 2008, 2011; Tooley, 2013; Tooley and Longfield, 2015; Oketch and Ngware, 2010; Oketch et al., 2010, 2012; Larbi et al., 2004). The rise in private schools has mainly been associated with decline in the quality of public schools especially after the introduction of free public primary education (Tooley et al., 2008, 2011; Tooley and Longfield, 2015; Oketch and Ngware, 2010; Oketch et al., 2010, 2012; Larbi et al., 2004). The majority of these schools reflect private initiatives mainly in urban informal settlements to establish schools that levy low fees, referred in the literature as low-cost private schools. These schools are generally lacking in terms of school infrastructure and learning facilities as well as trained teachers, relative to their public schools.

The effectiveness of private schools in developing countries has been discussed in the recent literature. The large majority of studies find that, relative to public schools, private schools, including low-cost private schools operating with very limited resources, are associated with better learning outcomes (Javaid et al., 2012; Andrabi et al., 2008; Pal, 2010; Bold et al., 2011a, 2013a; Thapa, 2015; Azam et al., 2015; French et al., 2010; Desai et al., 2009). Skeptics however argue that such private school premium could be due to spurious correlations between private school attendance and unobserved factors, mainly related to the household (Goldberger and Cain, 1982; Newhouse and Beegle, 2006; Altonji et al., 2005, 2000). For instance, in Kenya, evidence shows that poor parents bypass *free public primary schools* and send their children to otherwise *fee-paying low-cost private* schools due perceived better quality in private schools (Tooley et al., 2008; Oketch

[8] Private schools comprise education institutions not administered by the local, state or national government. They have the right to select their students and are funded in whole or in part by charging their students tuition, rather than relying on public (government) funding. We provide a detialed description in Chapter 4.

and Ngware, 2010; Oketch et al., 2010). Such parents, concerned with their children's education, despite being poor, are more likely to ensure that the home environment is favorable for learning for their children including investing in efforts such as helping their children with homework.

The differences in achievements between private and public students could therefore be due to such factors not easily observable by the researcher. The effects of private schools are likely to be over-estimated if unobservable factors such as home environment and parental motivation are not fully taken into account. In fact, a study by Newhouse and Beegle (2006) shows that the size of the private school effect sometimes declines or disappears when such unobservables are controlled for. Despite this, a recent review by Ashley et al. (2014) found that only a few studies have looked at the effectiveness of private school in sub-Saharan Africa while paying closer attention to the role of unobservables and the endogeneity of private school choice. The validity and magnitude of the private school effect is therefore still subject to further research especially in developing countries experiencing dramatic increases in private school provision.

Many schooling decisions, such as whether to enrol a child in school or not and whether to enrol a child in a public or private school, take place within the family. There are many ways in which the family can influence the education outcomes of a child. For instance, when faced with resource constraints parents may discriminate between children in terms of school investments (Basu and Van, 1998; Tenikue and Verheyden, 2010) especially with access to private schools which are generally not free of charge. While economic literature acknowledges that the family into which a child is born matters for children outcomes (Black et al., 2005), research on specific family characteristics that promote education outcomes in children is still inconclusive. Some of these characteristics include sibling gender, sibling size, birth spacing and birth order. Of these, sibling gender and birth order have received attention in the psychology and economics literature although their effect on children's learning outcomes remains open to research.

This thesis examines human capital formation of children in Kenya focusing on the three interrelated research issues that we have highlighted above. The first relates to the importance of teacher input and more so, the importance of teacher competence (knowledge) and teacher effort in the delivery of education services. The linkage between these aspects of teachers and student achievement has not been fully explored especially in the context of sub-Saharan Africa. The second relates to the effectiveness of private schools. There are concerns that the private school advantage (effect) documented in the literature could be a reflection of the endogenous selection of good students into private schools. The last one relates to the literature that examines the influence of the family environment on children's human capital development. While many schooling decision take place within the family, research on specific family characteristics that promote outcomes in children is still inconclusive (Black et al., 2005).

## 1.2 Research Questions

In view of the above, this thesis addresses the following three specific questions, each forming a distinct essay:

- What is the effect of teacher knowledge, pedagogy, effective instruction time and classroom practices on student test scores in Kenya?
- What is the effect of private schools on student achievement in Kenya?
- What is the role of gender and birth order on intra-household investments in, and educational outcomes of children in Kenya?

To address these questions, we use two data sets, namely, the Service Delivery Indicators survey and the Uwezo survey. The Service Delivery Indicators survey is a World Bank-led schools survey that administered grade 3 level language and maths tests to grade 4 students, randomly selected from 306 schools. The Uwezo survey is a household survey that administered a grade 2 level test assessment (in maths and languages) to children aged between 6 to 16 years. The SDI and Uwezo surveys are complimentary to each other. While the former involved assessment of learners at school, in the latter, learners were assessed at home. Analysis based on the two sample should provide us with a robust picture of student learning in Kenya. In chapter 2, we provide a details description these surveys.

## 1.3 Overview of Kenya's Education System

In this section, we give an overview of Kenya's education sector, focusing mainly on the primary sub-sector. Kenya's population, based on the 2009 national census, was estimated at 39 million, comprising 14 million school-going children (KNBS, 2009)[9]. Of the 14 million, 17 percent were four to five years old, potentially eligible for early childhood school programmes, 59 percent were of primary school-going age (6 to 13 years), and 24 percent were secondary school-going children (14 to 17 years).

[9]KNBS means Kenya National Bureau of Statistics

The promise of quality education for all Kenyans remains a national priority. The 2010 Constitution of Kenya underscores education as a basic right of every Kenyan and the government views education as fundamental to the success of all key national strategies. To this end, the government is a signatory to a number of international declarations that support children's education and well-being, including the Sustainable Development Goals (SDG), Education for All (EFA) and United Nations Convention on the Rights of the Child (UNCRC) alongside national policies and programs. The country follows the 8-4-4 education system of eight years of primary education, four years of secondary education and four years of university education. In this regard, children enter grade one officially at the age of six and are expected to complete primary education at the age of 13.

Education is provided by a number of actors. In terms of primary education, there were approximately 29,460 officially registered schools in 2014 (KIPPRA, 2016). Of these, close to 75 percent were government owned while the rest, 25 percent, were owned by non-state actors. The non-state actors that own the 25 percent of primary schools include non-governmental organizations, faith-based organizations, community-based providers and private-for-profit agents. In addition, there are hundreds of private non-formal schools mainly concentrated in urban informal settlements and operating outside government regulation (Edwards Jr. et al., 2015; Piper et al., 2014; Piper and Mugenda, 2010). In Chapter 4, we provide a detailed overview of non-state actor education provision in Kenya. Although education is provided by many actors, the government has overall authority in the management and regulation of education including curriculum development and design of education policy, among other roles.

The education sector accounts for a significant proportion of the total expenditure, maintaining about 25 percent of the national budget and about 6 percent of Gross Domestic Product (GDP) for the past five years (GoK, 2015; Bank, 2014). The high expenditure on education has been partly due to government commitment to provide free primary education, which was launched in 2003. This was the second attempt by the government to implement the policy (World-Bank, 2009). Following recommendations by Kenya's first post-independence education commission, the *Ominde Commission* of 1964, fees were abolished in 1974 for grades 1 to 4 and later extended to grades 5 to 7 in 1978. This policy led to an increase in primary gross enrolment rate (GER) level from 50 percent in 1963 to about 105.4 percent in 1989.[10] The policy was, however, reversed in the 1990s

[10] GER exceeds 100 percent because it includes students of all ages. GER includes students whose age exceeds the official age group (e.g. those who enrol early, those who enrol late and those who repeat classes). Therefore, if there is late enrollment, early enrollment, or repetition, as it is the case in Kenya, the total enrollment can exceed the population of the age group that officially corresponds to the level of education – leading to ratios greater than 100 percent.

following Kenya's adoption of structural adjustment programs. During the period 1990-2002, schools charged fees and children who could not afford them were not allowed to attend school. As a result, primary gross enrolment rates began to fall, from 105.4 percent in 1989 to 88.2 percent in 2002 (Bold et al., 2013b).

To reverse these trends, the newly elected National Rainbow Coalition (NARC) government, which won the landmark December 2002 elections, announced the abolition of fees in all public schools starting from 4 January 2003 (Bold et al., 2010, 2013b; Oketch and Somerset, 2010). Under the free public primary education policy, public schools were prohibited from collecting revenue from parents and communities. Instead, school fees were replaced with a capitation grant[11] that is paid directly into the schools account and managed by the School Management Committee (World-Bank, 2009).

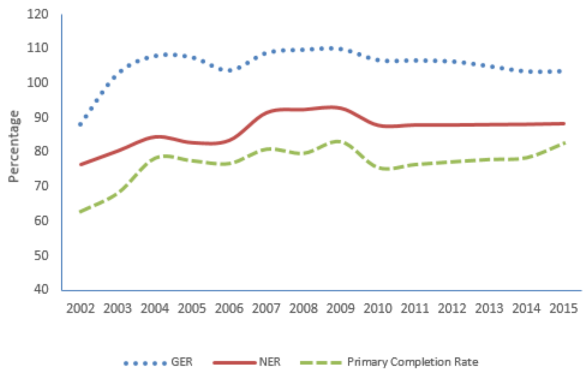
The free primary education policy was accompanied by ambitious programs to improve the quality of school infrastructure. Recent studies and school surveys confirm evidence of government success in efforts to improve school infrastructure. For example, while the average pupil-textbook ratio was 6:1 at Standard 6 and 9:1 at Standard 3 just a few years into the free user fee policy (Hardman et al., 2009; MoEHRD, 1999), this ratio had been reduced to the government target of 3:1 by 2013 (Martin and Pimhidzai, 2013; Piper and Mugenda, 2010). According to the Service Delivery Indicators survey, which we discuss in Chapter 2 and 3, 90 percent of schools have access to minimum teaching resources (chalk, pen, blackboard) and infrastructure (toilets and sufficiency of light for reading in the classroom). As we show later, there seems to be no statistically significant difference between private and public schools in a wide range of these indicators.

As expected, the removal of user fees in public primary schools (accompanied by improvement in the quality of school infrastructure) led to dramatic increase in enrolment in public schools (Oketch and Somerset, 2010; Wasanga et al., 2010). For example, enrolment increased from about 5.9 million in December 2002 to 6.9 million in January 2003 and to 7.4 million in December 2004. Gross enrolment rates increased from 88.2 percent in 2002 to about 108.0 percent in 2004. Similarly, net enrolment rates increased from 76.4 percent to 82.1 percent during the same period. In figure 1.3, we show official recorded enrolment rates mainly from registered public schools based on the Kenya National Bureau of Statistics (KNBS) data. As can be seen from the figure, there was a jump in enrolment rates (both gross and net enrolment rates) between 2002 and 2004 which began to slow down from 2005 on-wards. In fact, by 2006 gross enrolment rates had reduced to 104 percent from their 108 percent levels in 2004. A large number of credible studies show that the increase in enrolments following the removal of primary user fee was immediately

[11]The capitation grant is equivalent of USD 14.

accompanied by large quality shocks in public schools (Onsomu et al., 2005; Piper and Mugenda, 2012; Wasanga et al., 2010; Oketch and Somerset, 2010; Bold et al., 2011b; Oketch and Ngware, 2010)[12] and it did not take long before parents started transferring their children to private schools.

Figure 1.3: Gross enrolment, Net enrolment and Completion Rates at Primary level in Kenya.




*Source:* Kenya National Bureau of Statistics

This trade-off between quality and quantity after the abolition of school fees is well explored by Bold et al. (2011b). Using two consecutive, nationally representative, cross-sectional, household surveys collected in 1997 and 2006, the authors find that primary school net enrolment rates increased from roughly 75 percent in 1997 to 80 percent in 2006 (in the wake of the free primary education policy). They, however, find that this increase was almost entirely due to a tripling of the private sector, whose enrolment share increased from 3 percent to 9 percent. They find that enrolment in the public sector remained stagnant. Bold et al. (2011b) however find changes in the composition of enrolment in public sector schools despite enrolment levels remaining stagnant. Analyzing enrolment by parental background, they find a 5 percent increase in enrolment among children from low socioeconomic status, defined as children whose parents had completed primary education or less. On the other hand, enrolment among children whose parents had secondary education fell by 6 percent. Bold et al. (2011b) conclude that such demand response to a fall in price was *prima facie* evidence that removing school fees in public schools led to a decline in public school education quality, leading to an exit to private schools by children from higher economic status.

Another characteristic of Kenya's primary education system is that a significant number of children leave school before completing primary education. According to official

[12] We address issues quality issues in the next Chapter.

government statistics, as at 2015, 17 percent of learners do not complete primary education. This figure seems to be an understatement based on other sources. For instance, in the recent report by the Institute of Economic Affairs (IEA), it was estimated that 34 percent of close to 1.3 million children who joined primary schools at the start of free primary education in 2003 did not complete grade 8 (IEA, 2016).[13] In the next Chapter, we continue with this discussion on issues related to education access and quality in Kenya based on the Uwezo and the Service Delivery Indicators surveys. Before that, we outline the structure of the dissertation in the next sub-section.

## 1.4 Structure of the Dissertation

This dissertation is divided into six chapters. Chapter 1 has introduced the topic, area of research and key research questions. It has also provided an overview of Kenya's education system. In chapter 2, we provide a detailed description of the dissertation data sets, the Service Delivery Indicators (SDI) and Uwezo surveys. We further describe some of the key (dependent and independent) variables of interest and highlight key issues that are followed in subsequent chapters.

In the first essay (chapter 3), we begin by providing a description of the teacher knowledge, pedagogy, effective instruction time and classroom practices. We use the SDI survey data to link these aspects of teachers to student scores by way of an education production function, while controlling for attributes related to students, teachers, schools (including whether the school is private or public) and the communities where schools are located. Results indicate that teacher subject knowledge and pedagogical skill are critical for student achievements. For example, a one standard deviation increase in the teacher's knowledge in language (mathematics) increases student test scores in language (mathematics) by 0.075 (0.126) of a standard deviation. Teachers who spend more time on instruction related activities and can keep students engaged (on-task) during the lesson are associated with higher student test scores. An additional hour of teacher effective instruction time increases the student language and maths test score by 0.051 and 0.059 of standard deviation, respectively. A number of classroom teaching practices have an effect on student test scores although the effect differs between language and maths. For instance, the practice of using local language to illustrate learning reduces student test score in language by 0.161 of a standard deviation but it has no effect on maths.

One of the school related factors we control for when estimating the effect of teacher

[13]Find details of the report at: [http://www.nation.co.ke/news/education/Primary- schools-dropout-rates-Kenya/2643604- 2930304-sm2nvf/index.html]

knowledge, pedagogy, effective instruction time and classroom practices on student test scores in the first essay is *a dummy variable indicating whether a school is private or not.* Our results show that relative to public schools, private schools increase student scores by about 0.33 and 0.69 score standard deviations in language and maths, respectively. Following the discussion in the introduction section (section 1.1), could this private school effect be a reflection of spurious correlations between private school attendance and unobserved characteristics? Put differently, could it be that students who attend private schools already have disproportionately high academic potential and access to complementary educational resources than their counterparts in public schools? These questions form the motivation for the second essay (chapter 4). In this

In the second essay, we estimate the size of the effect of private school attendance on literacy (language) and numeracy (maths) skill acquisition among children drawn from lower primary grades (grades 2-4) in Kenya. We use the Uwezo survey, which, unlike the SDI survey, allows us to apply a number of approaches (OLS, fixed effects and propensity score matching) that deal with the endogenous nature of private school choice. Using a methodology advanced by Altonji et al. (2005), we estimate the extent of the influence of unobservables on our private school advantage in the OLS and fixed effects models. Similarly, following Rosenbaum (2002), we also check the extent to which our estimates of private school effects based on propensity score matching suffer from unobservables. We find a private school premium in maths ranging from 0.13 to 0.20 score standard deviation, based on the household fixed effects model and village fixed effects model, respectively. In the case of language, the premium ranges from 0.20 to 0.29 score standard deviation, based on the village and household fixed effects models, respectively. Household fixed effects yield tighter estimates due to their ability to account for unobservables at the household level

The analysis in chapter 4 shows that private schools (relative to public schools) are associated with better learning achievements. However, private schools in Kenya are not free of charge. If resources become scarce, it is possible that parents can decide to send some of their children to private schools and others to public schools. What family characteristics influence such decisions to take some children to private and others to public schools? This question forms the motivation for our third essay where we investigate the effect of the gender and order of birth of a child on *intra-household investments in*, and *educational outcomes of*, children in Kenya. From the second essay, we know that, relative to public schools, private schools significantly promote student scores yet they (private schools) are not free of charge. For this reason, we measure the intra-household education investment in children by the household's decision to enrol a child in a private school and define *educational outcomes* by two variables, namely, *completed years of education* and *relative grade attainment.*

We use the Uwezo survey that allows us to apply the family fixed effects models that address the potential endogeneity of children's gender, birth order and family size as well as factors that are unobservable at the household level. Although we do not find an intra-household gender preference in terms of investments in children's education, there is a female advantage in terms of the two measured education outcomes. For instance, relative to their male siblings, female siblings complete 0.138 more years of education and progress through school faster, accumulating 0.025 more years of education per year of schooling. Our results show significant negative effects of birth order on private enrolment, completed years of education and relative grade attainment. Our results are robust to different robustness checks including correction of selectivity bias originating to non-enrolment of children and further attempts to measure birth order more accurately. We find that family wealth plays a significant role in propagating the birth order (but not gender) effects we observe.

Chapter 6 provides a concluding remarks. Although beyond the scope of our study, we briefly discuss what we regard as potential drivers for the high performance of students in private schools. However, we call for further inquiry into this issue subject to data availability. The chapter also highlights the limitations of this thesis and points out areas for future research.

# Chapter 2

# The Study Data: The Service Delivery Indicators (SDI) and Uwezo Surveys

## 2.1 Introduction

Faced with the growing concern about the quality of education offered in schools in the sub-Saharan region as outlined in chapter 1, careful monitoring of learning outcomes is vital (Jones et al., 2014). The absence of reliable data on learning outcomes in developing countries has recently inspired a number of regional and national initiatives aimed at assessing how children learn in schools. In East Africa, two initiatives stand out: the Uwezo initiative and the Service Delivery Indicators (SDI) initiative. The Uwezo[1] initiative has been implementing large-scale household surveys that assess literacy and numeracy competencies of school age children since 2009 (Jones et al., 2014). The SDI is a World Bank-led initiative, launched in 2009 to collect data on service delivery at front-line primary service providers (e.g. schools and health facilities).

The Uwezo and SDI surveys are the main sources of data for this thesis. The motivation for using both Uwezo and SDI data is two-fold. First, the Uwezo survey involved assessment of students at home while in the SDI survey, students were assessed at school. Combined analysis of SDI and Uwezo should provide a robust picture of student's learning in Kenya. Secondly, the SDI survey involved classroom observation and assessment of teachers, which enables us to answer the first research question related to estimating

[1]Uwezo which means 'capability' in Kiswahili, is a non-governmental organization that aims to improve competencies in literacy and numeracy among children aged 6-16 years in Kenya. More details about Uwezo can be found at: http://www.uwezo.net/.

the effect of teacher knowledge, pedagogy, instruction time and classroom practices on student learning. A drawback of the SDI survey, is that it did not collect information regarding households or community related factors. In addition, its sample size is relatively small, especially with regard to children going to private schools. It is therefore not ideal for answering our second and third research questions which relate to estimating the effect of private schools and estimating the effect of gender and birth order on child education outcomes, respectively. To compensate for this, we use the household-based Uwezo survey.

This chapter provides a general overview of the two surveys. It highlights key issues that form the basis for our research questions that are followed in the subsequent chapters of the dissertation. We begin by providing a detailed description of how the surveys were undertaken including the sampling strategy. Based on selected indicators, we then provide a general picture of the home (using Uwezo survey) and school (using SDI survey) inputs that support student learning. Using the Uwezo micro data, we provide a brief discussion on two education outcomes variables *(net enrolment rates* and *relative grade progression)* since they are key variables of interest in Chapters 4 and 5. We end by providing an analysis of how children are learning in Kenya based on the Uwezo and SDI student test scores. In particular, we assess whether children in Kenya are acquiring and mastering the skills and competencies outlined in the curriculum of earlier grades.

A key point to note is that the SDI survey assessed grade 4 pupils. The Uwezo survey targeted children aged 6-16 years, both those enrolled in school and those who are out of school. In analyzing student tests scores in section 2.2.4 (and also when examining the effects of private schools in Chapter 4)[2], we restrict the Uwezo sample to children who are enrolled and are in grade 2 to grade 4 to make the two samples comparable.[3] There are a number of other reasons for imposing this restriction. First, there is scant information on learning achievement in lower grades in Kenya.[4] Second, in a typical developing country like Kenya, the sample of primary school children is likely to become more self-selective as one goes higher up due to drop-out rates. Focusing on grade 2 to 4 allows us to minimize such potential self-selection problems. Lastly, evidence shows that cognitive ability is most malleable at younger ages; hence the need to understand student learning at the lower levels (Cunha and Heckman, 2007).

[2]In Chapter 4, we motivate the reasons for imposing this restriction.

[3]We exclude grade 1 since the assessments were based on grade 2 syllabus.

[4]Only a few studies exist looking at learning achievements in lower grades in Kenya. These include Piper et al. (2015), Piper et al. (2014), Piper and Mugenda (2012) and Piper and Mugenda (2010) which focus on student learning at grade 1 and grade 2. These studies are a product of the on-going United States Agency for International Development (USAID) funded Early Grade Primary Mathematics and Reading Initiative. They are based on a Randomized Control Experiment trails and quite limited in terms of the sample size.

### 2.1.1 The Service Delivery Indicators (SDI) Survey

Launched in 2009, the Service Delivery Indicators (SDI)[5] is an initiative of the World Bank, the African Development Bank (AfDB) and the African Economic Research Consortium (AERC). The aim of the initiative is to collect data on how services are delivered at front-line primary service provider facilities in health (health facilities) and education (schools).

The SDI survey of education in Kenya conducted in 2012 is a cross-sectional survey covering 306 primary schools. A detailed description of how the SDI survey was conducted is provided in Martin and Pimhidzai (2013). The survey used a multistage cluster sampling strategy where counties[6] were categorized as (i) rural or urban, based on the 1999 national census data; (ii) relatively rich or poor, based on the 1999 national census data;[7] and (iii) high or low-performing based on county-level 2010 Kenya Certificate of Primary Education (PECK) pass rates. These three binary distinctions yielded 8 strata within which schools were sampled. Within each stratum, counties were randomly selected, followed by a random selection of locations within each county, and then a random selection of schools within the locations. The probability of selecting a county or a location was proportional to the population within it.[8] The data collection involved three major components briefly described below.

#### 2.1.1.1 Classroom Observation

One of the unique features of the SDI survey is the fact that it involved classroom observation. In every school, a trained surveyor[9] observed a teacher delivering a 35-minutes grade 4 lesson in either language (English)[10] or mathematics but not both.[11] The observations were based on an adapted version of the Stallings Classroom Snapshot instrument

[5]For details, please see: http://www.sdindicators.org/

[6]Counties are units of devolved government as envisioned in the 2010 Constitution of Kenya..

[7]The 1999 census was the latest data set on urbanization and poverty rates available to the researchers at the time of the sampling process for the SDI schools survey.

[8]Of the 47 counties in Kenya, 3 counties of the region previously known as North Eastern province were excluded due to security concerns at the time. North Eastern Province was one of eight administrative regions that preceded creation of the counties.

[9]Before going to the field, a week-long training was held for the surveyors led by a team of specialists from the World Bank in collaboration with Kimetrica (https://www.kimetrica.com/contacts/), an agency that had been subcontracted to collect the data.

[10]Throughout this document, instead of calling this an English test, we refer to it as language test.

[11]In the cases where there was more than one class of grade 4 (e.g grade 4A and 4B), the surveyor randomly selected one class using a methodology taught during the training. Schools were not informed of their selection and were not advised of the visits in advance. Teachers did not receive advance notice that they would be observed.

(Stallings, 1977; Stallings and Knight, 2003). The Stallings instrument uses a standardized coding grid to register minute by minute activities and materials being used by the teacher and students over the course of a single lesson(Bruns and Luque, 2014). For every minute, of the 35 minute lesson, the surveyor scanned the class in a 360-degree circle starting with the teacher and recorded what was happening. This *snapshot,* took about *15 seconds* and captured *what was happening at that instant* but not *what took place during the entire minute interval.*

Classroom observation took place in 276 schools. Recall that in each of these 276 schools, *one teacher was observed in either a language or mathematics lesson.* In 28 schools, teachers were absent from class and in 2 schools, classroom observation took place for creative arts and science subjects. We exclude these schools from the analysis. Of the 276 schools where classroom observation took place, language lessons were observed in 144 schools while mathematics lessons were observed in 132 schools. One might be concerned with the presence of systematic differences between the sample of schools (276 schools) where classroom observation took place and those where classroom observation did not take (30 schools). In appendix A (table A2.1), we use a wide range of school characteristics to show that there are no significant differences between these two samples.

#### 2.1.1.2 Pupil and Teacher Assessments

After the classroom observation, approximately 10 pupils from the class that had been observed were randomly selected and assessed in mathematics, language and non-verbal reasoning. The tests were largely based on materials up to grade 3 and were aimed at assessing the child's basic reading, writing, and arithmetic skills. They were designed by experts in international pedagogy and based on a review of primary curriculum materials from 13 African countries, including Kenya (Martin and Pimhidzai, 2013). They were administered as a one-on-one interaction, where the surveyor read out instructions to pupils. Where necessary, the surveyor read the instructions to the pupil in their mother tongue.

The student language test consisted of a number tasks ranging from alphabet and word recognition, to more challenging tasks like sentence and paragraph reading, and eventually tasks involving comprehension of written material. The mathematics test included tasks ranging from number identification and sequencing, to single and double digit addition and subtraction, to single digit multiplication and division. The non-verbal reasoning test consisted of tasks related to pattern recognition based on Raven matrices test (see Martin and Pimhidzai (2013) for a detailed description).

In addition, the survey assessed the knowledge of 1,679 primary teachers in language, mathematics and pedagogy. All current grade 4 mathematics and language teachers (including those observed in class) and those who taught grade 4 mathematics and language during the previous year (2011) were assessed. The language test administered to teachers consisted of 22 items involving grammar, cloze[12] and composition tasks. The mathematics test consisted of 15 items related to addition, subtraction, multiplication, division, fractions, interpreting graphs and data. The pedagogy test was designed to capture skills teachers would routinely be asked to apply when teaching.[13] As a courtesy to teachers, the teacher tests were designed as a marking exercise, in which teachers was asked to mark and correct a hypothetical student's exam (Martin and Pimhidzai, 2013).

Out of 276 teachers in 276 schools (one teacher per school) who were observed in class, only 222 teachers took part in the teacher assessments. The rest, 54 teachers, did not take part in the teacher assessments. We do not know why these teachers opted not to participate in the teacher assessment exercise. We however know that participation in classroom observation and teacher tests was voluntary. In appendix A (table A2.2), we show that there is no systematic differences, on a range of teacher classroom practices, between the 222 teachers (who were observed and tested) and 54 teachers (who participated in the classroom observation but not teacher tests).

This effectively means that our sample has 222 schools where one teacher was concurrently observed in class (either in language or mathematics) and assessed in the teacher tests. Of these, 109 teachers were observed in language and the rest, 113 teachers, were observed in mathematics.

#### 2.1.1.3 Teacher Absenteeism

Besides class observation and test assessments, the SDI survey involved an assessment of absenteeism of 2,960 teachers. During the first visit, the surveyor randomly selected a maximum of ten teachers from the list of all teachers in the school. In schools where there were less than 10 teachers all teachers were selected. The whereabouts of the selected teachers were then verified during *a second unannounced visit* based on five mutually exclusive options: (a) *teacher was in class teaching*; (b) *teacher was in class but not teaching*; (c) *teacher was present in school but not in class*; (d) *teacher was in school but teaching outdoors* and; (e) *teacher was absent from school.* We define absenteeism as the

[12]The cloze consisted of a passage with certain words removed (cloze text), where the teacher was asked to replace the missing words.

[13]Details about the mathematics, language and pedagogy test items administered to teachers are provided later in the text.

ratio of teachers (out of ten) who were *present in school but not in class (c above)* and *were absent from school (e above).* On average, the second unannounced visit took place about one or two weeks after the first visit.

The final part of the survey protocol was a structured interview with the school head-teachers (or substitute) to gather information about the school demographics including information about the teaching staff, school infrastructure and teaching resources.

### 2.1.2 Uwezo Survey

We used the third round of the Uwezo survey for Kenya collected in 2012. A detailed description of the sampling strategy is provided in Jones et al. (2014). The third round of the Uwezo survey was based on a two-stage random sampling design. First, 30 primary sampling units [14] from each district were selected with the probability of selection proportional to population size. Second, about 20 households in each enumeration area were selected via systematic random sampling.[15] Uwezo targets children aged 6-16 years who are regular residents of the household. Households without such children were therefore excluded.

#### 2.1.2.1 Household, School and Village Surveys

In each enumeration area, data collection involved three steps. First, data was collected from one randomly selected local public primary school within the enumeration area.[16] Information was gathered on school enrolment, teachers, classroom facilities as well as school facilities among others. Close to 4,465 schools were covered. Second, a questionnaire was administered to the village head of the sampled enumeration areas (villages). Among others, it gathered information on availability of: (i) social amenities (these included chief's office, shopping center and police post), (ii) infrastructure (these included tarmacked roads, all-weather roads, protected water points and electricity), and (iii) the number of educational and health facilities in the village.[17]

[14]Primary Sampling Units generally represent enumeration areas and/or villages

[15]The sample design was provided by the Kenya National Bureau of Statistics (KNBS).

[16]In cases where there was no public primary school in the sampled enumeration area, the nearest public school attended by the majority of children in the sampled enumeration area was selected. When more than one school was available in the enumeration area, the school that attended by a majority of the students was selected.

[17]Information gathered included the number of primary and secondary schools (public and private) as well as the number of village polytechnics. Data was collected on the number of health facilities run by government and non-governmental organizations.

Finally, households were visited. A questionnaire was then administered to the head of the household (or representative). For children aged 6-16 years, information was gathered about their age, gender, disability, school grade, whether they were enrolled in school and for those enrolled, the type of school they were enrolled in (private or public) and the time taken to arrive at school. The household questionnaire also collected information on parental age and education as well as indicators of household socioeconomic status. All children of school age (6-16 years) in the household, irrespective of their enrollment status, were assessed in language and mathematics. The 2012 Uwezo survey covered 145,564 children aged 6-16 from 72,000 households residing in close to 4,000 villages.

#### 2.1.2.2 Children (Student) Assessments

Unlike in the SDI survey, student assessments under the Uwezo initiative took place at home. Children were assessed in language proficiency (English and Kiswahili) and mathematics. The tests were based on the grade 2 level curriculum and only administered to children aged 6-16 years who were regular inhabitants of the household. In this study, we limit ourselves to English (which we call language) and mathematics tests.

The language (literacy) tests were designed to assess five principal competencies, namely: (1) letter recognition, (2) word recognition, (3) ability to read a paragraph, (4) ability to read a (short) story and (5) ability to comprehend information in the story (Wakano, 2016; Uwezo, 2012, 2014; Jones et al., 2014). Each competence level was assessed by a separate test item. However, due to the ordered nature of the competencies, not all children are assessed on each competency item (Jones et al., 2014).[18] In this regard, the assessment adopted some form of adaptive learning. It began with level 3 competency (reading a paragraph) and either stepped up (to comprehension) or stepped down (to letter level) in difficulty depending on the child's initial response. For instance, if the child read the paragraph correctly at the start, he/she was then presented with a short story of about 98 words and asked to read it. If the child read the story successfully, he/she was presented with two questions based on the story he/she had read.

However, if the child was unable to read the paragraph correctly at the beginning, he/she was presented with a list of 10 words and asked to read at least 5. If the child could not read up to at least 5 words, he/she was presented with 10 letters and asked to name any 5. If the child could not identify up to 5 letters, he/she was marked as knowing

[18]In this regard, comprehension of the paragraph (highest competence) requires ability to read story, process it, and understand its meaning. Knowing how to read a story implies ability to read a paragraph which in turn implies ability to recognize words. Ability recognize words implies ability to recognize letters (lowest competence).

nothing. Overall, children were classified into one of these five ascending categories: (1) knows nothing; (2) can identify a letter; (3) can identify a word; (4) can read a paragraph; (5) can read a short story and (6) can do comprehension.

The numeracy tests, structured and administered in a similar way to the literacy tests, assessed the following competencies: (1) counting, (2) number recognition (two digits), (3) rank ordering of two numbers, (4) addition, (5) subtraction, (6) multiplication and (7) division (Wakano, 2016; Uwezo, 2012, 2014; Jones et al., 2014). It began with the level 5 item (subtraction) and the level of difficulty was either stepped up (to division) or stepped down (to counting) depending on the child's initial response. Similarly, children were classified into one of these ascending categories: (1) knows nothing; (2) could count; (3) could identify a number; (4) could discriminate numbers; (5) could add (6) could subtract; (7) could multiply and (8) could divide.[19] Unlike SDI, Uwezo did not involve teacher assessments. In table 2.1, we show the information that was gathered in both surveys.

Table 2.1: Data gathered in SDI and Uwezo Surveys

| | **Uwezo Survey** | **SDI Survey** |
|---|---|---|
| ***Households Characteristics*** | | |
| Parental demographics | Y | N |
| Durable and livestock assets | Y | N |
| Lighting, dwelling and sanitation conditions | Y | N |
| ***Schools Characteristics (Public and Private schools)*** | | |
| School demographics (location, number of teachers etc) | N | Y |
| Teaching resources (chalk, board, textbook etc) | N | Y |
| Infrastructure (lighting, toilets etc). | N | Y |
| ***Teachers Characteristics (Public and Private schools)*** | | |
| Teacher test assessments | N | Y |
| Teacher classroom practices and time use | N | Y |
| Teacher effort: absence in school and in class | N | Y |
| Teacher classroom observations | N | Y |
| ***Student Characteristics*** | | |
| Age | Y | Y |
| Gender | Y | Y |
| Grade | Y | Y |
| Breakfast, disability and tuition status | N | Y |
| ***Village Characteristics (socioeconomic conditions)*** | Y | N |

Notes: (1) Y means Yes and N means No; (2) As noted, in the Uwezo survey, data was collected from one public primary school within the enumeration area. No private schools were covered. We however do not however have full access to the Uwezo schools data.

[19] Generally, subtraction facts are harder for children to learn than addition facts. Based on the topology of learning, children who were able to subtract were imputed as having the ability to add. Similarly, those who were able to add were imputed as having the ability to discriminate numbers. Lastly, those who were able to discriminate numbers were imputed as having the ability to identify and count numbers.

## 2.2 Survey Descriptives

### 2.2.1 Overview of Home and School Inputs

We begin by showing a general picture of home (based on the whole sample of the Uwezo Survey) and school (based on the SDI survey) inputs that support student learning (table 2.2). In subsequent chapters, we will show how these inputs affect student achievements. Table 2.2 (a) presents summary statistics for children's home education inputs. On average, there are six members per household. Majority of parents have primary education: mothers average six years of education while fathers average nine years of education (column 1). Children in private schools have significantly better educated parents and live in smaller households.

The Uwezo survey does not ask about household income or expenditure, two conventional measures of household living standards. However, the survey includes questions related to household ownership of durable assets (television, radio, computer, mobile phone, car, bicycle, motorbike and cart) and livestock assets (number of cattle, sheep, horses/donkeys/ camels, chicken etc.), type of material used to construct the wall of the dwelling unit, type of lighting regularly used by the household, number of meals taken per day and household sanitation status (whether the household has a source of water and a latrine at home). We use these household socioeconomic characteristics to construct an index of household wealth.[20]

We wish to briefly explain how the household wealth index is constructed since it will repeatedly be used in subsequent chapters. This index is constructed using the (ordinary) principal components analysis (PCA).[21] Details of the PCA approach are described and defended by Vyas and Kumaranayake (2006), Filmer (2005)and Filmer and Pritchett

[20]The variables used for the construction of the index are (1) a set of eight dummy variables which is equal to one if a household owns each of the following durable assets: television, radio, computer, mobile phone, car, bicycle, motorbike and cart; (2) a set of four dummy variables which is equal to one if a household owns each of the following livestock assets: cattle, donkey, camel and sheep/goat; (3) a set of four dummy variables which is equal to one if the household dwelling unit is made of the following materials: mud, iron, timber, and bricks/stone; (4) a set of two dummy variables which is equal to one if the household's regular source of lighting is: electricity and paraffin; (5) a set of three dummy variables which is equal to one if the household's number of meals consumed per day are one meal, two meals and three meals; (6) a set of two dummy variables which is equal to one if the household has a source of water and a toilet at home; (7) Number of years of education of the mother and father (entered as a continuous variable).

[21]Principal components analysis (PCA) is a technique that summarizes information contained in a large number of variables in a smaller number by creating a set of mutually uncorrelated components of the data (Filmer, 2005; Filmer et al., 2008). This is defined in such a way that the first principal component

Table 2.2: Selected Descriptive Statistics from Uwezo and SDI Surveys

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | | Uwezo Survey | | | | SDI Survey | | |
| | | All Mean | Public Mean | Private Mean | Public-Private Mean Diff. | All Mean | Public Mean | Private Mean | Public-Private Mean Diff. |
| (a) | **Household Characteristics** | | | | | | | | |
| | Household size | 6.54 | 6.65 | 6.04 | 0.61** | | | | |
| | Household is in a rural area | 0.76 | 0.79 | 0.62 | 0.17*** | | | | |
| | Mother's years of education achieved | 5.70 | 5.81 | 7.98 | -2.71*** | | | | |
| | Father's years of education achieved | 8.65 | 8.58 | 9.61 | -1.03*** | | | | |
| | Wealth index (normalized to 0-1 range) | 0.41 | 0.41 | 0.54 | -0.13*** | | | n/a | |
| | Household belongs to the upper wealth index | 0.28 | 0.26 | 0.56 | -0.31*** | | | | |
| (b) | **School Characteristics** | | | | | | | | |
| | School is rural | | - | | | 0.68 | – | – | – |
| | Classroom has a blackboard and a chalk (%) | | 0.96 | | | 0.99 | 0.99 | 1.00 | -0.01 |
| | Share of pupil with a pen & an exercise book (%) | | 0.94 | | | 0.98 | 0.97 | 0.99 | -0.01 |
| | Average number of students per textbook (maths) | | 3.00 | | | 2.59 | 2.81 | 1.91 | 0.9*** |
| | Average number of students per textbook (English) | | 3.09 | | | 3.61 | 4.03 | 2.09 | 1.9 |
| | School has toilets (%) | | 0.85 | | | 1.00 | 1.00 | 0.99 | 0.01 |
| | Sufficient light for reading from the back of the class (%) | | | | | 0.85 | 0.85 | 0.88 | -0.04 |
| | School has electricity connection (%) | | | | | 0.14 | 0.09 | 0.34 | -0.26*** |
| | Pupils per Teacher | | 33.1 | | | 30.2 | 34.9 | 19.7 | 15.2*** |
| (c) | **Teacher Characteristics** | | | | | | | | |
| | Teacher experience | | | | | 13.90 | 16.13 | 5.65 | 10.48*** |
| | Teacher language score | | n/a | | | 63.52 | 63.12 | 65.38 | -2.26*** |
| | Teacher maths score | | | | | 77.59 | 76.79 | 81.24 | -4.44*** |
| | Teacher absence from class | | | | | 44.93 | 47.97 | 34.07 | 13.90*** |
| (d) | **Child Characteristics** | | | | | | | | |
| | Student is female | 0.52 | 0.52 | 0.51 | 0.02** | 0.51 | 0.50 | 0.47 | 0.03 |
| | Student's age (in years) | 9.31 | 9.41 | 8.55 | 0.87*** | 10.43 | 10.60 | 9.74 | 0.9*** |
| | Student attends a private school | 0.14 | – | 1.00 | – | 0.22 | – | 1.00 | – |
| | Student had breakfast | | n/a | | | 0.87 | 0.85 | 0.94 | -0.1*** |
| | Student attends tuition | 0.36 | 0.33 | 0.69 | -0.37*** | | | n/a | |
| | Student has disability | 0.03 | 0.03 | 0.02 | 0.01** | | | | |
| | **Number of children** | **145,564** | **112,551** | **14,438** | | **2,953** | **2,378** | **575** | |
| | **Number of households** | **72,000** | **42,902** | **6,726** | | – | – | – | |
| | **Number of schools** | – | **3,525** | – | | **306** | **239** | **67** | |

*Source*: Own calculations based on Uwezo and SDI 2012. Notes: (1) n/a means that the respective information was not asked in the respective survey, for instance, the SDI survey did not ask information regarding households; and (2) ***significance<1 percent, ***significance<5 percent, ***significance<10 percent.

(2001) among others who show that the PCA wealth index performs just as well as traditional measures of household living standards such as household-size-adjusted consumption expenditures, in predicting household outcomes such as educational attainment.[22] Despite this, we acknowledge and are aware that this measure of household resources has flaws.[23]

Following De Haan et al. (2014), we normalize the household wealth index to the range of 0 and 1 and classify households with a wealth index of 0.5 and above as rich and those below this wealth index as poor. As can be seen in table 2.2 (a), the average wealth index (0-1 range) is 0.41. This means that majority of households surveyed in the Uwezo survey belong to the lower part of the wealth index and can therefore be classified as poor. For instance, only 28 percent of households can be classified as rich. Most of the households classified as poor send their children to public schools.

Table 2.2 (b) shows summary statistics of the school environment. This is based on the Uwezo survey that covered 4,486 public schools (one school per village) and the SDI survey that covered 306 schools (239 public and 67 private schools). In both samples, schools are almost universally equipped with minimum teaching resources, which we define as availability of: (a) functioning blackboard[24], (b) chalk (c) writing materials (pens and exercises books), and (d) number of students per textbook. For instance, over 90 percent of schools in both samples have classes with a blackboard and piece of chalk and students provided with writing materials (pencil/pen and an exercise book). Although there are more students per textbook in public relative to private schools, the government has nearly achieved its policy of three students per textbook at primary level, especially in mathematics. Schools also do well in terms of minimum infrastructure, defined as availability of: (a) functioning toilets (toilets that are clean, private, and accessible) and (b) sufficient light to read the blackboard from the back of the classroom. Over 85 percent of the schools have toilets.[25] Access to electricity, although not defined as a minimum functioning infrastructure requirement, is generally low, especially among public schools.

accounts for as much of the variability in the variables as possible. This first principal component can be interpreted as a *wealth index* on the assumption that the underlying variable with the largest explanatory power is a household's long-run wealth (Filmer, 2005).

[22]The PCA based wealth index has been used by many studies (Filmer and Pritchett, 2001; Tenikue and Verheyden, 2010) to investigate the determinants of education outcomes in the developing world and has been found to significantly determine child education outcomes.

[23]A detailed exposition of these flaws are discussed in Vyas and Kumaranayake (2006) and more recently Wittenberg and Leibbrandt (2017). The centered PCA index has been criticized for giving negative scores to assets that are mainly owned by rural households such as ownership of livestock in the case of Kenya leading to artificial increase in the rural-urban divide (Wittenberg and Leibbrandt, 2017).

[24]The blackboard is defined as functioning if a text written on it could be read at the front and back of the classroom.

[25]Furthermore, in over 90 percent of the schools, toilets were designated for boys and girls, accessible (unlocked and not overflowing) and private (had doors or separating entryway wall).

Table 2.2 (c) shows selected indicators capturing selected teacher *observable characteristics* (teacher experience), *knowledge* (teacher test scores in mathematics and language) and *effort* (absence in class). These are based on 1,679 teachers who were assessed in teacher test assessments as well as 2,960 teachers who were assessed in teacher absence. We provide a detailed description of these characteristics in the next chapter. The teacher's overall mean years of experience is 13 and private school teachers are less experienced. On average a public school teacher has more than 10 years of experience compared to his/her counterpart in a private sector. The overall mean performance was 63.52 percent and 77.59 percent in language and mathematics respectively. Private school teachers appear to have more subject knowledge than their counterparts in public schools. On average, four out of 10 teachers were absent from the classroom. Private school teachers are more likely to be in school and in class than their public counterparts. As shown in the table, a private school teacher was almost 13.90 percent points less likely *to be absent in class* relative to his/her counterpart in a public school.

Table 2.2 (d) summarizes children's characteristics based on both surveys. The overall mean age is 10.4 and 9.31 years for the SDI and Uwezo surveys, respectively. The statistics show that 14 percent and 22 percent of students in Uwezo and SDI surveys attend private schools. The majority of learners in the SDI survey (87 percent), reported they had breakfast (our proxy for socioeconomic status) before coming to school. In the Uwezo survey, about 36 percent of the children attend extra tuition classes.[26] In both surveys, private schools have relatively young students. Similarly, private school children are more likely to have had breakfast and more likely to attend tuition classes.

Generally, table 2.2(a) to (d) shows that children who attend private schools do seem to have disproportionately high academic potential and access to complementary educational resources relative to their counterparts who attend public schools. For instance, their parents have more years of education and they come from households with higher wealth index. They are also taught by more knowledgeable teachers and teachers are also more likely to be in school and in class. As pointed out in Chapter 1, this might raise concerns as to whether the higher performance in private schools is a reflection of endogenous selection of students from better backgrounds. In Chapter 4, we estimate the effect of private schools by employing different methods that deal with such potential endogenous selection into schools.

[26]These are extra remedial classes offered beyond the normal official scheduled school time.

### 2.2.2 Enrolment Rates

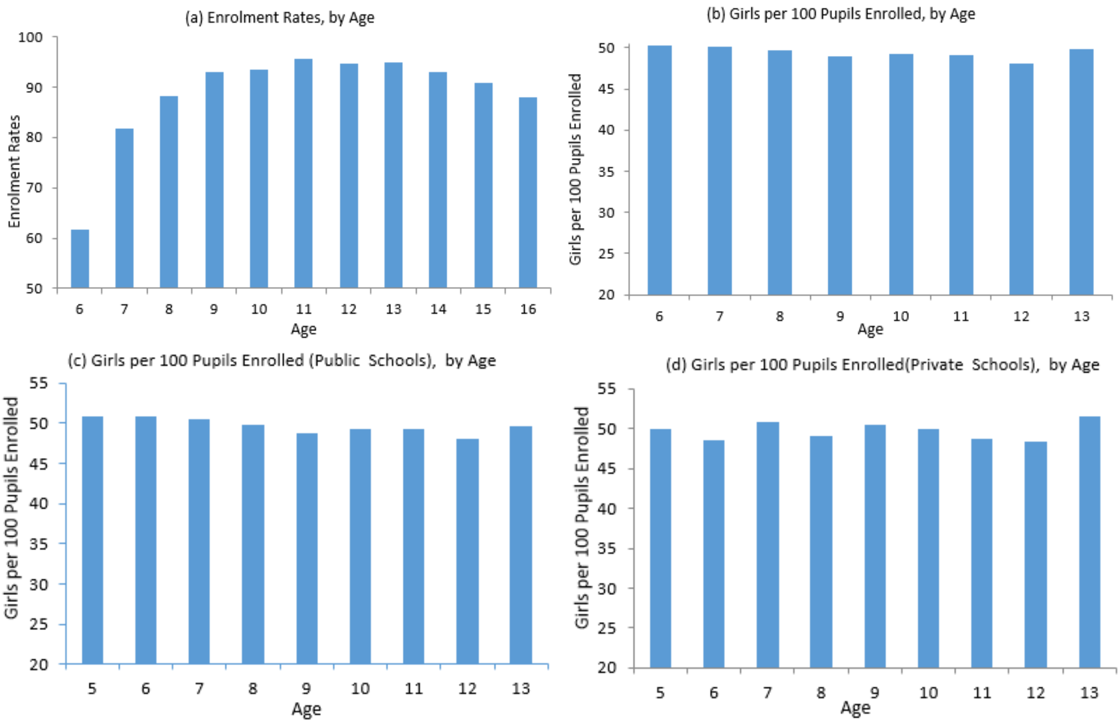
For children to learn and acquire minimum learning competencies, they need to be enrolled in and progress effectively through the schooling system. We briefly discuss trends in enrolment and grade progression, based on the whole sample of the Uwezo survey which collected information on the enrolment status of children. Out of 145,564 children of primary and secondary school going age (ages 6 to 16) covered in the Uwezo survey, 88 percent were enrolled, 11 percent were never enrolled and 1 percent had dropped out of school. Focusing on those who are enrolled, in figure 2.1(a), we show trends in enrolment rates by age. In figure 2.1(b), (c) and (d), we show the gender parity index, that is, the number of girls in every 100 children enrolled in all schools, public schools and private schools, respectively. [27]

Figure 2.1(a) confirms our core message from chapter 1: Kenya has made significant progress in getting children into schools. The enrolment rates peak at a relatively high level - almost 95 percent of children are enrolled in school at some point in their school age period. Efforts to get more girls into schools are also bearing fruits. Figure 2.1 (b) shows that at all ages, the number of girls per 100 children enrolled is almost equal to the number of boys enrolled. In fact, at age 6 and 7, there are slightly more girls than boys enrolled in primary school. Figure 2.1(c) and figure 2.1(d) further shows there is no significant gender preference in terms of enrolment in public and private schools, respectively. At all ages, the number of girls per 100 children enrolled is almost equal to the number of boys enrolled and in fact there are slightly more girls enrolled than boys. For instance, at age 13, there are slightly more girls enrolled in private schools than boys.

As also noted in Jones et al. (2014), there are two concerns that arise from Figure 2.1(a). First, children are relatively older than expected when they begin school. As can be seen in Figure 2.1(a), close to 40 percent of 6 year olds are not enrolled in school despite this being the official age for starting school in Kenya. Second, enrolment rates start to decrease at age 11 although this is not the official primary school completing age, meaning that a significant number of children do not complete their primary education. These two concerns conform to findings by Jones et al. (2014) who report that an average Kenyan child of primary school age level receives fewer years of education than expected.

[27] It is not surprising that the trends are quite similar to those presented in Jones et al. (2014) who pooled the Uwezo survey of 2011 and 2012.

Figure 2.1: enrolment Rates and the Gender Parity Index by Age



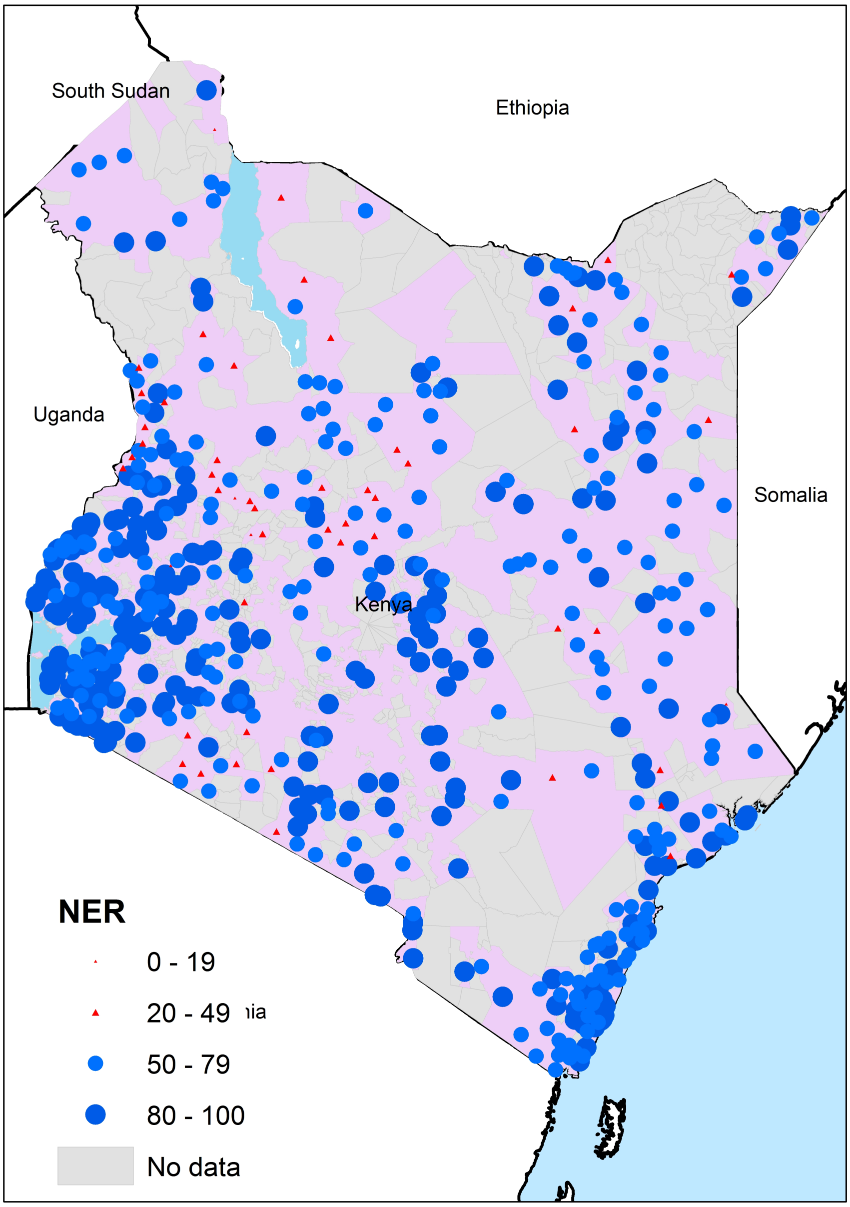

*Source*: Own calculation based on Uwezo 2012. Notes: enrolment rates and the Gender Parity Index are calculated as a percent of the age cohort.

There are also regional disparities in enrolment within Kenya. To show this, we calculate the average net enrolment rates (at primary level) and the proportion of girls per 100 pupils enrolled at the location level.[28] The Uwezo survey has about 1,845 locations. In figure 2.2, we show the spatial distribution of the primary net enrolment rates (NER) for each location.[29] Each of the symbol, the dot (●) and delta (▲), corresponds to the net enrolment rate level for a particular location. In locations with the dot symbol (●), the net enrolment rates are equal to or more than 50 percent. In locations with the delta symbol (▲), the rate of net enrolment rates are less than 50 percent. As it can seen from the figure, the majority of locations are characterized by high enrolment rates, falling within the range of 66-99 percent. Nevertheless, there are a number of locations (albeit being few) where more than half (50 percent) of primary school-going children are out of school. In fact, there are locations where less 20 percent of the primary age school going children are enrolled.

[28]Based on the 2009 census, Kenya is administratively divided into seven levels: Province, District, Division, Location, Sub-location and village (enumeration area). In the hierarchy of geographic boundaries in Kenya, the smallest unit is the enumeration area (village). A group of villages comprise a Sub-location. A group of Sub-locations comprise a Location. The Location is therefore the third administrative tier.

[29]We are grateful to Laban Maiyo, a Geospatial consultant based in Nairobi, for helping us with denoting data to specific locations.

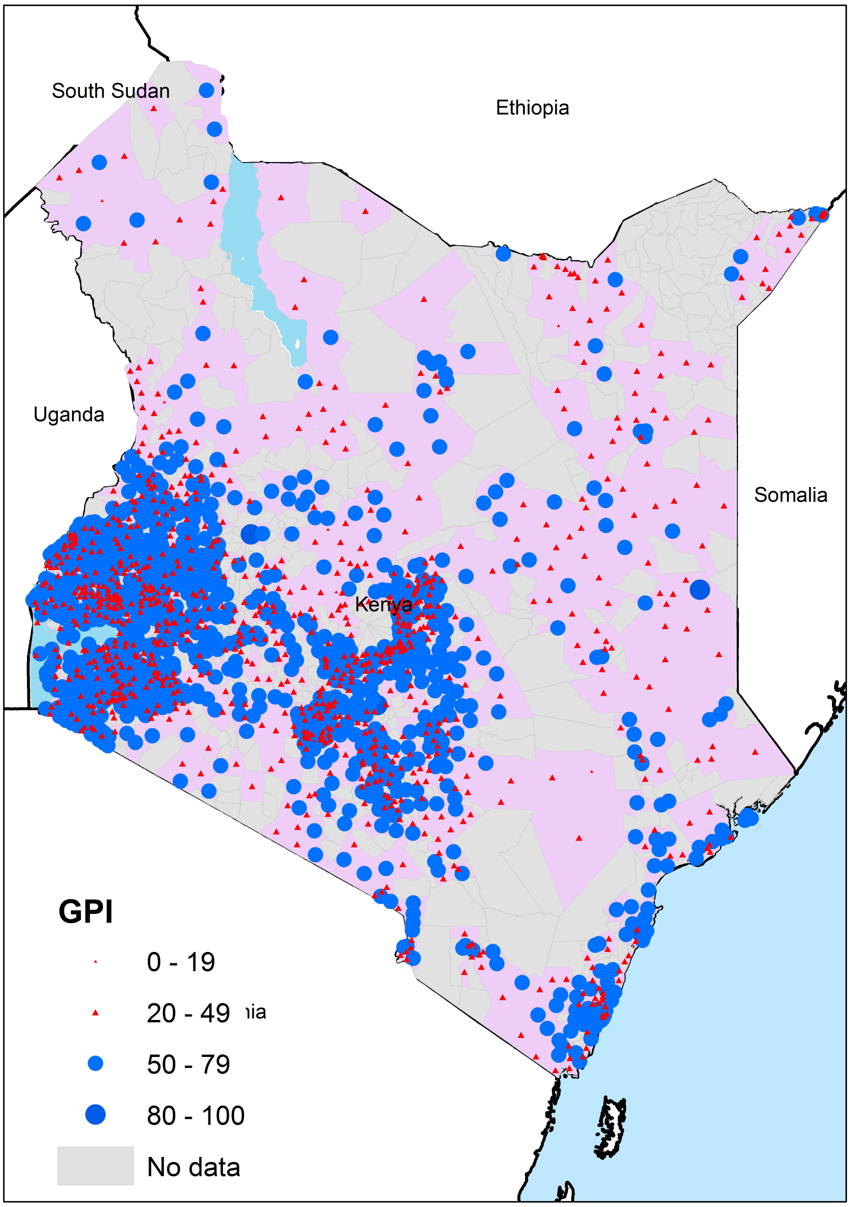
Figure 2.2: Net Enrolment Rates (NER) by Uwezo Survey sampled Locations




*Source*: Own calculation based on Uwezo 2012. In locations with the dot symbol (●), the net enrollment rates are equal to or more than 50 percent. In locations with the delta symbol (▲), the rate of net enrollment rates are less than 50 percent.

In figure 2.3, we show the spatial distribution of the proportion of girls per 100 pupils enrolled (gender parity index), calculated at the location level. In locations with the dot symbol (●), the proportion of girls per 100 pupils enrolled is equal or greater than 50 percent, meaning that there are equal or more girls than boys enrolled per 100 pupils. In locations with the delta symbol (▲), the proportion of girls per 100 pupils enrolled is less than 50 percent. As it can be seen from the figure, in nearly half of the locations, the proportion of girls enrolled is less than boys. There are locations where proportion of girls per 100 pupils enrolled is as low as 20 percent. This shows evidence of regional disparities in terms of girl's access to education opportunities in Kenya. We pick up this discussion in chapter 5 where we examine whether the gender and order of birth of a child in a household affects his/her enrolment (in private schools).

Figure 2.3: Gender Parity Index (GPI) by Uwezo Survey sampled Locations




*Source*: Own calculations based on Uwezo 2012. In locations with the dot symbol (●), the proportion of girls per 100 pupils enrolled is equal or greater than 50 percent, meaning that there are more girls than boys enrolled per 100 pupils. In locations with the delta symbol (▲), the proportion of girls per 100 pupils enrolled is less than 50 percent.

### 2.2.3 Relative Grade Progression

As we noted based on figure 2.1(a), a number of children start school when they are relatively older than expected and a good proportion leave before completing primary education. In other words, there seems to be a relatively high level of late entry and drop out rates (early exit). Researchers such as Mani et al. (2013) have advocated for an education outcome measure that accounts for such late entry and early exit. This measure is called the *relative grade progression* and is defined as *completed years of schooling* divided by *potential years of schooling.*[30] The potential years of schooling are *the total number of schooling years a child accumulates if he/she starts schooling on time*[31] *and adds one more in each subsequent year* (Mani et al., 2013).

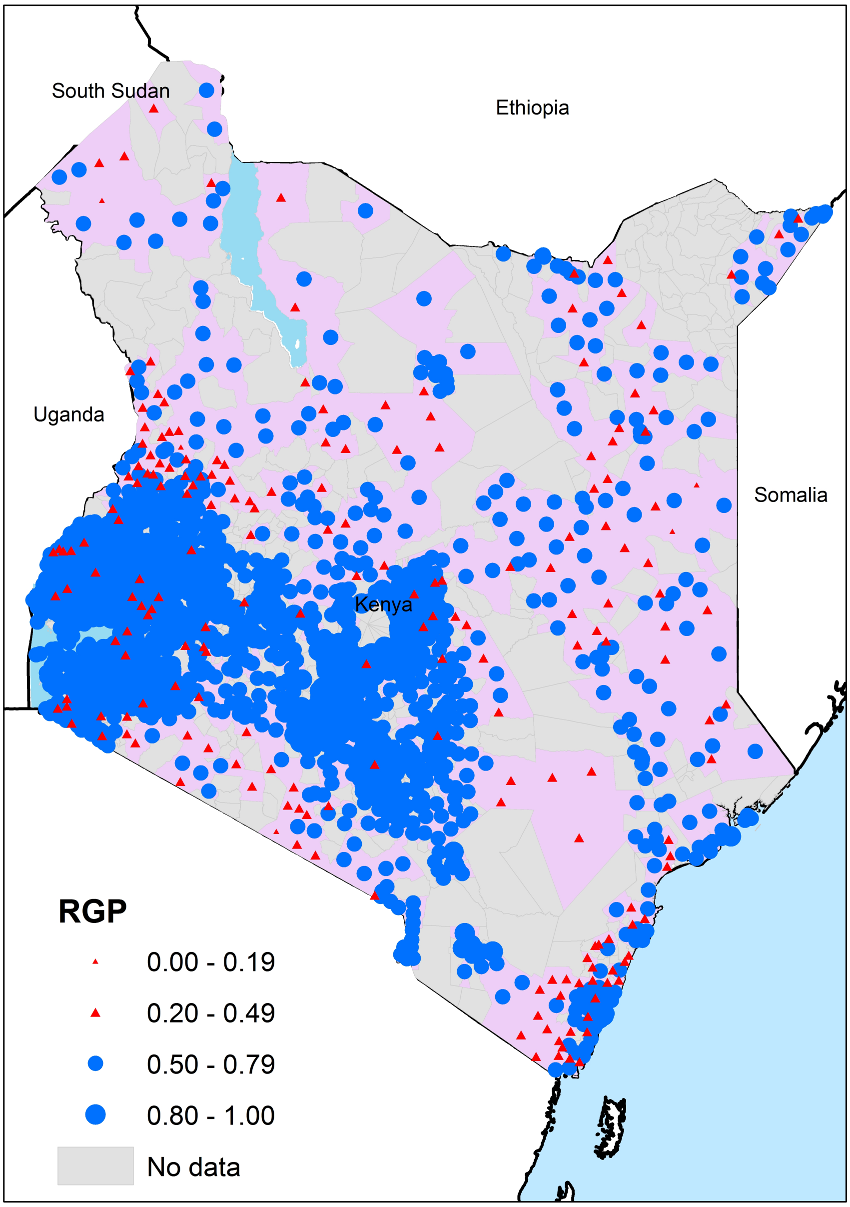
Ideally, if a child starts grade 1 at age 6 and does not repeat any class, he/she records a relative grade progression of 1, the most desired and maximum level and denotes high efficiency levels of the schooling system. Lower levels of relative grade progression denote high rates of late entry and/or grade repetition, which in turn show high levels of inefficiency in the schooling system. The overall relative grade progression for the whole country is 0.65 meaning that, on average, children accumulate 0.65 years of education per year of schooling.

In figure 2.4, we show the average relative grade progression per location. Each of the symbol (●) and (▲) corresponds to the average relative grade progression per location. In locations with the dot symbol (●), the average relative grade progression are equal to or more than 0.5 percent. In locations with the delta symbol (▲), the average relative grade progression are less than 0.50 percent. The figure shows that there is a good proportion of regions (locations) where children progress quite slowly through the schooling system due to late entry and/or early drop outs. In Chapter 5, we analyze whether the gender and order of birth of a child in a household affects his/her relative grade progression.

[30] Relative grade progression is calculated as $[\frac{Completed\, years\, of\, education}{(Age-6)}]$ where 6 in the denominator denotes the official age of starting school in Kenya.

[31] That is age 6 in the case of Kenya.

Figure 2.4: Relative Grade Progression (RGP) by Uwezo Survey sampled Locations




*Source*: Own calculations based on Uwezo 2012. In locations with the dot symbol (●), the average relative grade progression are equal to or more than 0.50 percent. In locations with the delta symbol (▲), the average relative grade progression are less than 0.50 percent.

### 2.2.4 Student Performance in Test Scores

When children enrol in school and progress through specific grades, they are expected to master specific competencies in each grade. Children are expected to master skills and competencies outlined in the curriculum from the earliest grades. As we have already noted, the child tests in SDI and Uwezo surveys were set at grade 3 and grade 2, respectively. These tests provide an effective way of assessing whether children at each grade, thus, grade 4 and above for SDI and grade 3 and above for Uwezo, have mastered competencies necessary for further learning.[32]

There are two ways we can proceed with assessing learning competencies based on Uwezo and SDI surveys. We can calculate the overall mean score for each tested competency or calculate the share of children achieving a specific competency level. Since Uwezo and SDI assessments are anchored in the content of the national curriculum, the second metric is more meaningful because it helps to assess whether children meet the expected numeracy and literacy competency requirements.

In table 2.3 and table 2.4, we show the proportion of children who meet specific competence levels in the SDI and Uwezo surveys for language and maths. We restrict the Uwezo sample to children who are enrolled and are in grade 2 to grade 4 in order to make the samples more comparable. Restricting the sample to grade 2 to 4 learners in Uwezo leaves us with about 52,196 students. In both surveys, slightly more than half of the sample are female students. Looking at the language scores in columns 1 and 4, students generally do well in simple literacy tasks such as letter and word identification. Nevertheless, about 10 percent of grade 4 students in the SDI and 25 percent of students (grade 2 to 4) in Uwezo could not identify or read correctly simple words presented to them. Oral reading fluency, which we measure by the ability to read connected text accurately, is still low among learners.[33] Although 72 percent of students in the SDI could read all the 10 words in a basic sentence, only 16 percent managed to read correctly and accurately all the 58 words in a paragraph even after three years of primary schooling. In the same vein, only 48 percent of students in Uwezo could correctly read all the 18 words in the paragraph and further only 28 percent could read all the 98 words in a story.

[32]The idea is not to directly compare student performance between Uwezo and SDI surveys. They are based on different test content and grade composition and grades. Rather, we provide a snapshot of learning in lower primary in the surveys, which we consider robust since its based on two surveys undertaken at school and home respectively.

[33]Oral reading fluency is the ability to read a connected text *accurately*, *quickly*, and with *expression*. Oral reading fluency therefore assesses three aspects: *speed*, *accuracy*, and proper *expression*. The test in the SDI and Uwezo largely assessed student's ability to read correctly (accurately) every word in the text. Aspects of speed and expression were not assessed. We therefore proxy for oral reading fluency by the student ability to read correctly (accurately) every word in a text presented to them.

Table 2.3: Student Test Scores in Language

| | SDI survey | | | Uwezo survey | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Sub-task** | Percent of students (combined public and private schools) | Percent of students (public schools only) | Percent of students (private schools only) | Percent of students (combined public and private schools) | Percent of students (public schools only) | Percent of students (private schools only) |
| Could identify letters[a] | 0.91 | 0.90 | 0.98 | 0.95 | 0.95 | 0.98 |
| Could identify words[b] | 0.89 | 0.87 | 0.98 | 0.75 | 0.73 | 0.88 |
| Could read sentence[c] | 0.72 | 0.67 | 0.94 | | n/a | |
| Could read a paragraph[d] | 0.16 | 0.11 | 0.40 | 0.48 | 0.46 | 0.69 |
| Could read a story[e] | | n/a | | 0.28 | 0.25 | 0.48 |
| Factual comprehension[f] | 0.39 | 0.29 | 0.79 | 0.25 | 0.23 | 0.44 |
| Analytical comprehension[g] | 0.45 | 0.38 | 0.74 | 0.21 | 0.18 | 0.37 |
| **Sample** | **2,953** | **2,378** | **575** | **52,196** | **45,940** | **6,256** |

*Source*: Uwezo and SDI 2012. Notes: (1) We show the share of students who managed to perform each literacy items tested; and (2) n/a means the sub-task was not examined in the respective survey.

[a]In the SDI, a child was shown 9 letters and asked to identify 3. In Uwezo, the child was shown 10 letters and asked to identify any 5.

[b]In the SDI, the surveyor read out 9 words to the student and asked him/her to identify any 3 of them. In Uwezo, a child was presented with 10 words and asked to read at least 5. Recall that in Uwezo, this sub-task was given to children who could not correctly read the 18 word paragraph at the start.

[c]In this sub-task, a student was presented with a 10 word sentence and asked to read.

[d]In SDI, a student was presented with one paragraph of 58 words and asked to read. In Uwezo, a student was presented with two paragraphs of approximately 18 words and asked to choose and read any one of them.

[e]This sub-task was given to children who had correctly read the 18 word paragraph. A student asked to read a story of about 97 words. Only those who managed this sub-task proceeded to the next task which was answering two questions based on the text (comprehension).

[f]The factual comprehension question measured the learner's ability to identify stated facts in the passage they had read.

[g]The analytical comprehension question required the learner to at least infer or draw conclusions from opinions or ideas implied or suggested in the text.

Table 2.4: Student Test Scores in Maths

| | SDI Survey | | | Uwezo Survey | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Sub-task** | Percent of students (combined public and private schools) | Percent of students (public schools only) | Percent of students (private schools only) | Percent of students (combined public and private schools) | Percent of students (public schools only) | Percent of students (private schools only) |
| Could count and match numbers | | n/a | | 0.99 | 0.97 | 0.98 |
| Could identify a number[a] | 0.98 | 0.97 | 0.99 | 0.88 | 0.87 | 0.93 |
| Could discriminate quantities[b] | 0.73 | 0.71 | 0.83 | 0.82 | 0.81 | 0.88 |
| Could do addition[c] | 0.89 | 0.88 | 0.96 | 0.77 | 0.76 | 0.85 |
| Could do subtraction[d] | 0.63 | 0.58 | 0.82 | 0.60 | 0.58 | 0.72 |
| Could do multiplication[e] | 0.54 | 0.49 | 0.74 | 0.43 | 0.41 | 0.58 |
| Could do division[f] | 0.41 | 0.35 | 0.64 | 0.29 | 0.27 | 0.43 |
| Multiplication (word problem) [g] | 0.16 | 0.11 | 0.40 | | n/a | |
| Complete sequence[h] | 0.26 | 0.23 | 0.34 | | n/a | |
| **Sample** | **2,953** | **2,378** | **575** | **52,196** | **44,373** | **6,256** |

*Source*: Uwezo and SDI 2012. Notes: (1) We show the share of students who managed to perform each numeracy items tested; and (2) n/a means the sub-task was not examined in the respective survey

[a] In the SDI, the surveyor read out 9 numbers (mixture of single and double numbers) to the student and asked him/her to identify any 3 of them. In Uwezo, a child was presented with 10 double digit numbers and asked to choose and read at least 5 of which 4 were supposed to be correct.

[b] In SDI, a student was presented with 6 numbers of different quantities and asked to order them in a descending order. In Uwezo, this task involved 8 pairs of two sets of numbers where in each pair, the student was asked to identify which one of the two is greater. They were required to get at least 4 correct

[c] In SDI, this tasked involved a student being asked to solve three addition problems involving respectively, single, double and triple digits. Here, we define a student as *'could do addition'* if he/she answered any of two problems correctly. In Uwezo, a student was presented with 8 double digit addition problems and asked to solve at least 3 of which 2 must be correct.

[d] In SDI, this task involved one single and one double digit subtraction. Here, we define a student as *'could do subtraction* if he/she answered the two problems correctly. In Uwezo, a child was presented with 8 double digit subtraction problem and asked to solve at least 3 of which 2 must be correct

[e] In SDI, this tasked involved a student being asked to solve three multiplication tasks involving respectively, single, double and triple digits. Here, we define a student as *'could do multiplication* if he/she answered any of two problems correctly. In Uwezo, this task involved 8 single digit multiplication problems where the student was asked to solve at least 3 of which 2 must be correct.

[f] In SDI, this task involved three one division tasks involving both single and double digits. We define a student as *'could do division'* if he/she answered any of two problems correctly. The task in Uwezo involved 8 single digit division problems where the student was asked to solve at least 3 of which 2 must be correct

[g] In this task, a student was presented with an arithmetic (single digit) multiplication task presented in a word format that required some level of thinking to solve.

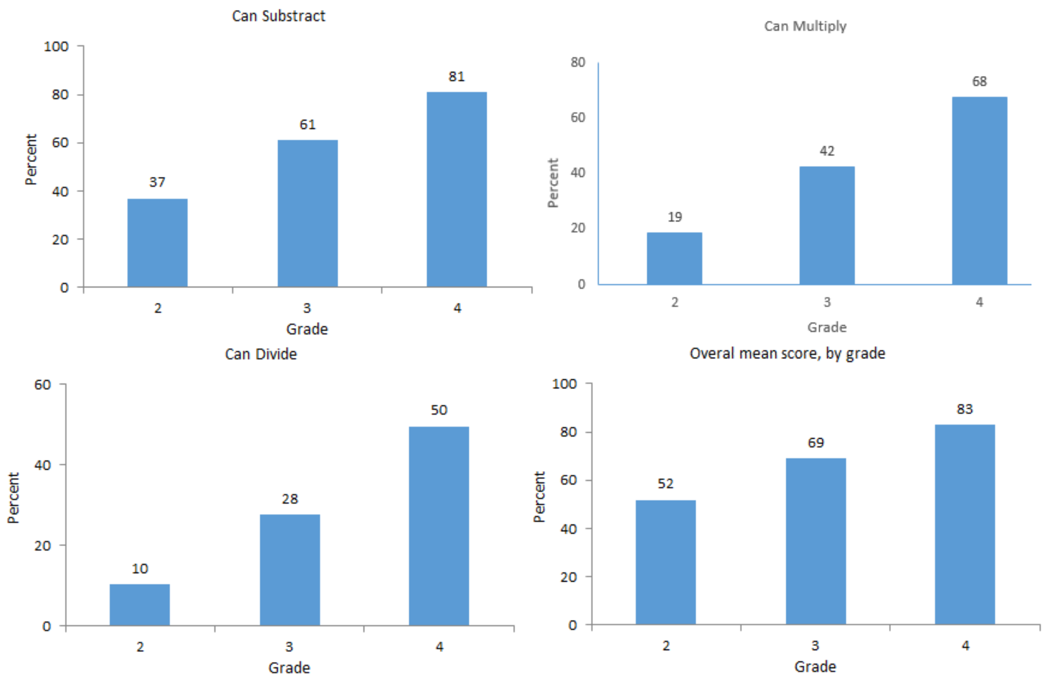
[h] In this task, a student was present with a descending number series following some pattern involving division by three with one last missing last value. He/she was asked to fill in the last missing value.

We find weak literacy skills when it comes to comprehension, that is the ability to implicitly and explicitly understand simple information that is stated in the text. As shown in columns 1 and 4, less than half of the students (39 percent in the SDI and 25 percent in Uwezo) could answer a question testing their ability to identify directly stated facts in the passage (factual comprehension). Equally, less than half of the students in both surveys could answer questions that required them to infer or draw conclusions from opinions or ideas implied or suggested by the author of the text (analytical comprehension). Surprisingly, as column 1 in table 2.3 shows, more students in the SDI could answer questions about a text (e.g. 39 percent answered correctly a factual comprehension question) than could read correctly all the words in the same text (e.g 16 percent could read all words in a paragraph). Furthermore, more students did better in analytical comprehension than in factual comprehension.

Table 2.4 shows student scores in maths. More than 70 percent of the learners in both surveys generally do well in items that require procedural fluency. They can comfortably count and match numbers, identify numbers, discriminate quantities and add. Learners however faced difficulty dealing with relatively complex tasks involving subtraction, multiplication and division. For instance, in column 1 and 4, we see that 37 percent of students in the SDI could not solve two subtraction problems, one involving single digits and another involving double digits. The trend is similar in Uwezo where almost half of the students could not solve two out of three simple double digit subtraction problems.

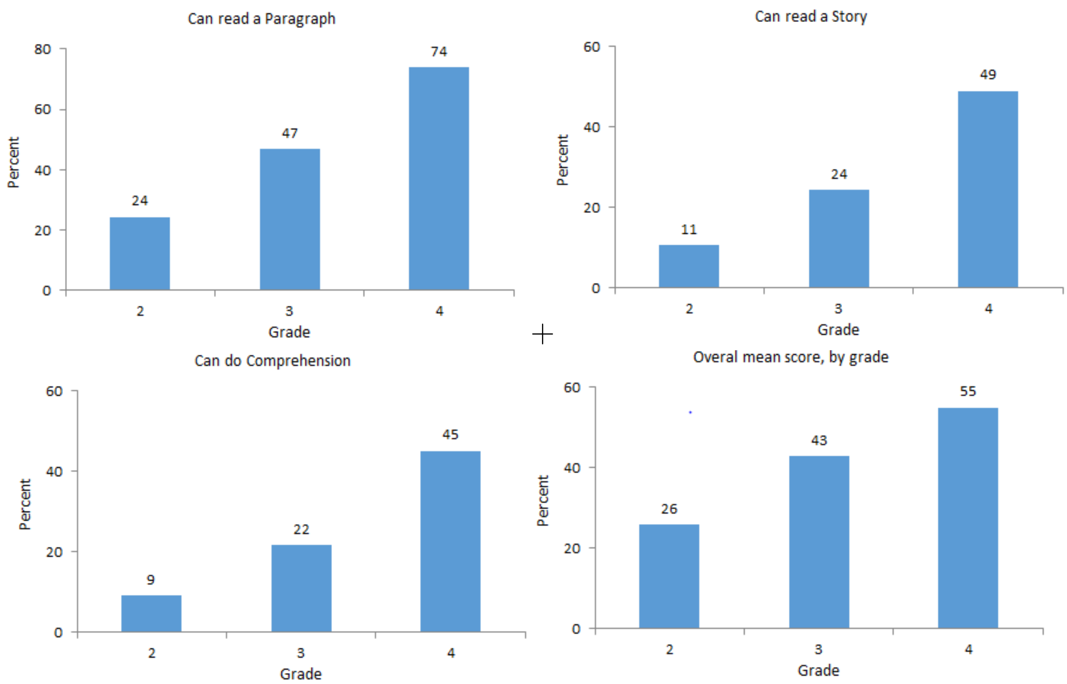
When presented with three multiplication problems involving single, double and triple digits, only 54 percent of grade 4 students in the SDI managed to solve at least two problems. Only 43 percent could answer two out of the three single digit multiplication problems in the Uwezo survey. Basic numeracy skills in division are particularly low among students; less than 30 percent of the students in both surveys were able to answer at least two out of three division problems involving mixed single and double digits. The SDI further shows that learners are generally weak at solving problems that require some level of analytical reasoning, especially arithmetic word problems; only 16 percent could solve a simple single digit multiplication problem presented in word format and only 26 percent could solve a simple division problem involving completing a series, both problems requiring some level of reasoning.

Figure 2.5: Numeracy Skill Competences by Grade of Attendance




*Source*: Own calculations based on Uwezo 2012.

Figure 2.6: Literacy Skill Competences by Grade of Attendance




*Source*: Own calculations based on Uwezo 2012.

Lastly, in figure 2.5 and figure 2.6, we show the proportion of children at grades 2, 3 and 4 in the Uwezo survey that met specific numeracy and literacy competence levels respectively. This gives a clear picture of the extent to which the children have mastered skills and competencies outlined in the curriculum from earlier grades. The results show that children are acquiring basic skills more slowly and later than expected. Further, the level of skill acquisition reduces with the rise in the difficulty of the competence. Using the case of grade 3 learners (the middle bar), we can see that nearly 40 percent of them cannot do a grade 2 level subtraction problem. The figure increases to 58 percent for those who cannot do a grade 2 level multiplication and 75 percent for those who cannot do a grade 2 level division. Overall, only 69 percent of grade 3 learners are able to pass the Uwezo grade 2 level literacy tests. Similarly, as shown in figure 2.6, 53 percent, 76 percent and 78 percent of grade 3 learners cannot read a grade 2 level paragraph, story and comprehension, respectively. Overall, **o**nly 43 percent of grade 3 learners are able to pass the Uwezo grade 2 level literacy tests.

## 2.3 Conclusion

In this chapter, we provide a general overview of the SDI and Uwezo surveys, our key dissertation data sets. We highlight key issues that form the basis for our research questions that are followed in subsequent chapters. We also define key dependent and independent variables for subsequent chapters. We find that the majority of the children come from households that can generally be classified as poor (based on household wealth index) and have parents with low education levels. Schools do well in terms of the availability of minimum teaching resources and infrastructure and there are no statistically significant differences in a wide range of these indicators between private and public schools. However, children who attend private schools are more likely to come from rich households. Their teachers are also more likely to be more knowledgeable and more likely to be in school and in class. We raise the concern that this is likely to reflect endogenous selection into private schools. In chapter 4 (essay 2), we estimate the effect of private schools while attempting to deal with such selection issue.

We report estimated enrolment rates and grade progression using the Uwezo survey. Generally, almost 95 percent of the children attend school at some point during their school age years. Besides, there is a gender balance in enrolment. However, a significant number of children start school late and a fairly good proportion drop out before completing primary education. There are also regional disparities in enrolment within Kenya. There is a good proportion of regions (locations) where children progress quite slowly through the schooling system due to late entry and/or early drop outs. In chapter 5 (essay 3), we examine how the gender and order of birth of a child affects his or her enrolment (private enrolment) and relative grade progression.

Finally, we analyze how children are learning in Kenya based on the Uwezo and SDI student test scores. In particular, we assess whether children in Kenya are acquiring and mastering the skills and competencies outlined in the curriculum of earlier grades. The results show that children are acquiring basic skills slowly and later than expected and the level of skill acquisition reduces with rise in the complexity of the competence. In the next chapter, we pick up in detail the teacher characteristics presented in table 2.2 (c).

# Chapter 3

# Teacher Human Capital, Teacher Effort and Student Achievements in Kenya

## 3.1 Background and Motivation

In chapter 2, we provide an overview of how children are learning in Kenya based on the Uwezo and SDI surveys. In table 2.2, several indicators are selected to provide a general picture of inputs that support student learning. Investment in schools is evident. We see that schools offer a relatively enriching environment for learning in terms of minimum functional infrastructure and teaching resources. For example, while close to nine students shared a textbook in grade 3 a few years into the free primary education policy (Hardman et al., 2009; MoEHRD, 1999), the SDI survey show that the government has nearly achieved its policy of three students per text book at primary level in English and maths. In general, however, children in Kenya have not mastered important areas of the curriculum they are supposed to have covered. The Uwezo survey shows that a good proportion of grade 3 learners cannot do grade 2 level numeracy and literacy tasks. For instance, almost three quarters of grade 3 learners cannot read a grade 2 level story.

Such poor learning outcomes, particularly in public schools, coming in the wake of increasing public spending on education inputs raises an important research question as to whether school inputs (e.g. school infrastructure and instructional inputs including teacher input) matter for student achievement and if they do, which inputs matter. A consistent finding in the literature, in the context of developed (Hanushek, 2006) and developing countries (Pritchet and Banerji, 2013; Glewwe et al., 2011), is that school inputs explain very little of the variation in student learning. Despite this, studies show that one school input, namely, the teacher input, matters for student achievement. Nevertheless, research is not clear on what makes an effective teacher (Aaronson et al., 2007). Most of the studies in developed (Boyd et al., 2006; Clotfelter et al., 2007; Rivkin et al., 2005; Rockoff et al., 2010) and developing (Glewwe and Jacoby, 1994; Aslam and Kingdon, 2011; Glewwe, 2002) countries have looked at the effect of characteristics of teachers that can easily be measured (observed) on student achievement. The majority of these studies find that these common observable characteristics such as certification, education, experience (as well as gender and age) often used for teacher remuneration and promotion, explain little of the variation in student performance(Rockoff, 2004; Rivkin et al., 2005; Clotfelter et al., 2007; Kukla-Acevedo, 2009; Dee, 2005).

Motivated by the lack of results on observable teacher characteristics, the literature has begun to emphasize the importance of two aspects of teacher input: teacher competence (knowledge) and teacher effort. According to this literature, when teachers, as key *education service providers,* exert the necessary effort and are appropriately skilled, then increased resource flows in schools can lead to better student outcomes (Spence and Lewis, 2009; Swanson et al., 2012; Hanushek, 2008; Pritchet and Banerji, 2013; Glewwe et al., 2011). An increasing number of studies have taken an empirical look at the effect of teacher knowledge (such as Shepherd et al. 2015; Shepherd 2013) and teacher effort, measured by *what teachers do in class* (such as Kane et al. 2011; Zakharov et al. 2014; Lavy 2011, 2012; Bietenbeck 2011; Hidalgo Cabrillana and Lopez-Mayan 2015; Jacob and Lefgren 2005; Kingdon 2006) on student achievements.[1]

These studies generally find that teacher knowledge and teacher classroom practices matter for student achievement. However, the findings are also not conclusive. For instance, Schwerdt and Wuppermann (2011) along with Van Klaveren (2011) study the effect of the percentage of time spent in lecture-style teaching using the Trends in International Mathematics and Science Study (TIMSS) wave of 2003 for the United States and the Netherlands, respectively. While Schwerdt and Wuppermann (2011) find that shifting time from problem solving to lecturing results in an increase in student achievement, Van Klaveren (2011) finds no relationship. In addition, these studies are based on data from developed countries. Therefore, the linkage between teacher knowledge, teacher effort and learning outcomes has not been fully explored in the context of sub-Saharan Africa countries, largely due to lack of data.

This paper contributes to this body of literature by examining the effect of *teacher human capital* and *teacher effort* on student achievement in maths and language in Kenya.

[1] The terms student test scores and student achievements will be used interchangeably throughout this thesis.

We define *teacher human capital* by two measures: *what teachers know* (teacher subject knowledge) and *whether the teachers know how to teach* (teacher pedagogical skill). *Teacher effort* is measured by three indicators, namely; (i) how teachers spend their time in class (effective instruction time), (ii) teacher's ability to keep students engaged during the teaching lesson and (iii) a number of teacher classroom practices. We use the SDI survey that allows us to directly link student test scores to the human capital and effort of their specific teachers while controlling for child, school, class and other teacher characteristics. This allows us to look at the education production function with greater depth than has been done before in the context of sub-Saharan Africa, and in particular Kenya.

Here is a summary of the results. We find that student test scores in maths and language are partially influenced by these measures of teacher human capital and teacher effort. A one standard deviation increase in the teacher's knowledge in language (maths) increases student test scores by 0.075 (0.126) score standard deviations in language (maths). An additional hour of teacher effective instruction time increases student achievement by 0.051 and 0.059 score standard deviations in language and maths, respectively. There is evidence that a number of classroom teaching practices, including the practice of challenging students by asking questions during the lesson, have an effect on student test scores although the effect differs between language and maths.

The chapter proceeds as follows. In section 3.2, we review the related literature followed by a presentation of theoretical and empirical strategy in section 3.3. Section 3.4 provides a detailed description of our measures of teacher human capital and teacher effort. Section 3.5 discusses our main results including robustness checks and finally section 3.6 provides the conclusion.

## 3.2 What teacher attributes matter for students achievements?

Teachers matter for student achievement. This consensus from various studies that examine the effect of teachers on student achievement is however, inconclusive on what attributes make a teacher more successful at enhancing student performance (Aaronson et al., 2007). Much of what exists in the literature are studies that link student outcomes to characteristics of teachers that can easily be measured (such as certification, education, experience, gender and age). Studies that use cross-sectional data have investigated this link by way of an educational production function in which student scores are related to the teacher characteristics. Evidence from these studies, mostly based in the USA, generally point to a positive effect of teacher certification on student test scores (Boyd et al., 2006; Clotfelter et al., 2007). However, a consistent puzzle is the absence of any significant effect on student scores of variables that are mostly used to inform teacher hiring and teacher salary decisions such as experience (Rockoff, 2004; Rivkin et al., 2005) and education (Clotfelter et al., 2007; Kukla-Acevedo, 2009; Monk, 1994) and other characteristics such as age and gender (Dee, 2005).

Evidence based on literature from developing countries is mixed. In Ghana, Glewwe and Jacoby (1994) find that teacher experience and teacher training has a significant positive effect on student achievement. Fehrler et al. (2009) focuses on primary education in 21 sub-Saharan African countries and finds that teachers' educational attainment and professional training alongside a number of instructional resources (textbooks and wall-charts) have a significant positive effect on student cognitive achievement. Glewwe et al. (2011) reviews 9,000 studies on student learning in developing countries between 1990 and 2010 and finds that in a number of countries, teacher experience and training have a positive effect on student achievement However, in India, studies by Aslam and Kingdon (2011) and Azam and Kingdon (2015) find that standard teacher characteristics (such as teacher gender, experience, level of education and certification) do not have a significant effect on student achievement.

Teacher subject knowledge is one characteristic that has been found to be positively associated with student achievement. Metzler and Woessmann (2012) use data from maths and language tests of grade 6 students and their teachers in Peru. To deal with possible omitted-variable and selection biases, they explore the within-teacher within-student variation[2] and find that teacher subject specific knowledge increases student achievement by 0.09 standard deviations in maths while it has zero effect on language student test scores. Shepherd (2013) explores the within-pupil between-subject, a method similar to that of Metzler and Woessmann (2012), to estimate the effect of teacher subject knowledge content on grade 6 combined language and maths test scores in South Africa. The author finds that teacher subject knowledge raises student scores by about 0.38 standard deviations although the effect disappears after controlling for student fixed effects.

Given the lack of consistent results on the effect of observable teacher characteristics on student test scores coupled with availability of richer data, a number of studies (such as Lavy 2011, 2010; Kane et al. 2011; Aslam and Kingdon 2011; Zakharov et al. 2014; Bietenbeck 2011; Hidalgo Cabrillana and Lopez-Mayan 2015) have shifted attention to look at the effect of classroom teaching practices (what teachers do in class) on student scores. Bietenbeck (2011) uses the 2007 Trends in International Mathematics and Science Study (TIMSS) data for the United States to contrast the effect of two teaching

[2]We provide the meaning of this estimation strategy later in the text.

practices - modern and traditional, based on student rating of their mathematics and science teachers. He classifies teaching that emphasizes group work, learning through experiment and student explanation of answers as modern while teaching that emphasizes rote and lecture style learning and use of textbooks as traditional. Estimating a student fixed effect model, he finds that traditional teaching has a positive effect on overall test scores while modern teaching has a statistically insignificant effect. Hidalgo Cabrillana and Lopez-Mayan (2015) adopt a similar definition of teaching practices as that of Bietenbeck (2011) to examine the effect of teacher classroom practices based on data from the Spanish assessment program of 4th grade pupils. Their identification strategy relies on between-class within-school variation in teaching styles. Unlike Bietenbeck (2011), they find that modern teaching practices have a positive and significant effect on achievement especially in language. They further find that traditional practices are detrimental to learning for both maths and reading.

Closely related to our paper in terms of teaching practices analyzed is the study by Aslam and Kingdon (2011) who examine the effect of teacher classroom practices on student test scores based on school data from Pakistan. The teacher classroom practices analyzed include amount of time teachers spend quizzing students and reviewing homework as well as indicators of whether teachers plan for lessons, explain in-class questions while lecturing and ask a lot of random questions while teaching. Relying on the within-pupil-across-subject (rather than across time) variation, they find that the practice of asking learners questions raises scores (language and mathematics pooled together) by about 0.03 score standard deviations while the practice of planning for a lesson raises scores by 0.23 standard deviations.

Another teaching practice that has received some attention in the literature is teacher instruction time or length of instruction. Using data from the 2006 wave of the Programme for International Student Assessment (PISA), Lavy (2010) estimates the effect of instructional time on maths, science and language scores in over 50 countries. He uses within-student variation to control for possible self-selection and sorting of students across schools. He finds that an additional hour of effective teaching per week raises students test score achievements by 0.07 standard deviations. Another study by Dobbie and Fryer Jr (2011), based on a sample of schools that operates independently but receives government funding (charter schools) in New York City finds that increased instruction time is associated with higher student achievement. Dobbie and Fryer Jr (2011) finds that a 25 percent increase in instruction time leads to a rise in student test scores in maths by 0.05 score standard deviations.

Our work adds to this body of literature in a number of ways. First, there seems to be limited empirical evidence of teacher classroom practices in sub-Saharan Africa and in Kenya in particular. A number of qualitative classroom observational studies exist for Kenya (such as Ackers and Hardman 2001; Hardman et al. 2009; MoEHRD 1999; Piper and Mugenda 2010) but none of them has empirically estimated the relationship between teacher classroom practices and student scores. Second, in contrast to existing literature, we estimate the effect of teacher knowledge and effort based on actual assessment and classroom observation of teachers. Most of the studies we have reviewed estimate teaching practices based on information reported by teachers and/or students. A study by Goe et al. (2008) discusses the potential advantages and disadvantages of using information reported by students and teachers. He argues that student responses are subject to bias in a number of ways. Students do not know all the aspects of classroom teaching and some of their responses about classroom teaching can be influenced by personality characteristics of the teacher. Similarly, teacher responses are also subject to potential biases. For instance, teachers may unintentionally misreport their practices because they believe that they are applying a certain practice when actually they are not. Our study tries to address these challenges by using data based on the direct observation of teachers.[3]

## 3.3 Methodology

### 3.3.1 Theoretical Framework

Our work is based on the production function framework, specified by among others, Glewwe (2002), Glewwe and Kremer (2006) and Orazem and King (2007). In this framework, learning outputs are as a result of a combination of various inputs. Here, a school is viewed as a *production firm* where inputs interact to produce outputs (Glewwe and Kremer, 2006; Todd and Wolpin, 2003; Glewwe, 2002). The output of this education production process can be measured by, for instance, student test scores.

The framework assumes that each household (in particular, the parents of the child) maximizes a utility function subject to constraints such as budget and credit constraints. The main arguments of this utility function are: (i) the consumption of goods and services including leisure and (ii) each child's learning (Glewwe and Kremer, 2006; Glewwe, 2002). Formally, utility is expressed as:

[3]We are also aware of the disadvantages of using direct classroom observation to construct teaching practices. For instance, teaching might modify or improve their teaching in response to their awareness of being observed (Bruns and Luque, 2014).

$$U_i = u(A_i, G_i) \tag{3.1}$$

where $A_i$ is child's academic achievement and $G_i$ is the household consumption possible after sending a child to school including leisure. In its general form, child $i$'s academic achievement, $A_i$, is hypothesized to depend on: the *child's characteristics* (e.g. age, gender, child's motivation and innate ability); *family background characteristics and home inputs into education* (e.g parent's education, preferences for their children education, books at home, time spent helping with homework); *school characteristics* (such as school infrastructure and instructional inputs including teacher input); and *community background characteristics*. This can be formally expressed as:

$$A_i = f\,(X_i,\, F_i,\, Q_i,\, V_i) \tag{3.2}$$

where: $X_i$, $F_i$, $Q_i$ and $V_i$ represent child, family, school and community background characteristics, respectively. Theoretically, teachers are part of the school based inputs as specified in equation (3.2). Because of market failure, a child's academic achievement, $A_i$ cannot be purchased, it has to be produced. Since equation equation (3.2) is a production function, its arguments must be proper inputs. By proper inputs we mean those inputs that *define* the frontier of production function but not *shift* it. In the case of equation (3.2), proper inputs into the child's education production function are contained in $Q_i$ and as we clarify in equation (3.4) (in the next sub-section), they include inputs as teacher's subject knowledge and pedagogical skills. Other inputs, such as those captured by $X_i$, $F_i$ and $V_i$ in are not proper inputs, rather shift parameters of the production function.

### 3.3.2 Estimation Strategy

Following Glewwe (2002); Todd and Wolpin (2003); Glewwe and Kremer (2006); Orazem and King (2007) and many other empirical studies, we estimate the linear functional form of equation (3.2), formally expressed as:

$$A_{ijkd} = \alpha + \delta X_{ijkd} + \xi_{ijkd} + \gamma T_{jkd} + D_d + \mu_{ijkd.} \tag{3.3}$$

where: $A_{ijkd}$ is the test score (in language or maths) of student $i$ taught by teacher $j$ in school $k$ located in region (division) $d$; $X_{ijkd}$ is a vector representing observable student, teacher, school and village characteristics; $\xi_{ijkd}$ is a measure of unobserved student ability captured by the non-verbal reasoning scores;[4] $T_{jkd}$ is our variable of interest and is a vector representing teacher $j$'s *human capital* and *effort*; $D_d$ is the division fixed effects[5] and $\mu_{ijkd}$ is the idiosyncratic unobservable factors affecting achievements.[6]

Naturally, the full elements of a teacher's true human capital and effort ($T_{jkd}$) are not easy to collect and some are not easy to observe. In our case, teacher human capital is measured by teacher's *subject knowledge* and *pedagogical skill* which were collected through the SDI survey teacher assessments. Similarly, we measure teacher effort by *effective instructional time, percent of student off-task during the lesson* and *a vector of classroom practices* obtained through the SDI survey classroom observations. We therefore replace the vector $T_{jkd}$ with information about teacher $j$'s *subject knowledge* denoted as $TK_{jkd}$, *pedagogical skill* denoted as $TP_{jkd}$, *effective instructional time* denoted as $TI_{jkd}$, *percent of student off-task* denoted as $TT_{jkd}$ and *classroom practices* denoted by the vector $CP_{jkd}$. We add the term $\eta_{jkd}$ to capture the error in using $TK_{jkd}$, $TP_{jkd}$, $TI_{jkd}$, $TT_{jkd}$ and $CP_{jkd}$ as measures of $T_{jkd}$. As a result, we estimate the empirical model shown in Equation (3.4):

$$A_{ijkd} = \alpha + \delta X_{ijkd} + \xi_{ijkd} + \gamma_1 TK_{jkd} + \gamma_2 TP_{jkd} + \gamma_3 TI_{jkd} + \gamma_4 TT_{jkd} + \gamma_5 CP_{jkd} + D_d + \eta_{jkd} + \mu_{ijkd}. \tag{3.4}$$

Equation (3.4) remedies the lack of clarity in equation (3.2) with regards to proper and improper inputs into the child's education production function. The variables $TK_{jkd}$, $TP_{jkd}$, $TI_{jkd}$ and $TT_{jkd}$ are proper inputs from free from distraction. They are the inputs into a child's human capital production and in our case they are our treatment variables, i.e., the factors of policy interest. As mentioned, these inputs define the frontier of the function but do not shift it. Observe that $CP_{jkd}$, measuring teacher classroom practices,

[4] Recall that part of the SDI survey student tests involved a non-verbal reasoning test that consisted of four items related to pattern recognition based on Raven matrices test. Aslam and Kingdon (2011) and Glewwe and Jacoby (1994) are among studies that measured unobserved student ability using non-verbal reasoning scores.

[5] A division is a forth tier administrative unit in Kenya after a location. A group of villages constitute a sub- location, which in turn constitute a location and then a division. Ideally, we should control for unobservables at the lower tiers than the division such as village, sub-location and location level. However, in the SDI survey, there is only one school per village (as well as per sub-location and location) and as a result, we can not also estimate a village (and/or sub-location or location) fixed effects model. We provide a more detailed explanation of this issue in details shortly.

[6] Among others, $\mu_{ijkd}$ accounts for variables in equation (3.2) that are not in the data. For instance, the general form of the production function as specified in equation (3.2) contains family characteristics. However, the SDI survey did not collect information related to home environments apart from a question asking whether the child had breakfast at home or not. Such omitted variables are absorbed in $\mu_{ijkd}$.

is an innovations that shifts the production function although is of policy interest.

We estimate equation (3.4) using Ordinary Least Squares (OLS) and correct for the correlation of students within class/school level by clustering standard errors at the class/school level (Wooldridge, 2003).[7] We also assume a contemporaneous production function when estimating equation (3.4). In this context, we assume that it is current inputs that mainly determine the observed learning achievements (see Todd and Wolpin (2003) for details about contemporaneous education production function).

As observed by previous studies (Glewwe (2002); Todd and Wolpin (2003); Glewwe and Kremer (2006); Orazem and King (2007); Case and Deaton (1999)), empirical estimation of equation equation (3.4) is extremely challenging due to a number of challenges: omitted variable bias, sample selection bias, and measurement error. Shortly, we discuss how we deal with these challenges in the light of the limitations of our data. Before that, in the section that follows, we present a detailed description of the measures of *teacher human capital* and *teacher effort*, our independent variables of interest.

## 3.4 Teacher Human Capital and Effort

For schools to properly function, they need teachers who are knowledgeable and skilled. First, teachers *need to know the subject they teach* (teacher subject knowledge) and second, they *need to know how to teach* (teacher pedagogy). We refer *teacher subject knowledge* and *teacher pedagogy* to as *teacher human capital.* Second, schools need teachers *who exert the necessary effort in applying their knowledge and skills* (*teacher effort*). In this section, we provide a quantitative description of the *teacher human capital* and *teacher effort* based on the SDI survey before empirically linking them to the student test scores.

[7] Recall that clustering standard errors at the school level in our case is similar to clustering at the class level since for each school, we are only interested in the subject teacher who was *observed* and *assessed in the teacher tests.*

Table 3.1: Descriptive Statistics of 2,960 Teachers Assessed for Absence from School and Class

| | (1) All Schools Mean | (2) Public Schools Mean | (3) Private Schools Mean | (4) Public-Private Difference |
|---|---|---|---|---|
| Female | 0.54 | 0.53 | 0.59 | -0.06*** |
| Age (in years) | 38.11 | 40.53 | 29.13 | 11.40*** |
| Experience ( in years) | 13.90 | 16.13 | 5.65 | 10.48*** |
| Highest Level of Education Completed | | | | |
| Secondary Complete | 0.30 | 0.28 | 0.35 | -0.06*** |
| Diploma/Certificate | 0.63 | 0.62 | 0.50 | -0.01 |
| University degree | 0.08 | 0.09 | 0.02 | 0.07*** |
| Highest Teacher Training Completed | | | | |
| None | 0.13 | 0.10 | 0.24 | -0.14*** |
| Certificate in Early Childhood Education | 0.10 | 0.07 | 0.23 | -0.16*** |
| Primary 1 and 2 certificate | 0.59 | 0.62 | 0.47 | 0.15*** |
| Degree | 0.18 | 0.22 | 0.07 | 0.15*** |
| Number of observations | **2,960** | **2,331** | **627** | |

*Source*: Own calculations based on SDI 2012. Notes: (1) These descriptive statistics are based on 2,960 teachers who were assessed for school and class absence; and (2) ***significance<1 percent, **significance<5 percent, *significance<10 percent

Before that, we present summary statistics on observable teacher characteristics based on 2,960 teachers who were assessed for teacher absence (table 3.1). As seen in the table, 54 percent of the teachers in the sample are female. The teacher's overall mean age is 38 years while the mean yeas of experience is 13. The majority of the teachers have a diploma or certificate as their highest level of education. When it comes to teacher training, most of the teachers, 59 percent, hold primary 1 and 2 certificate in teacher training. Interestingly, public schools teachers are more experienced, have higher education and teacher qualification than their counterparts in private schools.

### 3.4.1 Teacher Subject and Pedagogical Knowledge

We begin by discussing the aspect of *teacher human capital* based on the test score results for the 1,679 teachers who were assessed in language, maths and pedagogy.[8] In table 3.2, we show the teacher test scores by subject. The language test comprised of two sets of tasks. The first task, *spelling and simple grammar exercises*, involved tasks that were similar to student language tasks and largely covered lower primary curriculum materials.[9] To effectively teach a grade four student, the teacher needs to have knowledge that goes beyond the lower primary curriculum. As a result, the next two tasks, *cloze passage*[10] *and*

[8] As mentioned, teacher tests were administered to teachers as a marking exercise.

[9] The purpose of the *spelling and simple grammar exercises* was to assess if the teacher had knowledge equivalent to a grade 4 learner.

[10] The cloze consisted of a passage with certain words removed (cloze text), where the teacher was asked to replace the missing words.

*composition*,[11] covered materials that were slightly beyond the lower primary curriculum and hence a grade 4 child would have found these tasks relatively difficult.

In line with Martin and Pimhidzai (2013), we show an indicator, *the share of teachers with minimum knowledge,* defined as the proportion of teachers who marked 80 percent or more of *all the language tasks correctly.* Two main observations stand out from the language scores (table 3.2). First, content knowledge among Kenyan teachers is relatively low; only 13.16 percent of teachers can be classified as having *minimum knowledge* in language (column 1). Second, an increasing number of teachers struggle with tasks requiring some level of knowledge beyond lower primary curriculum. For instance, while nine out of ten teachers marked tasks involving *spelling and simple grammar exercises* correctly, almost half of them could not mark the *composition* sub-task, involving correcting spelling, grammar as well as punctuation mistakes in a child's letter.

Similarly, the maths tests contained tasks that were common across the student and teacher tests (such as addition and subtraction) as well as tasks that were slightly beyond the lower primary curriculum. In table 3.2, we dis-aggregate the scores by selected sub-tasks. Slightly more than half of the teachers, 56.34 percent, can be classified as having *minimum knowledge* in maths. Nevertheless, a high proportion of teachers also faced difficulties in relatively advanced tasks. For instance, nearly 32 percent of the teachers could not solve a problem involving division of fractions and close to 38 percent could not solve a problem involving interpreting information in a graph.

[11] In this sub-task, the teacher was given a sample letter written by a grade 4 child and asked to correct the letter for grammar, punctuation (between sentences and within sentences), spelling, syntax, and salutation.

Table 3.2: Teacher Test Scores by Subject

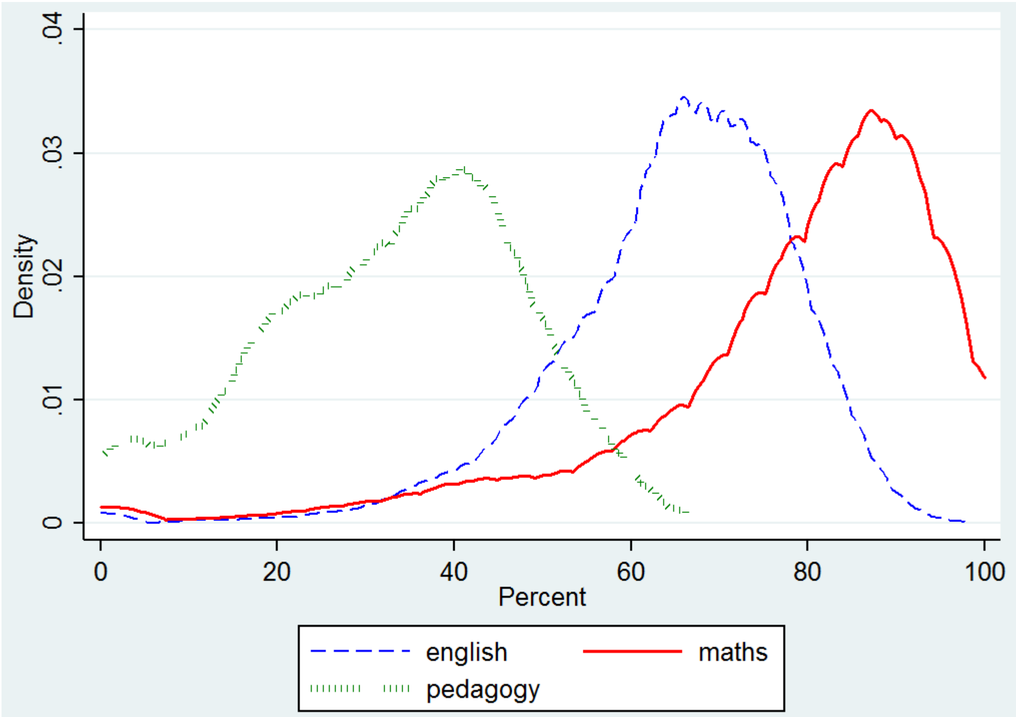
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All Mean | Public Mean | Private Mean | Public-Private Difference |
| *Language Test* | | | | |
| **Minimum knowledge in Language: 80 % correct** | 13.16 | 11.97 | 18.60 | -6.63*** |
| English Section mean score (% correct) | 64.97 | 64.55 | 66.87 | **-2.26*** ** |
| % correct in spelling and grammar exercises | 92.00 | 91.81 | 92.89 | -1.01 |
| % correct in cloze | 67.25 | 66.70 | 69.77 | -3.06*** |
| % correct in composition | 45.95 | 49.52 | 51.91 | -2.39*** |
| *Maths Test* | | | | |
| **Minimum knowledge in Maths: 80 % correct** | 56.34 | 54.14 | 66.45 | -12.31*** |
| Maths Section mean score (% correct) | 77.59 | 76.79 | 81.24 | **-4.44*** ** |
| % correct in double digit addition | 97.50 | 97.39 | 98.01 | -0.62 |
| % correct in double digit subtraction | 87.19 | 87.01 | 88.04 | -1.03 |
| % correct computing a perimeter of a rectangle | 80.05 | 78.59 | 86.71 | -8.12*** |
| % correct in one variable algebra | 72.66 | 71.48 | 78.07 | -6.59*** |
| % correct in division involving fractions | 68.43 | 66.40 | 77.74 | -11.34*** |
| % correct in interpreting data on a graph | 62.48 | 61.39 | 67.44 | -6.05*** |
| *Pedagogy Test* | | | | |
| **Minimum knowledge in Pedagogy: 80 % correct** | 0 | 0 | 0 | 0 |
| Pedagogy mean score (% correct) | **32.85** | 32.24 | 35.65 | **-3.41*** ** |
| % correct in lesson plan formulation | 43.60 | 43.19 | 45.46 | -2.27* |
| % correct in assessing child ability | 34.27 | 33.47 | 37.96 | -4.49*** |
| % correct in assessing child progress | 29.91 | 28.78 | 35.08 | -6.30*** |
| **Sample** | **1,679** | **1,378** | **301** | |

*Source*: Own calculations based on SDI 2012. ***significance<1 %, **significance<5 %, *significance<10 %

The pedagogy test consisted of three sub-tasks and was designed to capture skills teachers would normally use when teaching. In the first sub-task, teachers were asked to come up with a lesson plan based on a topic that was given to them on the spot allowing no time for prior preparation. In this sub-task, teachers were supposed to formulate (a) aims and objectives of the lesson, (b) questions to check student understanding and (c) questions to check student's to application of what they have learned to other contexts. In the second sub-task, teachers were given samples of writing from two grade 4 level students and asked to mark and comment on the strength and weakness of each student. Lastly, teachers were given raw scores for 10 students and asked to calculate the averages and comment on the performance.

As table 3.2 shows, teacher's pedagogical knowledge is exceptionally low. From column 1, we can see that no teacher could be considered as having minimum knowledge in pedagogy (none managed to mark correctly 80 percent of the pedagogy tasks). Furthermore, less than half of them (43.60 percent) could adequately prepare the lesson plan. On the other hand, only 34.27 percent of teachers could contrast between sample writing of two students and only 29.91 percent could turn raw scores into averages and comment on student performance. Private teachers performed better than public teachers in almost all subject categories although the general lack of pedagogical skills appear to be similar in public and private schools. Figure 3.1 shows the distributions of the test scores.

Figure 3.1: Teacher Test Scores in Pedagogy, Language and maths.




*Source*: Own calculations based on SDI 2012.

### 3.4.2 Teacher Effort

Education delivery in most parts of the world requires the physical presence of teachers in school and in class. Put differently, for students to learn, teachers need to exert the necessary effort in applying their knowledge and skills. They need to turn up to school and to class and once in class, spend time on instruction. Teacher's *presence in school (or absence from school)* has dominated literature as a measure of teacher effort (Chaudhury et al., 2006; Alcazar et al., 2006). However, even when in school, teachers are not necessarily in class. As such, teacher effort has also been measured by the presence of teachers *not just in school but in class.* Most recently, studies have begun to measure teacher effort by the *amount of time teachers spend on instructional activities while in class* (Bruns and Luque, 2014). Next, we discuss these three aspects of teacher effort (*absence from school, absence from class and time-on-task)* and show how they correlate with student achievements.

#### 3.4.2.1 Teacher Absence from School and Class

As mentioned in Chapter 2, up to 10 teachers in each school were randomly selected from the teacher roster. A total of 2,960 teachers were selected. After 1-2 weeks, an unannounced visit was conducted during which surveyors identified whether the sampled teachers were in the school, and if they were, whether they were in class teaching. We derive two indicators of teacher effort based on this information. The first is *absence from school*, defined as the share (out of 10) of teachers who could not be found on the school premises during the second unannounced visit. The second indicator is *absence from class,* defined as a combined share (out of 10) of teachers who were *absent from school* and *absent from class but present on the school premises.*[12]

In addition, during the second visit, the surveyor physically counted the number of classrooms with students and noted whether a teacher was inside the classroom or not. We divide *the number of classrooms that had students but no teacher by the total number of classrooms that contained students* to obtain another complimentary measure of teacher effort, which we call o*rphaned classrooms.*

Table 3.3: Teacher Effort Indicators: Teacher Absence from School and Class.

| | All Mean | Public Mean | Private Mean | Public.-Private Mean Difference |
|---|---|---|---|---|
| Absence from class (percent) | 44.93 | 47.97 | 34.07 | 13.90*** |
| *of which* | | | | |
| Absence from school (percent) | 16.68 | 17.51 | 13.74 | 3.79 |
| Absent in class but present in school (percent) | 28.25 | 30.46 | 20.33 | 10.13*** |
| Orphaned classes (percent) | 34.88 | 38.46 | 22.10 | 16.36*** |
| **Sample** | **306** | **239** | **67** | |

*Source*: Own calculations based on SDI 2012. Notes: (1) Results collapsed at school level; (2) We calculate absence from class as the sum of the indicators (a) absence from school and (b) present in school but absent in class; and (3) ***significance<1 %, **significance<5 %, *significance<10 %

[12] It is possible that some teachers could have been on the school premises and not in class because it was not their teaching time. As a result, the surveyor used the official school timetable to verify that the teachers who were present on school premises and not in class were indeed supposed to be in class teaching at that time.

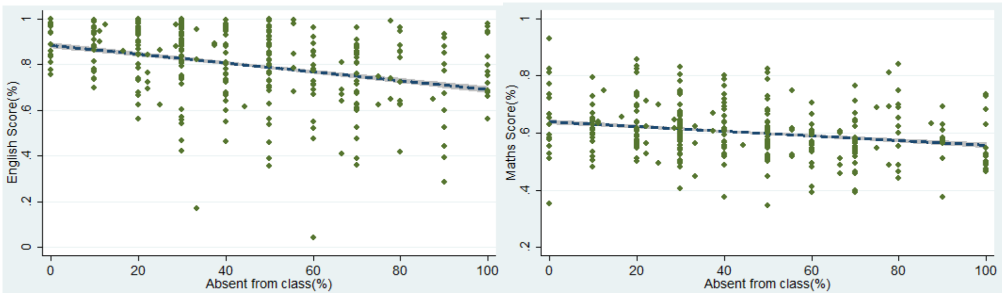
As table 3.3 shows, on average, 16.68 percent of teachers were absent from school. Although absence from school is slightly higher among teachers in public schools, we do not find any significant differences between public and private school teachers on this indicator. The table further shows that a larger proportion of teacher's lost time is actually lost in schools. We see that 28.25 percent of teachers *were present in school but absent from the classroom* and there are significant differences in this indicator between public and private schools. Recall that the indicator absence from class is defined as a combined share (out of 10) of teachers who were *absent from school* and *absent from class but present on the school premises*. In relation to table 3.3, it means that 44.93 percent of the teachers were absent from class and a large proportion of these teachers are from public schools. On the orphaned classrooms indicator, we find that about 35 percent of classes had pupils with no teacher. The mean differences between public and private is quite significant for this indicator.[13]

In figure 3.2a and figure 3.2b, we plot student test scores (in language and maths) against *teacher absence in class* indicator and *percent of orphaned classes* indicator, respectively. Both are calculated at the school level. The results consistently show that students perform worse in test scores in schools where teachers are more likely to be absent from class and in schools with high proportion of orphaned classes. The correlation is particularly stronger for language scores.

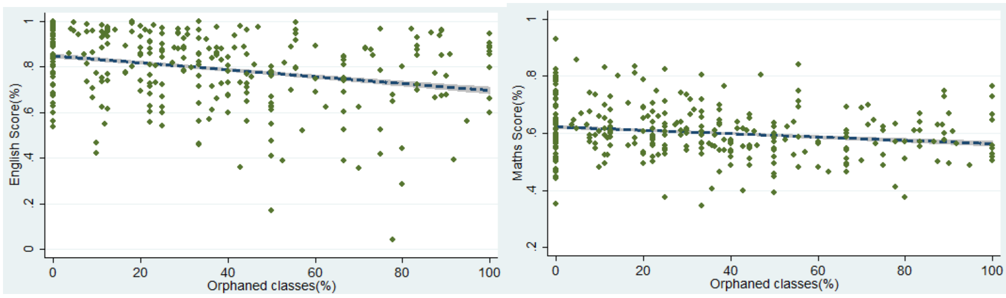
[13]The percent of orphaned classes in table 3.3 is not an average of (i) absence from school and (ii) absent in class but present in school. This is because the indicators (i) absence from school and (ii) absent in class but present in school are only based on 10 teachers who were sampled for teacher absence.

Figure 3.2: Correlations between Teacher Effort Indicators and Student Test Scores

(a) Correlation between Absence from Class and Student Scores

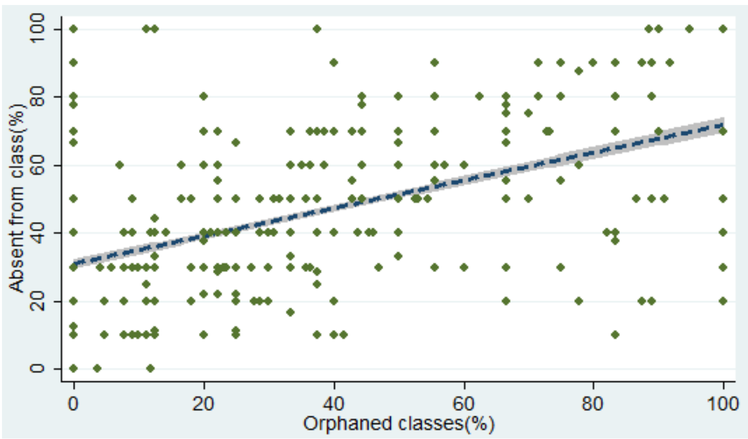



(b) Correlation between Percent of Orphaned Classes and Student Test Scores




*Source*: Own calculations based on SDI 2012.

Figure 3.3: Correlation between Percent of Orphaned Classes and Absence from Class




*Source*: Own calculations based on SDI 2012.

In calculating absence from school and class, we do not account for the fact that some teachers could have been absent from school and/or class for legitimate reasons. This is likely to over-estimate teacher absence rate, in school and in class. The absence of a teacher from class, is nevertheless a missed learning opportunity for children in most Kenyan schools given evidence of lack of substitute teachers generally in sub-Saharan

Africa and the developing world (Alcazar et al., 2006). The possibility of lack of substitute teachers is evident in figure 3.3 where we find that when a large share of teachers were absent from class, unsurprisingly, a large share of classrooms were only occupied by students.

#### 3.4.2.2 Teacher Effort Inside the Classroom

Even when teachers show up in class, a certain percentage of teaching time is likely to be lost to non-instruction activities (Bruns and Luque, 2014). We use the classroom observation snapshots to quantify how much time is spent inside the classroom between instruction and non-instruction related activities. This section is based on observation of 276 teachers who participated in the classroom observation.[14] In taking the snapshots, the surveyor coded two key aspects of the classroom dynamics: (i) how the teacher was using the class time between two mutually exclusive activities: *instruction activities*[15] and *non-instruction activities*[16] (*off-task* activities) and (ii) the number of students who were visibly not following the teacher, taken after every 5 minutes. Table 3.4 shows our approximation of how teachers spent their time in class.

On average, the lessons lasted 35 minutes. When calculating how teachers spent their time in class, we however, consider the first 30 minutes.[17] On average, teachers spent about 86.01 percent of the teaching time on instructional/teaching activities. Application of Stallings instrument in U.S schools over several decades led Stallings and Knight (2003) to observe that high-performing schools achieve an average of 85 percent of class time spent on instruction (Bruns and Luque, 2014). Private school teachers spent slightly more time on instruction related activities although there is no significant difference between public and private schools. In the previous section, we found that public school teachers are about 16 percent points more likely to be absent from class relative to their counterparts in private schools. This means that the challenge in Kenya is getting public school teachers

[14] As reported in Chapter 2, of the 306 schools, classroom observation for maths and language took place in 276 schools. That is, 276 teachers (144 language and 132 maths teachers) were observed. In 28 schools teachers were absent from class and in two schools classroom observation took place for creative arts and science subjects, which we exclude from the analysis. Using the t-test, we do not find systematic differences in terms of schools and teacher characteristics between schools where classroom observations took place and where it did not take place (see details in the last Chapter).

[15] If the time was being used for instruction, what instructional activities were happening and how was the teacher-pupil interaction (whole group; small group or one-on-one).

[16] If the time was being used for off-task activities, what activities was the teacher involved in.

[17] There are few instances (in about 4 schools) where the surveyor arrived relatively late when the lesson had started. This does not affect our estimates of how teachers spent their time in class since we are taking percentage use of time based on the length of the lesson that was observed.

Table 3.4: How Time is Spent in the Classroom

| | Task[a] | All subjects | by School Type: Public | Private | Diff | by Subject: Maths | Language | Diff |
|---|---|---|---|---|---|---|---|---|
| **Teachers** | **1. Instruction Activities (as % of total lesson time)**[b] | **86.01** | **85.64** | **87.28** | -1.65 | **84.35** | **87.51** | -3.15** |
| | of which: | | | | | | | |
| | Active Instruction[c] | 61.13 | 61.92 | 58.43 | 3.4 | 58.80 | 63.22 | -4.41 |
| | Passive Instruction [d] | 38.87 | 38.08 | 41.57 | -3.49 | 41.20 | 36.78 | 4.41 |
| | **2. Off-task Activities (as % of total lesson time)** | **13.99** | **14.36** | **12.72** | 1.65 | **15.65** | **12.49** | 3.15** |
| | of which: | | | | | | | |
| | Classroom Management (percent) [e] | 65.75 | 63.15 | 74.79 | -9.00 | 62.00 | 69.43 | -9.12 |
| | Teacher reporting late and/or leaving earlier (percent)[f] | 34.25 | 36.85 | 25.21 | 9.00 | 38.00 | 30.57 | 9.12 |
| **Students** | Students off-task (as a % of the class size) [g] | **12** | **14** | **7** | 7** | **13** | **13** | |

*Source*: Own calculations based on SDI 2012. Notes: (1) Calculations based on Stallings and Knight (2003) framework; and (2) ***significance<1 percent, **significance<5 percent, *significance<10 percent

[a] Here we are interested how the teacher spent their time in class based on the classroom observation data. As such we only consider 276 teachers who were in class and were observed. Unfortunately, we do not have any other reference source on the use of instruction time in the classroom in Kenya from which to compare our results.

[b] We account for the first 30 minutes of the lesson.

[c] Activities under *active instruction* time include among others: teacher reads or lectures to the pupils; teacher supervises pupil(s) writing on the board; teacher leads kinesthetic group learning activity (students carrying out physical activities, rather than listening to a lecture or watching demonstrations); teacher writing on blackboard and teacher listening to pupils recite/read.

[d] *Passive instruction* activities include among others: teacher waiting for pupils to complete task and teacher testing students in class/giving assignment to students and teacher going round the class to monitor learners.

[e] Classroom management activities mainly include teacher maintaining discipline in class among others.

[f] Recorded qualitative data from the surveyor teams show various reasons for teachers reporting late and/or leaving early: sometimes, teachers were attending to other administrative matters in or outside the school premises. Sometimes, they waited for learners to settle. Sometimes, they were socializing with fellow teachers and students. In cases where teachers taught only some part of the lesson and left earlier, some left learners unattended while others gave them assignments.

[g] For every 5 minutes, the surveyor scanned through the room in a 360-degree circle and recorded the number of students who were visibly not following the teacher. In total, 6 snapshots were taken during the 35 minutes lesson. To arrive at this indicator, we take the average number of students who were off-task over the 6 snapshots as a share of the total number of students in class.

into classrooms. Once in class, there seems to be no discernible difference in performance between public and private teachers.

Following Stallings and Knight (2003), we break down the expenditure of instructional time into *active* and *passive* related activities as shown in table 3.4. The most common instructional activities are those related to *active instruction* (taking 61.13 percent of total instructional time) involving the teacher directly engaging students, mainly as a whole class, through lecture and explanation.[18] Correspondingly, 38.87 percent of total instructional time is spent on passive instruction methods, which according to (Bruns and Luque, 2014) can be characterized by students doing assignments at their seats with teachers moving around the classroom monitoring progress as they wait for students to finish the tasks.

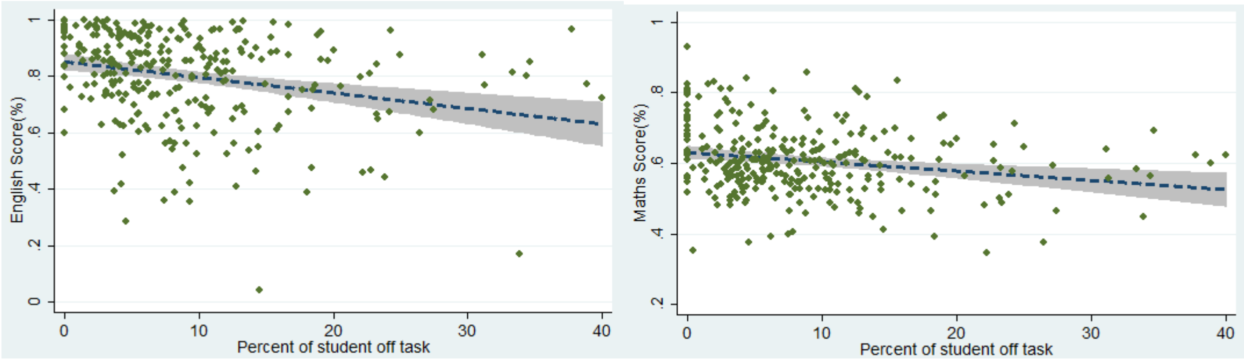
Table 3.4 further shows that at least 13.99 percent of the lesson time is lost to off-task activities or non-instructional activities.[19] A major part of the time here, 65.75 percent, is tied up in classroom management activities involving teachers doing paper work, arranging seating positions and maintaining discipline among other tasks. The rest of the off-task activities are absorbed by teachers arriving late to class and/or leaving early.

As table 3.4 shows, about 12 percent of students were not engaged over the 35 minutes lesson. The percentage is higher in public schools relative to private schools probably due to large classes in public schools. There are significant variations across schools in terms of the percentage of students not engaged. Outcomes range from all students fully engaged to as much as over 60 percent of students not engaged. Research based on schools in the USA shows that highly effective teachers keep the share of students off-task below 6 percent (Stallings and Knight, 2003). Figure 3.4 shows that students perform worse, especially in classes where a higher proportion of students are not following the teacher.

[18]This is often punctuated by pupil copying from the board, teacher asking pupils questions, learners solving problems on the board and choral answer responses. This kind of classroom interaction is similar to what has been reported by others in the context of Kenya (Ackers and Hardman, 2001; Hardman et al., 2009; Pontefract and Hardman, 2005; MoEHRD, 1999; Ngware et al., 2014; Trudell and Piper, 2013).

[19]Our estimate of off-task activities is quite conservative and in fact on the lower bound. We do not include teachers who were totally absent. Including them will definitely shift the estimated value of off-task activities upwards.

Figure 3.4: Correlations between Student Test Scores and Percent of Students Off-task




*Source*: Own calculations based on SDI 2012.

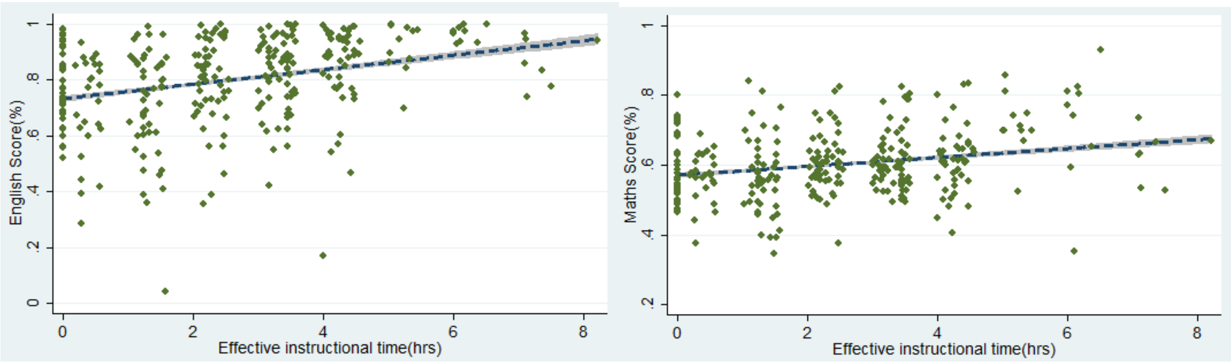
Following Martin and Pimhidzai (2013), we adjust for the time teachers are absent from the classroom at the school level, and for the time the teachers teach while in the classrooms to derive a measure of the amount of time teachers spend teaching in a school during a normal day, known as *teacher effective instruction time or time-on-task*. Table 3.5 shows how this indicator is computed. First, the reported average length of the school day devoted to teaching excluding all the breaks (short breaks and lunch breaks) as provided by the school head during the structured interview with the surveyor is 5 hours and 38 minutes. However, on average four out of 10 teachers were either absent from school or from class at any given time (see table 3.3). This reduces the school level scheduled teaching time to 3 hours and 23 minutes. Based on the case of grade 4, we have shown that roughly 86 percent of any typical lesson is devoted to teaching while the rest is lost to non-instructional related activities. This further reduces teaching time to 2 hours 54 minutes, which we call *teacher effective instruction time or time-on-task*. Figure 3.5 shows that students perform better in tests in schools with higher effective instruction time.

Table 3.5: Effective Instruction Time or Time-on-Task

| **Item** | | Final Time |
|---|---|---|
| Reported school level teaching time excluding breaks per class (hrs) | | 5hrs 38min |
| *of which* | | |
| Lost due to absence from class (hrs) | 0.4*(5 hours 38 minutes) | 2hrs 15min |
| Remaining school level teaching time (hrs) | 0.6*(5 hours 38 minutes) | 3hrs 23min |
| *of which* | | |
| Lost to off-task activities (hrs) | 0.14*(3hrs 23min) | 28min |
| Effective instruction time (hrs) | 0.86*(3hrs 23min) | 2hrs 54min |

*Source*: Own calculations based on SDI 2012.

Figure 3.5: Effective Instructional Time and Student Test Scores




*Source*: Own calculations based on SDI 2012.

In addition to the minute to minute classroom recording, the surveyor answered *a set of questions* designed to capture various aspects of classroom teaching practices based on their own observations, except for questions that required teacher answers. These included teacher demeanor, interaction and feedback to students, use of teaching aid, introducing and summarizing the lesson, assigning and review of homework as well as instructional language usage. The questions required a *yes* or *no* answer and they were filled out just after the classroom observation. Danielson (1996) has developed a framework that identifies aspects of an effective teacher, which she calls *domains*, that are known to promote improved student learning.[20] We end this section by classifying the classroom teaching practices based on Danielson (1996) Framework for Teaching, as shown in table 3.6.

With regards to domain 1, preparation and planning, it is interesting that most teachers (over 80 percent) had a lesson plan and scheme of work (judged by the surveyors to be well prepared) yet a majority of them performed poorly in the pedagogy test that literally tested lesson planning and preparation, raising questions as to whether having a lesson plan or scheme of work translates to better student scores. Domain 2, which generally measures the teacher-student classroom interactions, shows that the classroom environment seems to be generally conducive for learning. For instance, a majority of teachers, over 80 percent, instilled some level of trust in students by calling them by their names and giving them feedback, praise and moral encouragement. Some teacher feedback to students was scolding at a mistake and a small percent hit or slapped students.

In terms of domain 3, which constitutes the core of teaching, less than half of the teachers surveyed (43 percent) challenged students intellectually by asking questions that

[20] A comprehensive review of this framework can be found at: http://tpep-wa.org/the-model/framework-and-rubrics/instructional-frameworks/danielson-framework/

Table 3.6: Teacher Classroom Teaching Practices

| | All Schools | Public Schools | Private Schools | Public-Private |
|---|---|---|---|---|
| | Mean | Mean | Mean | Mean Diff. |
| **Domain 1: Planning and Preparation**[a] | | | | |
| Teacher had a well planned lesson plan | 0.86 | 0.85 | 0.87 | -0.02 |
| Teacher had a well planned scheme of work | 0.82 | 0.84 | 0.75 | 0.09 |
| **Domain 2: Creating an environment for learning**[b] | | | | |
| Teacher called children by name | 0.87 | 0.87 | 0.87 | 0.00 |
| Teacher gave feedback of praise and moral encouragement | 0.85 | 0.85 | 0.84 | 0.01 |
| Teacher gave student feedback that was scolding at a mistake | 0.19 | 0.19 | 0.19 | 0.00 |
| Teacher hit or slapped children | 0.03 | 0.03 | 0.02 | -0.02 |
| **Domain 3: Teaching for learning**[c] | | | | |
| Teacher challenged students (through questions) | 0.43 | 0.42 | 0.48 | -0.06 |
| Teacher used local language and local information | 0.33 | 0.36 | 0.20 | 0.16*** |
| Teacher reviewed homework | 0.38 | 0.35 | 0.47 | -0.13 |
| Teacher assigned homework | 0.69 | 0.65 | 0.83 | -0.18*** |
| Number of observations | **276** | **213** | **63** | |

*Source*: Own calculations based on SDI 2012. Classification of the teaching practices is based on Danielson (1996) Framework for Teaching, ***significance<1 percent, **significance<5 percent, *significance<10 percent

[a] The components in Domain 1 outline how a teacher organizes the content of what students are expected to learn, in other words, how the teacher designs instruction.

[b] The components in domain 2 consist of interactions that occur in the classroom that are generally non-instructional. These consist of creating an environment of respect and rapport among the students and the teacher, establishing a culture for learning, managing classroom procedures, managing student behavior, instilling some level of trust among students.

[c] The components in Domain 3 constitute the core of teaching – the engagement of students in the learning contest. These include communicating clearly and accurately, using questioning and discussion techniques, engaging students in learning, providing feedback to students, and demonstrating flexibility and responsiveness.

required learners to demonstrate their understanding of what they had learned during the lesson. We also find that 33 percent of teachers used local language (mother tongue) and local information to illustrate learning. More teachers assigned than reviewed homework. Private school teachers were significantly less likely to use local language and local information to illustrate learning and more likely to assign homework.

## 3.5 Education Production Function Estimates

Next, we link measures of teacher human capital and teacher effort to student literacy and numeracy test scores by way of an education production function as outlined in equation (3.4). The estimates we present are based on the sample of 222 schools where in each school, one grade 4 teacher was *(concurrently) observed in class* and *assessed in the teacher tests.* In 109 schools covering a total of 1,034 students, a language lesson was observed and in the rest, 113 schools covering a total of 1,077 students, a maths lesson was observed. [21]

For our teacher effects $\gamma$ in equation (3.4) to be causal, the measure of teacher human capital and teacher effort need to be uncorrelated with unobserved student ($\mu_{ijkd}$) and teacher ($\eta_{jkd}$) traits. The challenge of using cross-sectional data is how to deal with the non-random sorting of students and teachers into schools. True random-assignment of teachers and students in schools and in classes within schools is rare in any education context and more so, in the developing country context (Lavy, 2010). Due to this, we make no claim that our teacher estimates represent causal effects. Nevertheless, in what follows, we offer some discussion as to why we think our teacher estimates will not be completely driven by *within* and *between-school* sorting and suggest strategies to deal with these challenges.

### 3.5.1 Within-School Sorting

One natural concern is the possible non-random allocation of students into classes based on observed and unobserved factors such as student motivation or ability (*within-school* sorting). This results from the influence of teachers, school administrators or parents (Dieterle et al., 2015; West and Wobmann, 2006; Clotfelter et al., 2006; Aaronson et al., 2007; Todd and Wolpin, 2003). This problem rises if, for instance, a school has more than one stream of grade 4 (say grade 4A and 4B) and brighter or highly motivated students are assigned to a certain stream and matched to better or highly motivated teachers, who

[21] See Chapter 2, section 2.1.1

in turn adopt certain teaching practices based on their student ability.[22] Within-school sorting also arises if there are unobserved teacher attributes that have a direct impact on student performance, while they are correlated with the teaching style[23] (Aslam and Kingdon, 2011; Hidalgo Cabrillana and Lopez-Mayan, 2015).

We think that our estimates will not be so much influenced by within-school sorting because of the following reasons. First, our sample is restricted to one stream of grade 4 and all the students in the sampled stream are taught by the same language or maths teacher within the school.[24] Second, in determining student achievements in Equation (3.4), we include teaching process variables (how teachers spend their time in the classroom and what teachers do in class), collected during the classroom observation, alongside observable teacher characteristics (such as education, experience or training). In most studies, these teaching process variables are generally considered to be part of the teacher unobservables, $\eta_{jkd}$ (Aslam and Kingdon, 2011). Their inclusion therefore helps to reduce some of the bias associated with the possible correlation of unobserved teaching traits with observed teacher and student characteristics (Aslam and Kingdon, 2011).

The next reasons are largely institutional and contextual. First, there is evidence to show that parents in Kenya, especially those in rural areas, have little influence on choices made in schools, including those related to teacher allocation (Spernes, 2011; Echaune et al., 2015; Makori et al., 2015). Bold et al. (2011b) observe that the free public primary education in Kenya created the notion that schools belong to the government and not the local communities, thereby eroding parental involvement in what goes on inside schools.[25] Second, in our sample, 85 percent of the schools can be classified as *public* and *private-not-for-profit* while the rest, 15 percent, are *private-for-profit* and mostly located in urban areas.[26] In Kenya, within-school sorting is likely to be more prevalent in *private-for-profit* schools than in *public* or *private-not-for profit schools* for a number of reasons.

[22] In this case our measures of teacher knowledge and effort in Equation (3.4) will be biased because they are correlated with student unobservables ($\mu_{ijkd}$) (Hidalgo Cabrillana and Lopez-Mayan, 2015).

[23] This would happen if unobserved teacher ability or motivation affect the choice of the teaching style, while they have a direct effect on student test scores, aside from the effect through the teaching style. In this case the measures of teacher knowledge and effort in Equation (3.4) will be biased because they are correlated with teacher unobservables ($\eta_{jkd}$).

[24] As observed by Aslam and Kingdon (2011), within-school sorting would have been a serious problem if data was collected from more than one section (stream) of grade 4 within a school. In each school, we are only looking at students from one stream of grade 4.

[25] We come back on this point in Chapter 6.

[26] *Private-for-profit entities* are educational institutions operated by private agents and are primarily profit-seeking businesses mainly located in middle-and high-income urban areas as well as in peri-urban areas (Piper and Mugenda, 2010). *Private-not-for-profit entities* are educational institutions mainly operated by non-governmental organizations, majority of whom are faith-based organizations and are primarily not for profit-seeking businesses, targeting children from poor households in urban informal settlements (Heyneman and Stern, 2014; Tooley and Longfield, 2015; Tooley et al., 2011; Dixon and Tooley, 2012; Larbi et al., 2004; Oketch and Somerset, 2010; Oketch et al., 2012; Dixon, 2012).

For public schools, the Basic Education Act No. 14 of 2013[27] calls for equal treatment of students in all public schools and forbids public schools from admitting students based on previous academic records and tracking children in class by ability. Actually, one of the well documented reasons for the declining quality of education in public schools especially following the free public primary education is the unrestricted and unlimited entry into public schools of low aptitude students (Onsomu et al., 2005; Piper and Mugenda, 2012; Wasanga et al., 2010).

For *private-not-for profit schools*, their operational environment makes it difficult for them to track students by ability or even require entry exams, an issue we treat in detail in the next chapter. Generally, most private-not-for profit schools in Kenya are concentrated in informal settlements whose populations are largely poor and comprise labor migrants leading to a high teacher and student turn-over (Heyneman and Stern, 2014; Tooley and Longfield, 2015; Tooley et al., 2011; Dixon and Tooley, 2012; Larbi et al., 2004; Oketch and Somerset, 2010; Oketch et al., 2012; Dixon, 2012). Evidence shows that admission to these schools is granted at the discretion of the head teacher and not mainly based on previous academic record and once in school, children are less likely to be tracked by ability(Edwards Jr. et al., 2015).

Lastly, the fact that we are focusing on grade 4 also alleviates much of the concern regarding *within-school* sorting. We noted from our conversation with staff at the Ministry of Education, Science and Technology that the incentive to track students in class by ability is likely to happen as children advance to higher grades such as grade 7 or 8 when schools are preparing learners for the end of primary cycle examinations, often viewed as a strategy to improve the schools performance. Also, in a typical developing country like Kenya, the sample of children in schools is likely to become more and more self-selective with the rise in grades due to high drop-out rates.[28] Focusing on grade 4 learners minimizes such selection biases that arise due to high dropouts in later grades.

### 3.5.2 Between-School Sorting

The second concern is *between-school* sorting, which is the endogenous selection of teachers and students across schools, mainly based on factors that are unobservable to us (Todd and Wolpin, 2003; Aaronson et al., 2007). An example of between-sorting in Kenya is parental or teacher preference of certain regions given their socioeconomic conditions such as better schools. Related to this, some parents may prefer certain schools, for instance, private

[27]More details about the Act can be found at: http://www.kenyalaw.org.

[28]For instance, enrolment rates we presented in the previous Chapter, based on the Uwezo survey show that a significant proportion of children do not complete their primary education.

schools, based on characteristics such as past student performance or teaching philosophy. Table 3.2 and table 3.3 show that private school teachers are more knowledgeable and invest more effort than public school counterparts. Since private schools are not free in Kenya, fee paying parents in private schools may take greater interest in the school and be involved in monitoring the quality of education in schools (Bold et al., 2011b).

There exists a number of estimation strategies in a cross-sectional data setup to deal with such selection biases. Some of these include school fixed effects (Aslam and Kingdon, 2011; Altinok and Kingdon, 2012), within-teacher within-student variation (Metzler and Woessmann, 2012) and within-pupil across-subject approach (Shepherd, 2013; Shepherd et al., 2015). The application of any of these methods depends on the nature of the data at the researcher's disposal. For our case, we cannot estimate a school fixed effects model since there is *no within school variation* in the variables capturing *teacher human capital* and *effort* as only *one teacher was concurrently observed* and *assessed in the teacher tests* in every school.[29] To estimate a within-teacher within-student variation or a within-pupil across-subject approach in our context, data would have to be gathered from schools where: (i) *students are taught by the same teacher in both subjects (math and language)* and (ii) *that this teacher was concurrently assessed in the teacher tests* and *observed in both subjects* (see Shepherd (2013); Shepherd et al. (2015); Metzler and Woessmann (2012)).[30] Estimating a school fixed effects model and/or within-teacher within-student variation is therefore not possible with the data we have.

To minimize between-school sorting, we include division fixed effects, $D_d$, within the OLS estimation as shown in Equation (3.4). Through the division-level fixed effects, we are able to remove all sources of observed and unobserved heterogeneity at the division level.[31]

[29]Recall that we are directly linking student test scores to the human capital and effort of their teachers who were observed and observed. However, in each school, only one teacher was concurrently observed and tested. In other words, there is only one single observation for indicators of teacher human capital and effort per school. Such lack of *within school variations* hampers estimation of a school fixed effects model. A school fixed effects model in our context would have been possible if: (i) two or more teachers from different streams (e.g 4A and 4B) and/or from different grades (e.g grade 3 and grade 4) were observed and assessed in the teacher tests. Recall that in our case, only one teacher was concurrently observed and tested in every school. So our measures of teacher effort do not vary within a school to allow estimation of a school fixed effects model.

[30]The idea behind the within-student variation approach and/or a within-pupil across-subject approach is that by testing and observing the same teacher taking the students in both subjects, we are able to estimate whether the *same student* taught by the *same teacher* in *two different academic subjects* (e.g. maths and language) performs better in one of the subjects (e.g. maths) if the teacher's knowledge and efforts are relatively better in this subject (e.g. maths) thus allowing us to infer causality. The within-teacher within-student variation and within-pupil across-subject approaches can identify the effect based on within-teacher within-student variation by controlling for student fixed effects, teacher fixed effects, and subject fixed effects (see Shepherd (2013); Shepherd et al. (2015); Metzler and Woessmann (2012) for a detailed exposition about these approaches).

[31]Ideally, we should control for unobservables at the lower tiers than the division such as village, sub-location and location level. However, in the SDI survey, there is only one school per village (as well as

Including division fixed effects does not, however, effectively deal with the endogenous selection of students in public and private schools as there are private and public schools within a division. Since we cannot run a school fixed effects, we undertake separate estimation for public schools and see how our estimates compare with those in the main regression.[32]

While teachers and students are likely to sort across schools mainly on the basis of unobservable characteristics (Todd and Wolpin, 2003; Aaronson et al., 2007), we are of the opinion that such teacher and student across school sorting is in fact more likely to be on the basis of observed factors such as education, training, experience and gender among others. With this in mind, we follow a method employed by Aaronson et al. (2007) to provide an idea of the extent of *between-school* teacher and student sorting in our data on the basis of observable characteristics. We use the 1,679 teachers who were assessed in teacher tests and all the 2,954 students in our sample.

In this method, we begin by computing the within-school standard deviation for selected observable characteristics of teachers based on the actual data as it is. Low values of within-school standard deviation means that there is a lot of sorting, hence similar teachers are in the same schools. Second, using a simulation[33], we compute the average within-school standard deviation assuming that teachers were randomly sorted into schools. Basically, we sort teachers using a random variable which is essentially a white noise and based on this random variable compute the average within-school standard deviation (see Aaronson et al. (2007) for more details). Thirdly, we compute the average within-school standard deviation assuming that teachers were perfectly sorted into schools. Here, instead of sorting teachers using a random variable (white noise), teachers are sorted based on actual data (the respective variable) (see Aaronson et al. (2007) for more details). We perform a similar operation for selected observable characteristics of children. We do this for all schools and then separately for public and private schools.

For each variable, we compare the average within-school standard deviation for actual distribution, random distribution and perfect/non-random distribution. The results reported in table 3.7 to table 3.9 show that the actual distribution is closer to the random than non-random distribution. There is some level of evidence to show that teachers in our data, in all schools combined and in public and private schools, are not perfectly

per sub-location and location) and as a result, there are no variations in the variables measuring teacher human capital and effort at the village, sub-location and location level.

[32] The sample comprising only private schools (both for-profit and not-for-profit schools) is quite small. As a result, we do not undertake a separate estimation for private schools.

[33] We are greatly indebted to Deon Filmer and Stacy Brian of the World Bank for the assistance and inputs regarding the STATA routine for running the simulations based on methodology proposed by Aaronson et al. (2007).

sorted across schools on the basis of teacher knowledge, experience and age.

Table 3.7: Sorting of Teachers and Students Across Schools (Public and Private)

| Teacher sorting | | | | Students sorting | | | |
|---|---|---|---|---|---|---|---|
| | Actual | Random | Non-random | | Actual | Random | Non-random |
| Math Score | 0.738 | 0.899 | 0.008 | NVR* score | 0.898 | 0.970 | 0.006 |
| Language Score | 0.850 | 0.909 | 0.010 | Maths Score | 0.797 | 0.964 | 0.009 |
| Pedagogy Score | 0.802 | 0.947 | 0.006 | Language Score | 0.681 | 0.909 | 0.005 |
| Experience | 0.789 | 0.975 | 0.006 | Age | 0.840 | 0.967 | 0.008 |
| Teacher Age | 0.777 | 0.978 | 0.007 | Breakfast status | 0.221 | 0.289 | 0.001 |
| No. of Teachers | | **1,679** | | No. of Students | | **2,954** | |
| No. of Schools | | **306** | | No. of Schools | | **306** | |

*Source*: Own calculations based on SDI 2012. * Non-Verbal reasoning

Table 3.8: Sorting of Teachers and Students Across Schools (Public)

| Teacher sorting | | | | Students sorting | | | |
|---|---|---|---|---|---|---|---|
| | Actual | Random | Non-random | | Actual | Random | Non-random |
| Math Score | 0.746 | 0.903 | 0.009 | NVR* score | 0.924 | 0.968 | 0.008 |
| Language Score | 0.866 | 0.942 | 0.012 | Maths Score | 0.850 | 0.971 | 0.012 |
| Pedagogy Score | 0.824 | 0.962 | 0.008 | Language Score | 0.740 | 0.933 | 0.006 |
| Experience | 0.888 | 0.976 | 0.008 | Age | 0.879 | 0.967 | 0.013 |
| Teacher Age | 0.876 | 0.963 | 0.008 | Breakfast status | 0.684 | 0.871 | 0.006 |
| No. of Teachers | | **1378** | | No. of Students | | **2378** | |
| No. of Schools | | **239** | | No. of Schools | | **239** | |

*Source*: Own calculations based on SDI 2012. * Non-Verbal reasoning

Table 3.9: Sorting of Teachers and Students Across Schools (Private)

| Teacher sorting | | | | Students sorting | | | |
|---|---|---|---|---|---|---|---|
| | Actual | Random | Non-random | | Actual | Random | Non-random |
| Math Score | 0.722 | 0.867 | 0.048 | NVR* score | 0.879 | 0.956 | 0.032 |
| Language Score | 0.787 | 0.907 | 0.050 | Maths Score | 0.844 | 0.979 | 0.028 |
| Pedagogy Score | 0.716 | 0.963 | 0.320 | Language Score | 0.571 | 0.722 | 0.033 |
| Experience | 0.658 | 0.793 | 0.045 | Age | 0.798 | 0.971 | 0.040 |
| Teacher Age | 0.727 | 0.777 | 0.042 | Breakfast status | 0.565 | 0.639 | 0.038 |
| No. of Teachers | | **301** | | No. of Students | | **575** | |
| No. of Schools | | **67** | | No. of Schools | | **67** | |

*Source*: Own calculations based on SDI 2012. Notes. (1) This include for-profit and not-for-profit private schools, (2) * Non-Verbal reasoning

Similarly, students are also not perfectly sorted on the basis of subject knowledge, age and socioeconomic status (measured by an indicator for whether a student had breakfast before attending school).

Of particular interest is the fact that students are not sorted across schools based on the unobserved student ability ($\xi_i$) in equation (3.4) which is captured by non verbal reasoning scores. As noted by Filmer et al. (2015), if one is to take the non-verbal reasoning scores of students as a measure of innate intelligence quotient (IQ) that is not immutable directly by schooling, then there is no evidence that more innately gifted students are concentrated in certain schools. To conclude, we do not in any way claim that our estimates of teacher human capital and efforts that we present next are causal. These estimates should be interpreted in the context of the limitations we have raised. There is however good reason to think that selection bias is fairly small. That said, our results shed some light on important teacher factors that influence student achievements and provides an opportunity to take this work further especially after considering the SDI data limitations we have raised.

### 3.5.3 Model Estimation Results

#### 3.5.3.1 Effect of Teacher Human Capital and Effort

In table 3.10 and table 3.11, we present the estimated effects of our measures of the human capital and effort of teachers on student achievements for language and maths respectively. The dependent variable is the student score, which is standardized to the mean of zero and standard deviation of one. We run separate regressions for maths and language. For language, we have 109 schools covering a total of 1,034 students. These are schools where a teacher was observed (teaching a language class) and assessed (in teacher tests) thereafter. For maths, we have 113 schools covering a total of 1,077 students. Similarly, these are schools where a teacher was observed (teaching a maths class) and assessed. We control for a comprehensive set of teacher, school, classroom and pupil related variables. This is one credible way to deal with endogeneity when exclusion restrictions are impossible to find (Stock, 2010).

We also control for the village socioeconomic conditions measured by *village wealth index* based on the 2009 Kenya Population and Housing Census. Unlike the Uwezo survey, the SDI survey does not contain a village level module. However, with the support of staff at the National Bureau of Statistics in Kenya, we mapped the schools to the 2009 Kenya Population and Housing Census enabling us to extract village level information corresponding to the respective schools.[34] The census data includes questions related to

[34]The extensive matching process was made possible by the use of the school GPS coordinates. Staff at the the National Bureau of Statistics in Kenya helped us to link every school to its respective enumeration area/village. The SDI and the Kenya Population and Housing Census data are only two years apart. Unlike Uwezo, here we are mainly controlling for village level conditions for which schools are located. To

the household ownership of durable and livestock assets, type of material used to construct the wall of the dwelling unit, type of lighting regularly used by the household and household sanitation status among others. We construct a *village wealth index,* using the principal components analysis (PCA), based on these individual and household characteristics *aggregated at the village level.*[35] The index has 21 continuous variables based on indicators shown in table B3.1 in appendix B.

In model 1, we enter our measures of teacher human capital, effective instruction time and teacher's ability to keep students engaged. In model 2, we add our indicators of teacher classroom practices. These indicators are based on the SDI classroom observations and closely match measures of classroom practice explored in other studies (such as Ackers and Hardman (2001); Hardman et al. (2009); Ngware et al. (2014); MoEHRD (1999); Piper and Mugenda (2010); Aslam and Kingdon (2011)). Each practice is a binary indicator of whether or not the teacher engaged in it. In model 3, we control for other teacher observable characteristics. In model 4, school and classroom related variables are entered while model 5 includes student attributes. In table 3.10 and table 3.11, we only show the coefficients for the measures of the human capital and effort of teachers as well as teachers' observable characteristics. The full set of results, including the coefficients for schools, students and village controls are shown in table B3.2 and table B3.3 in appendix B.

Although they are not causal, what do these results tell us? First, even though we have not controlled for family background information, all models exhibit a relatively strong goodness-of-fit, as shown by the value of R-squared statistics. Moreover, much of the variations in the student test scores is explained by our measures of teacher human capital and effort. Jones et al. (2014) observe that R-squared statistics from estimated education production functions in most developed countries are often in the bracket of 10 percent and 30 percent while those from developing countries range around 30 percent. Second, addition of extra controls, including those related to teacher observables, does not dramatically change the direction of the effect and magnitude of the measures of teacher human capital and effort.

large extent, this also captures socioeconomic condition of villages (communities) where children come from especially in rural areas where children are likely to attend schools within their villages. This might not necessarily be the case for children in urban areas who are more likely to attend schools outside their villages. This survey does not allow us to know whether the child attends a school in the village or not.

[35]The practice of aggregating individual and household socioeconomic characteristics to construct measures of welfare (wealth/poverty) at the higher levels (e.g village, district etc) is quite common in the literature. For instance, in Costa Rica, Cavatassi et al. (2004) uses individual and household socioeconomic characteristics from the census to construct district level poverty index using principal components analysis (PCA).

Table 3.10: Teacher Human Capital, Teacher Effort and Student Language Test Scores

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| Teacher subject knowledge | 0.053* | 0.079** | 0.103*** | 0.080** | 0.075** |
| | (0.027) | (0.032) | (0.029) | (0.031) | (0.031) |
| Teacher pedagogical knowledge | 0.001 | -0.038 | -0.033 | -0.011 | -0.007 |
| | (0.043) | (0.042) | (0.043) | (0.048) | (0.053) |
| Effective instruction time (in hours) | 0.051* | 0.045* | 0.071*** | 0.056** | 0.051** |
| | (0.026) | (0.023) | (0.022) | (0.024) | (0.023) |
| Percent of student off-task (average) | -0.005 | -0.018*** | -0.018*** | -0.029*** | -0.030*** |
| | (0.007) | (0.006) | (0.006) | (0.008) | (0.008) |
| **Teacher Classroom Practices** | | | | | |
| Teacher reviews and assigns homework | | 0.181* | 0.353*** | 0.451*** | 0.383*** |
| | | (0.097) | (0.094) | (0.113) | (0.135) |
| Teacher uses local language to illustrate learning | | -0.243*** | -0.177** | -0.171* | -0.161** |
| | | (0.089) | (0.084) | (0.094) | (0.081) |
| Teacher challenges students by asking questions | | -0.121 | -0.189*** | -0.225*** | -0.190** |
| | | (0.079) | (0.062) | (0.073) | (0.074) |
| Teacher keeps a lesson plan and scheme of work | | -0.251* | -0.296** | -0.242* | -0.263* |
| | | (0.139) | (0.126) | (0.132) | (0.112) |
| Teacher instills discipline in students | | -0.392*** | -0.329*** | -0.365*** | -0.298*** |
| | | (0.113) | (0.108) | (0.100) | (0.101) |
| **Teacher Controls** | | | | | |
| Teacher is female | | | 0.201** | 0.136 | 0.078 |
| | | | (0.084) | (0.099) | (0.097) |
| Teacher experience (in years) | | | 0.035** | 0.035** | 0.035** |
| | | | (0.017) | (0.016) | (0.015) |
| Teacher experience squared (in years) | | | -0.001** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) |
| Teacher is on contract (Ref: government) | | | -0.457*** | -0.220 | -0.250 |
| | | | (0.137) | (0.162) | (0.172) |
| Teacher's highest education level is a diploma or a degree (Ref: Secondary) | | | 0.054 | 0.055 | 0.105 |
| | | | (0.094) | (0.093) | (0.088) |
| Teacher has ECD or primary certificate in teaching (Ref: Diploma or degree) | | | -0.075 | -0.183 | -0.175 |
| | | | (0.087) | (0.121) | (0.137) |
| **Controls** | | | | | |
| School and Classroom Controls | N | N | N | Y | Y |
| Student Controls | N | N | N | N | Y |
| Village Controls | Y | Y | Y | Y | Y |
| Division fixed effects | Y | Y | Y | Y | Y |
| Observations | 1,077 | 1,077 | 1,077 | 1,077 | 1,077 |
| R-squared | 0.376 | 0.396 | 0.407 | 0.413 | 0.495 |

Notes: (1) The estimates are based on 113 schools; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class) and assessed in the teacher tests; (3) School controls include: *a set of dummies which indicate whether the school is public, rural and located near a tarmack.* Other school characteristics are *classroom size, number of pupils per teacher, an index of school infrastructure* (based on the following items, given equal weight: (a) presence of toilets that were judged as designated for boys and girls, accessible, private and clean, (b) availability of electricity and (c) sufficient light for reading from the back of the class) and *an index of classroom equipment* (based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book (in language), (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls of the classroom); (4) Student controls include: *student age, age squared, whether the student is female, student score in maths, student non-verbal reasoning ability and whether the student ate breakfast*; (5) Standard errors are in parenthesis and are clustered at the class (school) level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

Table 3.11: Teacher Human Capital, Teacher Effort and Student Maths Test Scores

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| Teacher subject knowledge | 0.173*** | 0.172*** | 0.175*** | 0.166*** | 0.126*** |
| | (0.055) | (0.051) | (0.057) | (0.046) | (0.045) |
| Teacher pedagogical knowledge | 0.039 | 0.005 | -0.023 | 0.111*** | 0.112*** |
| | (0.053) | (0.051) | (0.045) | (0.038) | (0.035) |
| Effective instruction time (in hours) | 0.150*** | 0.137*** | 0.199*** | 0.087** | 0.059* |
| | (0.039) | (0.041) | (0.038) | (0.034) | (0.030) |
| Percent of student off-task (average) | -0.018** | -0.020*** | -0.010 | -0.005 | -0.002 |
| | (0.008) | (0.007) | (0.008) | (0.006) | (0.005) |
| **Teacher Classroom Practices** | | | | | |
| Teacher reviews and assigns homework | | -0.208* | -0.217* | -0.463*** | -0.377*** |
| | | (0.113) | (0.114) | (0.087) | (0.084) |
| Teacher uses local language to illustrate learning | | -0.262** | -0.162 | -0.106 | -0.073 |
| | | (0.129) | (0.135) | (0.089) | (0.096) |
| Teacher challenges students by asking questions | | 0.211 | 0.219 | 0.348*** | 0.273*** |
| | | (0.150) | (0.134) | (0.114) | (0.102) |
| Teacher keeps a lesson plan and scheme of work | | 0.012 | -0.038 | -0.243* | -0.248* |
| | | (0.152) | (0.163) | (0.120) | (0.115) |
| Teacher instills discipline in students | | 0.037 | 0.111 | 0.338** | 0.217 |
| | | (0.178) | (0.174) | (0.156) | (0.156) |
| **Teacher Controls** | | | | | |
| Teacher is female | | | -0.267** | -0.091 | -0.165* |
| | | | (0.134) | (0.091) | (0.085) |
| Teacher experience (in years) | | | -0.065*** | -0.078*** | -0.082*** |
| | | | (0.018) | (0.016) | (0.016) |
| Teacher experience squared (in years) | | | 0.002*** | 0.002*** | 0.002*** |
| | | | (0.001) | (0.000) | (0.000) |
| Teacher is on contract (Ref: government) | | | 0.019 | 0.243* | 0.247* |
| | | | (0.185) | (0.133) | (0.131) |
| Teacher's highest education level is a diploma or a degree (Ref: Secondary) | | | 0.284* | -0.041 | -0.008 |
| | | | (0.155) | (0.132) | (0.129) |
| Teacher has ECD or primary certificate in teaching (Ref: Diploma or degree) | | | -0.096 | 0.080 | 0.090 |
| | | | (0.160) | (0.118) | (0.103) |
| **Controls** | | | | | |
| School and Classroom Controls | N | N | N | Y | Y |
| Student Controls | N | N | N | N | Y |
| Village Controls | Y | Y | Y | Y | Y |
| Division fixed effects | Y | Y | Y | Y | Y |
| Observations | 1,034 | 1,034 | 1,034 | 1,034 | 1,034 |
| R-squared | 0.302 | 0.313 | 0.332 | 0.370 | 0.430 |

Notes: (1) The estimates are based on 109 schools; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a maths class) and assessed in the teacher tests; (3) School controls include: *a set of dummies which indicate whether the school is public, rural and located near a tarmack.* Other school characteristics are *classroom size, number of pupils per teacher, an index of school infrastructure* (based on the following items, given equal weight: (a) presence of toilets that were judged as designated for boys and girls, accessible, private and clean, (b) availability of electricity and (c) sufficient light for reading from the back of the class) and *an index of classroom equipment* (based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book (in maths), (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls of the classroom); (4) Student controls include: *student age, age squared, whether the student is female, student score in maths, student non-verbal reasoning ability and whether the student ate breakfast;* (5) Standard errors are in parenthesis and are clustered at the class (school) level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

We begin by interpreting results for language in table 3.10. Consistent with findings of Metzler and Woessmann (2012), Shepherd (2013) and others, our results show that teacher's subject specific knowledge has a positive and statistically significant effect on student language scores. For instance, model 5 shows that a one standard deviation increase in teacher's language knowledge increases student test score in language by 0.075 of a standard deviation.[36] The estimated effect of teacher pedagogical skill on student language test scores is effectively zero.

The estimated coefficient of the first measure of teacher effort, that is, *teacher effective instruction time,* is 0.051 and is statistically significant. This result means that *an additional hour of effective instruction* increases the test score in the language exam by 0.051 of a standard deviation. The variable *percent of students off-task* is negatively related to student scores in language meaning that teachers who keep students engaged (on-task) are likely to produce students with higher language test scores. Results show that a one percent increase in the number of students off-task reduces the language test score by 0.030 of a standard deviation.

Turning to teacher classroom practices, we find that the practice of reviewing and assigning homework increases the language test score by 0.383 of a standard deviation. However, the use of local language and local information reduces it by 0.161 of a standard deviation. There is vast literature on how local language influences learning concepts in second (foreign) language. One branch of this literature argues that illustrating concepts to students in local language and testing them in foreign language can be detrimental. Corder (1982) argues that students make errors when applying rules learned in the first language (local language) to the second language (English). He defines errors as deviations from correct usage of the second language since the student does not know its correct rules.[37]

The estimated effects of some classroom teaching practices are however puzzling. For instance, the practice of challenging students intellectually by asking them questions reduces reduces the test score in the language exam by 0.190 of a standard deviation. Unfortunately, our measures of classroom practices are binary indicators and simply indicate whether or not the teacher observed in the classroom engaged in the specific practice or not. In this regard, we do not know the nature of questions that teachers posed to learners and the type of learners that the questions were directed to. However, a number of qualitative studies (Ackers and Hardman, 2001; Hardman et al., 2009; Ngware et al., 2014; MoEHRD, 1999) report that classroom interaction in Kenyan schools is mainly characterized by teacher-initiated questions often calling for choral responses. Studies

[36]Unless otherwise, we concentrate on model 5, which we consider as our headline/preferred regression since our variables of interest do not change substantially, in sign and level of coefficient, with the progressive addition of controls.

[37]McLaughlin (2013) further observes that errors due to second language problem should not be confused with mistakes, arguing that the latter can be corrected by the student him/herself while the former can only be corrected by the teacher, a person well conversant with the second language.

by MoEHRD (1999) and Hardman et al. (2009) report that open-ended questions and questions initiated by pupils are rare, estimated at less than 1 percent of the questioning exchanges. Furthermore, boys are nearly twice as likely to be asked a question by teachers than girls (Hardman et al., 2009; MoEHRD, 1999). It is therefore likely that such environment of teacher-student classroom question interface is unlikely to facilitate student performance, more so, for girls.

Strangely, we also find that having a lesson plan and scheme of work does not translate to better student scores. This result is contrary to Aslam and Kingdon (2011) who found that being taught by a teacher who plans for the lesson raises scores (language and maths pooled together) by 0.23 standard deviations in Pakistan. Again, this is a binary indicator as to whether the teacher had a lesson plan and scheme of work, simply judged by the surveyors to be well prepared. We do not have a way to further ascertain the quality of these teaching tools. Nevertheless, as shown in table 3.2, teachers performed poorly in the pedagogy sub-task that asked them to prepare a lesson plan.[38] With such low levels of knowledge in lesson planning among teachers, it is unsurprising that merely having a lesson plan and/or scheme of work is unlikely to promote student learning. In fact, a recent study by Piper and Mugenda (2010) based on 220 schools randomly selected from three regions (Nairobi, Thika and Nakuru) of found that regions where teachers were judged to have well prepared lesson plans were associated with lower student achievements in both maths and language.

It is not surprising that the practice of instilling discipline in students by hitting and/or scolding them while giving feedback during a lesson leads to low student performance. We find that teachers who engage in this practice reduce the test score in the language exam by 0.298 of a standard deviation.

Turning on the estimates for the maths regression as shown in table 3.11, we find a significant and positive effect of teacher's subject knowledge on student maths scores (model 5). Unlike in language regression, there is evidence that teacher's pedagogical skill has a significant effect on student maths test scores. A one standard deviation increase in teacher's pedagogical knowledge increases the test score in the maths exam by 0.112 of a standard deviation. Similarly, teacher's effective instruction time positively and significantly affects student test scores in maths. Teacher's effort, measured by teacher's ability to keep students engaged becomes insignificant once we control for teacher observables.

The results on classroom teaching practices seem to suggest that students learn differently between language and maths. Unlike the case of language, the practice of assigning

[38] A lesson plan is a teacher's detailed description of the course of instruction, or 'learning trajectory' for a lesson. It is therefore a tool through which teachers demonstrate how they can translate their subject knowledge into meaningful teaching (pedagogical skills).

and reviewing homework is associated with lower student maths test scores. Aslam and Kingdon (2011) finds similar results in Pakistan and explains that homework could be taking away time that could be spent learning new materials. The use of local language has a negative effect which turns insignificant when we control for teacher observables. The practice of challenging students intellectually by asking questions, which had a negative and significant effect on language regression, now has a positive and significant effect on maths test scores. Similarly, classes where a teacher had a lesson plan are associated with lower student maths test scores. Finally, the practice of instilling discipline in students by hitting and/or scolding them while giving feedback during a lesson does not seem to have any effect on student test scores.

In table 3.12, we show the direction of the effect of each measure of the teacher human capital and effort based on model 5 of table 3.10 and table 3.11. The effect of teacher subject specific knowledge and effective instruction time go in the same direction for the two subjects. The estimates for the classroom teaching practices seem to suggest that students learn differently between language and maths.

Table 3.12: Teacher Human Capital, Teacher Effort and Student Language and Maths Test Scores

| Variable | **Language** | **Maths** |
|---|---|---|
| Teacher subject specific knowledge | + | + |
| Teacher pedagogical knowledge | Insignificant | + |
| Effective instruction time (in hours) | + | + |
| Percent of student off-task (average) | – | Insignificant |
| | | |
| **Teacher Classroom Practices** | | |
| Teacher reviews and assigns homework | + | – |
| Teacher uses local language to illustrate learning | – | Insignificant |
| Teacher challenges students by asking questions | – | + |
| Teacher keeps a lesson plan and scheme of work | – | – |
| Teacher instills discipline in students | – | Insignificant |

Notes: Columns for language and math that these are effects. That is, the results refer to effects of the variables listed – not to the variables themselves.

#### 3.5.3.2 Robustness Checks

In this section, we implement a number of robustness tests to check the validity of our results. The first robustness check is methodological. Some authors argue that OLS produces statistically unbiased estimates of the relationships among variables but its standard errors are biased downward because it does not take account of the nesting of students in schools or classes (Gelman and Hill, 2006; Hox, 2010; Fielding, 2010). As a

Table 3.13: Teacher Human Capital, Teacher Effort and Student Language Test Scores

| | Language | | | | Maths | | | |
|---|---|---|---|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| | HLM Model Estimation | Pure Public Schools | Public and non-profit private Schools | Rural Schools | HLM Model Estimation | Pure Public Schools | Public and non-profit private Schools | Rural Schools |
| Teacher subject knowledge | 0.075** | 0.196*** | 0.072 | 0.111** | 0.126** | 0.127*** | 0.136*** | 0.154*** |
| | (0.038) | (0.049) | (0.048) | (0.048) | (0.049) | (0.046) | (0.043) | (0.021) |
| Teacher pedagogical knowledge | -0.007 | 0.010 | 0.121** | 0.187*** | 0.112** | 0.088** | 0.069* | 0.022 |
| | (0.052) | (0.050) | (0.050) | (0.065) | (0.045) | (0.040) | (0.036) | (0.023) |
| Effective instruction time (in hours) | 0.051* | 0.043* | 0.029 | 0.048** | 0.059 | 0.092** | 0.113*** | 0.321*** |
| | (0.026) | (0.022) | (0.020) | (0.021) | (0.040) | (0.045) | (0.028) | (0.027) |
| Percent of student off-task (average) | -0.030*** | -0.020*** | -0.028*** | -0.050*** | -0.002 | 0.014 | 0.011 | -0.033*** |
| | (0.008) | (0.006) | (0.006) | (0.006) | (0.008) | (0.008) | (0.006) | (0.003) |
| **Teacher Classroom Practices** | | | | | | | | |
| Teacher reviews and assigns homework | 0.383*** | 0.535*** | 0.639*** | 0.967*** | -0.377*** | -0.419*** | -0.338*** | -0.135*** |
| | (0.124) | (0.126) | (0.115) | (0.158) | (0.103) | (0.105) | (0.093) | (0.033) |
| Teacher uses local language to illustrate learning | -0.161* | -0.188*** | -0.146* | -0.075 | -0.073 | 0.008 | 0.010 | 0.213** |
| | (0.089) | (0.057) | (0.080) | (0.073) | (0.108) | (0.095) | (0.075) | (0.082) |
| Teacher challenges students by asking questions | -0.190** | -0.305*** | -0.138** | -0.255*** | 0.273** | 0.356*** | 0.411*** | 0.377*** |
| | (0.088) | (0.066) | (0.065) | (0.077) | (0.122) | (0.110) | (0.104) | (0.040) |
| Teacher keeps a lesson plan and scheme of work | -0.263* | -0.228* | -0.152 | -0.110 | -0.248* | -0.156 | -0.158 | -0.533*** |
| | (0.140) | (0.115) | (0.121) | (0.142) | (0.129) | (0.163) | (0.119) | (0.062) |
| Teacher instills discipline in students | -0.298** | -0.387*** | -0.225** | -0.242** | 0.217 | 0.053 | 0.020 | -0.552*** |
| | (0.139) | (0.089) | (0.087) | (0.097) | (0.181) | (0.199) | (0.163) | (0.111) |
| **Controls** | | | | | | | | |
| **Teacher Controls** | Y | Y | Y | Y | Y | Y | Y | Y |
| **School and Classroom Controls** | Y | Y | Y | Y | Y | Y | Y | Y |
| **Student Controls** | Y | Y | Y | Y | Y | Y | Y | Y |
| **Village Controls** | Y | Y | Y | Y | Y | Y | Y | Y |
| **Division fixed effects** | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1,077 | 877 | 944 | 769 | 1,034 | 806 | 875 | 674 |
| R-squared | | 0.473 | 0.481 | 0.474 | - | 0.375 | 0.414 | 0.495 |

Notes: (1) The estimates are based on 113 schools for the language regressions and 109 schools for the maths regressions; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class for the language regressions and a maths class for the language regression) and assessed in the teacher tests; (3) School controls include: *a set of dummies which indicate whether the school is public, rural and located near a tarmack, classroom size, number of pupils per teacher, an index of school infrastructure* (based on the following items, given equal weight: (a) presence of toilets that were judged as designated for boys and girls, accessible, private and clean, (b) availability of electricity and (c) sufficient light for reading from the back of the class) and *an index of classroom equipment* (based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book, (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls of the classroom); (4) Student controls include: *student age, age squared, whether the student is female, student score in maths, student non-verbal reasoning ability and whether the student ate breakfast*; (5) Standard errors are in parenthesis and are clustered at the class (school) level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

result, hierarchical linear modeling has become a popular way to analyze data with such statistical dependency.[39] We therefore estimate all the models in table 3.10 and table 3.11 using hierarchical linear modeling estimation strategy.

Models 1 in table 3.13 show results based on HLM for language and maths (based on model 5 of table 3.10 and table 3.11). As can be seen from the tables, the patterns of estimates based on hierarchical linear modeling are similar to those based on OLS. We still find that teacher subject knowledge and effective instruction time are positively related to student achievement in maths and language. As before, teacher pedagogical skill promotes student test scores in maths and not language. Similarly, we find that an increase in the percent of students off-task is negatively related to student test scores in maths and language. We also do not see dramatic changes in the effect of teacher classroom practices.

The next robustness checks attempt to address whether the estimates in our main regressions (in table 3.10 and table 3.11) reflect some level of endogenous selection into schools. Next, we test whether our estimates are driven by possible endogenous selection into private schools. We proceed as follows. First, we undertake separate estimation for a sample comprising *pure public* schools. Second, we undertake another separate regression for a sample comprising of *pure public* schools and *private-not-for-profit* schools. As noted, *private-not-for-profit* schools are similar to pure public schools in many ways. Like public schools, these schools are not driven by the profit motive. They also do not admit learners based on previous academic record and once in school, children are less likely to be tracked by ability (Edwards Jr. et al., 2015).[40]

If our estimates are driven by between-school sorting, we expect the estimates based on these two restricted samples to be dramatically different from the estimates in our main regressions in table 3.10 and table 3.11. Models 2 of table 3.13 report estimates based on the sample of pure public schools for language and maths. In model 3 of the same table, we report estimates based on the sample of combined *pure public* and *private-not-for-profit* schools for language and maths.

Looking at the results based on both pure public schools (models 2) and the combined *pure public* and *private-not-for-profit* schools (models 3), the estimates of the indicators of teacher human capital and teacher effort for the two restricted samples are not dramatically different from those in our regressions in model 5 of table 3.10 and table 3.11.

[39] Hierarchical linear modeling does not correct bias in the regression coefficient estimates compared with an OLS model but it produces unbiased estimates of the standard errors associated with the regression coefficients when the data are nested (Gelman and Hill, 2006; Fielding, 2010; Bryk and Raudenbush, 1992; Hox, 2010).

[40] We do not undertake a separate regression for pure private schools since the sample is too small.

However, the variables teacher's subject knowlegde and effective instruction time, which were positively and significantly related to student language scores in the main regression, now have zero effects in the combined sample of *pure public* schools and *private-not-for-profit* schools (models 3). The results in the maths regression are practically similar to those in the main regressions in table 3.11 (model 5).

Another way to check if our estimates in table 3.10 and table 3.11 reflect some level of endogenous selection into schools is to undertake a separate estimation for rural schools. As we discuss in the next chapter, the prevalence of private schools is quite low in rural areas. Unlike urban areas, parents in rural do not have a wide variety of private school choices and are less likely to influence school choice for their children. Besides, parents in rural areas are less likely to influence choices made in schools (Spernes, 2011; Echaune et al., 2015; Makori et al., 2015). Models 4 of table 3.13 reports the estimates based on the rural schools for language and maths (based on model 5 of table 3.10 and table 3.11). Again, the results are closely comparable to those in the main regressions.

In chapter 2, we noted that classroom observations took place in 276 schools. In each of these schools, one grade 4 teacher was observed in either language or maths lesson. Of the 276 teachers who were observed, 222 teachers (in 222 schools) took the teacher assessment tests. The rest, 54 teachers (in 54 schools), did not take the teacher tests for reasons we are not aware. Since our interest has been to estimate the effect of teacher human capital and effort, the estimates we have presented so far are based on a sample of 222 schools where a teacher was observed and tested.

One might be be concerned about the presence of a systematic pattern with respect to the teachers who did not write the test. In table A2.2 in appendix A, we show that there are no significant differences between the 222 teachers who were observed and tested and the 54 teachers who were only observed. We further account for the 54 teachers to see if our estimates change. To proceed, we estimate the regressions in table 3.10 and table 3.11 for the 276 teachers but account only for the measures of teacher effort since we do not have data on teacher test scores for 54 teachers. Results are shown in table 3.14. The estimated coefficients of our measures of effective instruction time, teacher ability to keep students engaged and teacher classroom practices are similar to those we present in the main regressions in table 3.10 and table 3.11. This means that our headline results do not reflect a systematic pattern with respect to the teachers who did not write the test.

Lastly, we calculated our measure of *effective instruction time* by accounting for teacher absence from class and how teachers spend their time while teaching. In order to address potential reservations of how this variable is defined, especially the aspect of adjusting for teacher absence from class, we check the direct effect of *teacher absence*

Table 3.14: Teacher Effort on Student Test Score (excluding measures of Teacher Human Capital)

| | Language | | | | | Maths | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
| Effective instruction time (in hours) | 0.043* | 0.046* | 0.047** | 0.050** | 0.048** | 0.130*** | 0.107*** | 0.132*** | 0.083** | 0.059* |
| | (0.022) | (0.021) | (0.020) | (0.020) | (0.020) | (0.038) | (0.037) | (0.036) | (0.037) | (0.033) |
| Percent of student off-task (average) | -0.007 | -0.009** | -0.014*** | -0.016*** | -0.014*** | -0.016** | -0.016** | -0.011** | -0.014** | -0.012** |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.004) | (0.007) | (0.007) | (0.005) | (0.006) | (0.005) |
| **Teacher Classroom Practices** | | | | | | | | | | |
| Teacher reviews and assigns homework | | 0.107 | 0.163** | 0.186** | 0.160** | | -0.125 | -0.097 | -0.231** | -0.194** |
| | | (0.076) | (0.068) | (0.074) | (0.069) | | (0.105) | (0.098) | (0.106) | (0.088) |
| Teacher uses local language to illustrate learning | | -0.089 | -0.080 | -0.055 | -0.057 | | -0.196* | -0.147 | -0.055 | -0.079 |
| | | (0.081) | (0.073) | (0.079) | (0.074) | | (0.103) | (0.105) | (0.097) | (0.085) |
| Teacher challenges students | | -0.172** | -0.159** | -0.186** | -0.182** | | 0.335*** | 0.234** | 0.404*** | 0.325*** |
| | | (0.076) | (0.064) | (0.071) | (0.070) | | (0.116) | (0.115) | (0.117) | (0.108) |
| Teacher has a lesson plan and scheme of work | | -0.249* | -0.270** | -0.269** | -0.365*** | | 0.311** | 0.262* | 0.224* | 0.220** |
| | | (0.133) | (0.111) | (0.115) | (0.121) | | (0.131) | (0.149) | (0.128) | (0.108) |
| Teacher instills discipline in students | | -0.149 | -0.204** | -0.260*** | -0.208** | | -0.051 | -0.098 | -0.033 | -0.027 |
| | | (0.122) | (0.101) | (0.095) | (0.092) | | (0.125) | (0.091) | (0.099) | (0.108) |
| **Controls** | | | | | | | | | | |
| **Teacher Controls** | N | Y | Y | Y | Y | N | Y | Y | Y | Y |
| **School and Classroom Controls** | N | N | Y | Y | Y | N | N | Y | Y | Y |
| **Student Controls** | N | N | N | Y | Y | N | N | N | Y | Y |
| **Village Controls** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| **Division fixed effects** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1,365 | 1,365 | 1,365 | 1,365 | 1,365 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 |
| R-squared | 0.331 | 0.340 | 0.357 | 0.363 | 0.461 | 0.285 | 0.303 | 0.327 | 0.343 | 0.412 |

Notes: (1) The estimates in the language regression are based on 144 schools where classroom observation involved a language lesson. Similarly, in the maths regression, the estimates are based on 132 schools where classroom observation involved a maths lesson; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class for the language regressions and a maths class for the language regression) and assessed in the teacher tests; (3) School controls include: *a set of dummies which indicate whether the school is public, rural and located near a tarmack, classroom size, number of pupils per teacher, an index of school infrastructure* (based on the following items, given equal weight: (a) presence of toilets that were judged as designated for boys and girls, accessible, private and clean, (b) availability of electricity and (c) sufficient light for reading from the back of the class) and *an index of classroom equipment* (based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book, (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls of the classroom); (4) Student controls include: *student age, age squared, whether the student is female, student score in maths, student non-verbal reasoning ability and whether the student ate breakfast*; (5) Standard errors are in parenthesis and are clustered at the class (school) level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

*from class* on student test scores. In this case, we estimate our models in table 3.10 and table 3.11 by replacing the variable *teacher effective instruction time* with the variable teacher absence.

Results are shown in table 3.15. First, the results show that schools with higher *teacher class absence rate* are associated with lower student test scores in both subjects. For instance, we find that after accounting for teacher, school, class and student controls, a one percent increase in teacher absence in class reduces the test score in the language and maths by 0.004 and 0.002 of a standard deviation, respectively. Second, the estimates of our measures of teacher human capital and teacher effort for the two restricted samples are not dramatically different from those in our main regressions in table 3.10 and table 3.11. The estimated effect of teacher subject knowledge on student language test scores however losses its significance level but retains its sign as before.

## 3.6 Conclusion

In this paper, we examine the effect of *teacher human capital* and *teacher effort* on student achievement in maths and language among grade 4 students in Kenya. We let teacher subject knowledge and teacher pedagogical skill to represent teacher human capital. We measure teacher effort by *effective instruction time, teacher's ability to keep students engaged during the lesson* and by *a number of teacher classroom practices*. These measures of teacher effort were collected through teacher classroom observation. We control for a detailed set of variables related to teachers, schools and children as well as information capturing the socioeconomic conditions of the regions where schools are located. Our estimates are based on the OLS model with division-level fixed effects to control for potential sources of common unobservables at the divisional level.

We find that student test scores in maths and language are partially influenced by our measures of teacher human capital and teacher effort. We find that a one standard deviation increase in teacher knowledge in language increases the student language test score by 0.075 of a standard deviation. The effect for maths is 0.126 of a standard deviation. Teacher's pedagogical skills matter only for maths test scores. A one standard deviation increase in teacher pedagogical skill increases the maths test score by 0.112 of a standard deviation. Our results further show that an additional hour of effective teaching is associated with an increase in the language and maths test score by 0.051 and 0.059 of a standard deviation, respectively. Teachers ability to engage students during the lesson also matters for language and maths achievement.

The effects of classroom teaching practices on student tests scores are not uniform across the two subjects. For example, using local language to illustrate learning reduces

Table 3.15: Teacher Human Capital, Teacher Effort and Student Scores: Using Teacher Absence from Class

| | Language | | | | | Maths | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Teacher subject knowledge | 0.047 | 0.005 | 0.031 | 0.029 | 0.013 | 0.160*** | 0.142** | 0.132** | 0.150*** | 0.149*** |
| | (0.036) | (0.032) | (0.033) | (0.032) | (0.035) | (0.057) | (0.055) | (0.062) | (0.047) | (0.048) |
| Teacher pedagogical knowledge | 0.012 | -0.055 | -0.003 | 0.022 | 0.027 | 0.041 | -0.001 | -0.024 | 0.121*** | 0.121*** |
| | (0.043) | (0.039) | (0.043) | (0.050) | (0.051) | (0.054) | (0.053) | (0.050) | (0.036) | (0.037) |
| Teacher absence from class (percent) | -0.003* | -0.002 | -0.004*** | -0.003** | -0.004*** | -0.005* | -0.003 | -0.006** | -0.004** | -0.003* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Percent of student off-task (average) | -0.005 | -0.017*** | -0.019*** | -0.028*** | -0.029*** | -0.023*** | -0.025*** | -0.013 | -0.006 | -0.005 |
| | (0.006) | (0.005) | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.006) | (0.005) |
| Teacher reviews and assigns homework to students | | 0.155 | 0.360*** | 0.478*** | 0.382*** | | -0.201 | -0.201* | -0.472*** | -0.419*** |
| | | (0.100) | (0.103) | (0.126) | (0.142) | | (0.121) | (0.115) | (0.083) | (0.084) |
| Teacher uses local language to illustrate learning | | -0.228** | -0.173* | -0.155 | -0.136 | | -0.235* | -0.183 | -0.103 | -0.105 |
| | | (0.088) | (0.090) | (0.097) | (0.088) | | (0.140) | (0.157) | (0.092) | (0.092) |
| Teacher challenges students | | -0.092 | -0.142** | -0.202*** | -0.167** | | 0.319** | 0.308** | 0.362*** | 0.317*** |
| | | (0.077) | (0.068) | (0.073) | (0.076) | | (0.144) | (0.144) | (0.121) | (0.118) |
| Teacher has a lesson plan and scheme of work | | -0.416*** | -0.257** | -0.146 | -0.306** | | 0.075 | 0.063 | -0.318*** | -0.336*** |
| | | (0.141) | (0.129) | (0.140) | (0.144) | | (0.145) | (0.161) | (0.112) | (0.110) |
| Teacher instills discipline in students | | -0.372*** | -0.302*** | -0.324*** | -0.233** | | 0.022 | 0.051 | 0.341** | 0.308* |
| | | (0.118) | (0.114) | (0.103) | (0.101) | | (0.193) | (0.186) | (0.164) | (0.161) |
| **Teacher Controls** | N | N | Y | Y | Y | N | N | Y | Y | Y |
| **School and Classroom Controls** | N | N | N | Y | Y | N | N | N | Y | Y |
| **Student Controls** | N | N | N | N | Y | N | N | N | N | Y |
| **Village Controls** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| **Division fixed effects** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1,077 | 1,077 | 1,077 | 1,077 | 1,077 | 1,034 | 1,034 | 1,034 | 1,034 | 1,034 |
| R-squared | 0.377 | 0.394 | 0.405 | 0.411 | 0.495 | 0.288 | 0.303 | 0.318 | 0.370 | 0.388 |

Notes: (1) The estimates in the language and maths regression are based on 113 and 109 schools respectively; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class for the language regressions and a maths class for the language regression) and assessed in the teacher tests; (3) School controls include: *a set of dummies which indicate whether the school is public, rural and located near a tarmack, classroom size, number of pupils per teacher, an index of school infrastructure* (based on the following items, given equal weight: (a) presence of toilets that were judged as designated for boys and girls, accessible, private and clean, (b) availability of electricity and (c) sufficient light for reading from the back of the class) and *an index of classroom equipment* (based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book, (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls of the classroom); (4) Student controls include: *student age, age squared, whether the student is female, student score in maths, student non-verbal reasoning ability and whether the student ate breakfast*; (5) Standard errors are in parenthesis and are clustered at the class (school) level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

student achievement. It reduces maths and language scores by 0.161 and 0.073 standard deviations, although the effect is insignificant for maths. The practice of challenging students by asking them questions has a statistically significant positive effect on maths but a statistically significant negative effect on language. Reviewing and assigning homework has a statistically significant positive effect on language but a significant negative effect on mathematics.

We do not in any way interpret our estimates as causal due to the potential selection of students and teachers into schools. Our results shed some light on important teacher factors that influence student achievements, in particular aspects of teachers that have not been widely investigated in the sub-Sahara Africa literature. These findings suggest that intervention at the level of teacher knowledge and effort as policy instruments may improve tests scores.

# Chapter 4

# Private Schools and Student Learning Achievement

## 4.1 Introduction

To estimate the effect of teacher human capital and teacher effort in chapter 3, we controlled for characteristics related to: teachers, schools (including a variable capturing whether a school is private or public), classes, students and communities (villages) where schools are located. One of the results in that emerge from main regression (see full regression results in appendix B, table B3.2 and table B3.3), which we did not discuss is that private schools are consistently associated with better student test scores. Specifically, the results in these tables show that attending a private school is likely to increase student scores by 0.334 and 0.696 of a standard deviation in language and maths, respectively. A number of recent studies (such as Javaid et al. (2012); Andrabi et al. (2008); French (2008); Desai et al. (2008); Pal (2010); Bold et al. (2011a, 2013a)) focusing on developing countries also find that private schools are associated with better student attainments.

Despite this, the validity and magnitude of the private school premium is still debated and, in fact, questioned. Researchers such as Goldberger and Cain (1982), Newhouse and Beegle (2006) and Altonji et al. (2000, 2005) urge that such private school advantage may be due to spurious correlations between private school attendance and unobserved student and family characteristics. Households that choose private schools differ from those that choose public schools and therefore, the differences in achievements between private and public students could be due to factors not easily observable by the researcher (Goldberger and Cain, 1982; Newhouse and Beegle, 2006; Altonji et al., 2000, 2005)

That students who attend private schools differ from those that choose public schools can be seen in table 2.2 in chapter 2. As discussed earlier, Table 2.2 (a) shows that children who attend private schools are more likely to come from rich households. As discussed earlier, table 2.2 (c) shows that private school students are also more likely to be taught by more knowledgeable teachers and teachers who are more likely to be in school and in class. The effect of private schools is likely to be over-estimated if such observable and more importantly unobservable factors[1] are not fully taken into account. In fact, evidence elsewhere shows that accounting for unobservable factors and selection bias can wash away or dramatically reduce such private school advantage. In Indonesia, Newhouse and Beegle (2006) account for selection effects and finds that private schooling has, in fact, a significant negative effects on test scores.

Private schooling in Kenya has expanded dramatically over the past decade (Tooley et al., 2008; Heyneman and Stern, 2014; Tooley and Longfield, 2015; Edwards Jr. et al., 2015; Piper and Mugenda, 2010; Oketch et al., 2010, 2012; Piper et al., 2015). However, there is a dearth of studies that look at the effectiveness of these schools. Research has mostly focused on understanding why households, mainly poor households, choose to enrol their children in low-fee paying private schools and not in free public schools. The reasons are varied. Tooley et al. (2008) and Oketch and Somerset (2010) find that perceived better quality of private schools is a key driver of parents' choice of private schools. Oketch et al. (2012) focusing in urban areas and Nishimura and Yamano (2013) focusing in rural areas both find that an increase in household wealth is likely to lead to the household enrolling a child in a private school.

In this chapter, we use the Uwezo survey to estimate the effect of private schools on literacy (language) and numeracy (maths) skill acquisition among children mainly drawn from lower primary grades in Kenya. Private schools are defined as independent, non-governmental, and/or nonstate schools, not administered by local, state or national governments. Our main contribution lies in accounting for the endogeneity of private school choice while estimating the effect of private schools. We do so by using different econometric techniques. We begin with the OLS as a baseline model. We then estimate the village and family fixed effects[2] models that control for unobservables at the village and household levels, respectively. Using a methodology advanced by Altonji et al. (2005), we estimate the potential size of any bias on the estimated coefficient of the private school variable due to unobservable selectivity in the OLS and the fixed effects models. We

[1] Even for children who attend private schools from poor households, the fact that poor parents bypass public schools and send their children to otherwise fee-paying low-cost private schools means that they are more concerned about the education of their children. Such parents, despite being poor, are more likely to ensure that the home environment is favorable for learning. Such aspects of parental motivation are unobservable to the researcher.

[2] The term family and household are used interchangeably throughout this thesis.

supplement the OLS and fixed effects models with a non-parametric estimation technique, that is, propensity score matching (PSM). Similar to Altonji et al. (2005)'s approach in the case of OLS and fixed effects model, we follow a method by Rosenbaum (2002) to check the extent to which our estimates based on PSM suffer from hidden bias (unobservables).

As pointed out by French et al. (2010), each of the above estimation (method) strategies has its own strengths and weaknesses and no strategy on its own can yield convincing estimates of the private school premium. It is for this reason that we apply different methods to see if they lead to similar conclusions about the effect of private schools on children literacy and numeracy skill acquisition. This comparative analysis also provides us with a sense of the range (upper and lower bound) of the size of the private school effects in Kenya.

To our knowledge, only one study in Kenya by Bold et al. (2013a) has estimated the effect of private schools on student scores while addressing the endogeneity of school choice in Kenya. The authors find a large private school premium, equivalent to one standard deviation based on grade 8 tests scores (end of primary cycle examinations). Their study however suffers from two shortcomings. First, in a typical country like Kenya, the sample of children in school becomes more and more self-selective as one advances to higher grades due to relatively high drop-out rates. As we discussed in chapter 2, a significant proportion of primary school age children in Kenya drop out of school before completing primary cycle (see figure 2.1(a). The estimates based on Bold et al. (2013a) are, therefore, likely to suffer from sample selection bias.

Second, the fact that a pupil sits for end of primary cycle examinations (grade 8 tests) at a private school does not mean that he or she has been in that school from grade 1. Evidence in Kenya shows that since the majority of private schools are not formally registered (Tooley et al., 2008; Heyneman and Stern, 2014; Tooley and Longfield, 2015; Edwards Jr. et al., 2015; Piper and Mugenda, 2010; Oketch et al., 2010, 2012; Piper et al., 2015), most parents send their children to these schools but transfer them to public schools for their end of primary cycle exams in grade 8 (Edwards Jr. et al., 2015). Therefore misattribution may occur by assessing private school effectiveness based on end of primary cycle examinations (grade 8 tests). To deal with these challenges, we restrict our sample to children in lower primary grade 2 to grade 4. We are not aware of any study that focuses on the importance of private schools on cognitive development of children from *lower primary grades* in Kenya.

Here is a preview of our results. We find a positive and significant private school advantage across all the estimated methods. Our results however seem to suggest that the OLS, village fixed effects and propensity score matching regressions overestimate the true primary school effect while the household fixed effects model underestimates the private school effect. From this, we have a sense of the range of the private school premium. In maths, the premium ranges from 0.13 to 0.20 of a standard deviation, based on the household and village fixed effects model, respectively. In the case of language, it ranges from 0.20 to 0.29 score standard deviation, based on the household and village fixed effects model, respectively. Otherwise the chapter unfolds as follows. Section 4.2 provides the context of private sector education provision in Kenya while in section 4.3, we review literature on private school effectiveness. In section 4.4, we detail the estimation techniques and in section 4.5, we provide the empirical results. Section 4.6 offers our concluding remarks.

## 4.2 The Context: Private School Provision in Kenya

Kenya has a long history of private sector education provision. Private sector education providers include non-governmental organizations, faith-based organizations, community-based providers and private-for-profit agents (Tooley et al., 2008; Heyneman and Stern, 2014; Tooley and Longfield, 2015; Edwards Jr. et al., 2015). Faith-based organizations and community-based providers have supported education provision since the early 1960s. Through the 1980s and 1990s, private education provision expanded owing to structural adjustment programs (SAPs) that led to the reduction in public education funding (Nishimura and Yamano, 2013). This period saw the entry of private-for-profit agents. Despite these developments, access to private schools by children from poor and rural households was limited due to poor financing of community school projects (Olembo, 1985).

Currently, Kenya's primary education provision is characterized by free public provision of education and a huge market for private fee-charging schools. As noted in Chapter 1, the fall in the quality of education offered in public schools mainly following the introduction of free primary education led to an increase in private school provision (Bold et al., 2013b; Oketch and Somerset, 2010; Oketch et al., 2010). Private school provision accounts for about 25 percent of the total primary school sector in Kenya (KIPPRA, 2016). This does not, however, account for the highly unregulated and unregistered non-formal private sector schools in urban informal settlements, which we briefly describe below.

As noted, private schools in Kenya comprise independent, non-governmental, and/or nonstate schools, not administered by local, state or national governments. These schools have the right to select their students and are funded in whole or in part by charging their students tuition, rather than relying on public (government) funding. In Kenya, these schools currently reflect a diverse range of institutions, ranging from: (a) highly unregulated and sometimes unregistered non-formal schools mainly located in informal settlements[3]; (b) formal private academies in middle and high-income urban areas and (c) very few old traditionally exclusive private schools (Piper and Mugenda, 2010; Piper et al., 2014). The main development in the sector during the post-free public primary school era has been the mushrooming of non-formal schools located in urban informal settlements whose goal has been to meet the high demand for school places in those urban informal settlements (Tooley et al., 2008; Heyneman and Stern, 2014; Edwards Jr. et al., 2015; Tooley and Longfield, 2015; Piper et al., 2014, 2015). These schools levy low fees to make them affordable for children from poor urban informal settlements. Parents with children in these institutions pay tuition fees that average less than USD 10 per month (Piper and Mugenda, 2010; Piper et al., 2014). They are the main source of education for children in urban informal settlements. As pointed out by Piper et al. (2014), for some families in urban informal settlements, the choice may be between the non-formal school and no school at all.

The majority of these low-cost private schools are generally lacking in terms school infrastructure and facilities. Others operate with similar level of school resources as public schools. For instance, table 2.2 (b) in chapter 2 shows that the private schools in the SDI survey sample, a characteristic of low-cost private schools, operate with the same school resources like public schools. Low-cost private schools (and generally private schools in general) in Kenya are however lacking in terms of qualified teachers, relative to their public counterparts. Table 2.2 (c) in chapter 2 shows that private school teachers, in the SDI survey sample, are less experienced and have lower education and teacher qualifications compared to counterparts in public schools. Not only are public school teachers more qualified (in terms of experience and level of training), they are also paid better than those in low-cost private primary schools (Bold et al., 2012; Tooley and Dixon, 2005).

As noted in the last chapter, admission to these low cost private schools is sometimes quite informal and only a few schools conduct interviews for new students as part of the selection process. Although some are registered and receive some form of support from the government[4], the majority run with limited engagement with the government. In fact,

[3]Our conversation with staff at the Ministry of Education shows that most of these schools are mainly in urban areas of big municipalities like Mombasa, Eldoret, Nairobi, Thika, Nakuru, Kisumu and Kitale.

[4]Starting in 2005, the government, through the Ministry of Education has been supporting low-fee paying private schools in informal settlements. Through the Instructional Materials initiative, schools have been receiving funding to pay for learning materials, such as books, pens and chalk. In order to qualify for this government support, the school should: (i) be registered, (ii) be assessed by Ministry

as discussed in Edwards Jr. et al. (2015), low cost private schools operate within the same constraints as households living in their catchment area. According to Edwards Jr. et al. (2015) low cost private schools in urban informal settlements have little or no security of tenancy, are highly unregulated, lack space or sanitation facilities and are vulnerable to the challenges that characterize densely populated and volatile urban informal settlements in Kenya (see also Tooley et al. (2008); Heyneman and Stern (2014); Piper et al. (2014); Tooley and Longfield (2015); Piper et al. (2015); Piper and Mugenda (2010)).[5] They are characterized by high student and teacher turnover.

It is puzzling that students from these low-cost private schools perform better than counterparts in public schools with almost similar school inputs (infrastructure) and less qualified teachers. In table 2.3 and table 2.4, we show that private schools in Uwezo and SDI survey data perform better than those in public schools. Tooley and Dixon (2005) compared student achievement between students attending low-cost private schools and those attending public schools in Kibera - Kenya's largest informal settlement in maths, language and Kiswahili. Pupils in private schools were reported to have performed significantly better in both math and English when the researchers controlled for background variables. Our interest in this chapter is to account for possible endogeneity of school choice and see if such private-public score gap persists.

## 4.3 Do Private School Children achieve better Learning Outcomes than counterparts in Public Schools?

To estimate the effect of private schools, the earliest studies estimated the effect of private schools using a dummy variable indicating whether a child is attending a private school or not alongside other characteristics related to students and their families. Some of these include; Hammersley et al. (1981) for the United Kingdom, Psacharopoulos (1987) for

of education officials in terms of location, sanitation, safety etc and (iii) have a School Management Committee comprising of teachers and two representatives of the parents Edwards Jr. et al. (2015). The number of schools under government support had increased from 59 in 2004 to 410 in 2009.

[5] While a lot has been documented with regard to low cost non-formal private schools in urban informal settlements, there is little information regarding private schools in rural areas as well as private academies in middle and high-income urban areas. There are indications of remarkable penetration of such schools in rural areas. We are only aware of a study by Nishimura and Yamano (2013) which looked at determinants of school choice in rural Kenya. This study is based on a panel survey of 76 randomly selected rural sub-locations from Western and Central provinces. The authors found that between 2003 and 2007, 35 (out of 119) new private schools were established in these regions relative to only six (out of 318) public schools, reflecting a clear increasing demand for private schools in rural Kenya.

Colombia and Tanzania, Govinda and Varghese (1993) for India, McEwan and Carnoy (2000) for Chile and McEwan (2002) for Argentina and Chile, among others. Using OLS estimation, these studies generally find that attending private schools is associated with an increase in the student test scores. The main challenge with all these studies is that they treat private school choice as exogenous which is not likely to be the case.

Most recent studies have dealt with the endogeneity of school choice through different approaches. One such approach is the use of experimental data where students are randomly assigned to schools, mainly through school vouchers. Angrist et al. (2002) examines the impact of a program that used a lottery to distribute vouchers that covered the cost of private secondary school education in Colombia. Students were randomly awarded or denied private school vouchers and as such, vouchers provided a convenient method of *randomly assigning* students to private schools. The study finds that after three years, voucher winners attending private schools, scored 0.2 score standard deviations higher than their public school counterparts in achievement tests comprising tasks in maths, reading and writing.

Despite its attractiveness, the use of experimental data has weaknesses. It depends on the accuracy of the randomization process and secondly, it is quite expensive to roll out randomization programs. As a result, most studies are based on non-experimental data and have employed a number of approaches in an attempt to estimate the true effect of private schools on learner test scores. The instrumental variable (IV) approach is an example. In this approach, certain variables (instruments) which affect private school attendance but not student achievement are used to estimate the casual effect of private schooling (Goldhaber and Eide, 2003; Wooldridge, 2010).

Different instruments have been explored in the literature. Angrist et al. (2002) uses *receipt of a voucher* as an instrument for attending private school to determine the effect of private schools in Colombia. The argument is that those who obtain a voucher actually attend private school, but receiving the voucher in itself does not guarantee that one excels in school. The study finds that attending a private school increases the probability of finishing eighth grade by 13 to 15 percentage points, and increases test scores by 0.29 score standard deviations in combined tasks involving maths, reading and writing. In Pakistan, Andrabi et al. (2008) use *distance to the private school* as an instrument for private school enrolment. They find that attending a private school is associated with increase in student test scores by 0.8 to 1 standard deviations (depending on the subject). Evans and Schwab (1995) use *religious affiliation* as an exogenous source of variation in Catholic school (private school) attendance. They find that attending Catholic schools increases high school graduation by 12 percentage points and college attendance by 14 percentage points[6].

Although the use of instruments is appealing, finding a credible instrument is challenging. As a result, other studies adjust for selection bias using propensity score matching to estimate the causal effect of private schools. Using the data from a nationwide survey of 452 schools and 22,500 secondary level students in Nepal, Thapa (2015) adjusts for selection bias using propensity score matching and still finds that attending a private school increases student scores by about 8 percentage points in school leaving certificate exams. In India, Azam et al. (2015) use propensity score matching to examine the effect of attending private secondary schools on student test scores in standardized maths test in two Indian states, Orissa and Rajasthan. They find a private school advantage of 0.4 and 1.3 score standard deviations in rural and urban areas of Rajasthan. The results in Orissa depend on the location where the household is located. For instance, they find a private school advantage of 0.3 score standard deviations in rural Orissa and no evidence of private school advantage in urban Orissa.

Most recently, studies have used other estimation approaches such as the family/household fixed effects models, which control for household level observable and unobservable factors, in estimating the causal impact of private schools. In India, French et al. (2010) estimate a household fixed effects model and finds a private school premium of 0.17 score standard deviations in combined student maths and language test scores. Similarly, Javaid et al. (2012) estimates a household fixed effects model using household survey data from Pakistan and reports a private school premium of 0.04 score standard deviations in combined student maths and language test scores. Besides family fixed effects models, both studies estimate cluster fixed effects at different levels (province, district and village). In comparison, the household fixed effects models produce the lowest estimates; showing it is effective in reducing the unobservables associated with private school choice.

In summary, there is evidence of a private school advantage documented in the literature and studies have adopted different methods to find the true effect of private schools. As noted by Ashley et al. (2014), much of this literature in developing countries is based on South Asian countries, India and Pakistan in particular. We add to this literature by estimating the effect of private schools using the case study of Kenya, a country from Sub-Sahara Africa.

[6]Availability of private school in the child's residential area has also been used as an instrument. Studies measure this instrument differently. In Nepal, Shama (1999) cited in French (2008) instruments private school attendance using the number of private schools in the child's residential area. In India, Desai et al. (2008) uses a dummy variable on whether a child's region has a private school or not as an instrument for private school attendance.

## 4.4 The Theoretical and Empirical Framework

### 4.4.1 Theoretical Framework

In estimating the private school premium, we specify an education production function as shown in equation (4.1) where the child's achievement is a function of characteristics related to himself/herself, the school which the child attends, his/her family and the community where the child's family is located. Equation (4.1) is a linear form of equation (3.2) (specified in chapter 3). The theoretical framework in this chapter is therefore still grounded in the production function framework where learning outputs (outcomes) are as a result of a combination of various inputs (Glewwe and Kremer, 2006; Todd and Wolpin, 2003; Glewwe, 2002; Orazem and King, 2007). Our input of interest in this case is the type of school the student attends. We provided the theoretical foundation of this production function in chapter 3 and in the interest of brevity, we do not elaborate it once more here.

### 4.4.2 Estimation Strategies

Our intention is to triangulate the effects of private schools on student achievement using methods that try to control for endogeneity of school choice by households. These include OLS, fixed effects model and propensity score matching. As mentioned, each of this method has its strengths and weakness. It is for this reason that we try multiple methods to get a sense of the range of the private school premium in Kenya. In this section, we lay out these methods.

#### 4.4.2.1 Parametric Estimation: Ordinary Least Squares Method

We begin with the basic ordinary least squares technique. Here, the educational outcome of student $i$ in household $j$ located in village $k$, denoted as $A_{ijk}$, depends on the type of school attended, (where $PRIV_{ijk}$ is a dummy variable that equals 1 if the child attends a private and 0 if a child attends a public school) and the vector of: (a) individual characteristics, $X_{ijk}$, (b) family characteristics, $\psi_{ijk}$, (c) village characteristics, $\phi_{ijk}$. $\varepsilon_{ijk}$ is a random error with the mean 0 and variance $\sigma^2$. Formally,

$$A_{ijk} = \beta_0 + \beta_1 PRIV_{ijk} + \beta_2 X'_{ijk} + \beta_3 \psi'_{ijk} + \beta_4 \phi'_{ijk} + \varepsilon_{ijk} \tag{4.1}$$

The main concern of this paper is the endogeneity of $PRIV_{ijk}$. A major assumption of OLS is that $PRIV_{ijk}$ is uncorrelated with $\varepsilon_{ijk}$ conditional on $X$, $\psi$ and $\phi$. However, even after controlling for a comprehensive set of individual, family, village controls in the Uwezo survey data, it is possible that in equation (4.1), there are factors that determine student achievement but have been omitted, mis-measured or unobserved. As we discuss shortly, some of these factors include within-household child-varying factors such as child ability and/or motivation. Such factors are not easy to observe or gather in a typical survey like Uwezo. If such factors are correlated with private school attendance, then the estimates of $PRIV_{ijk}$ will be biased either upwards or downwards. In what follows, we explore how to deal with this potential endogeneity of $PRIV_{ijk}$.

#### 4.4.2.2 Village Fixed Effects Approach

The first step towards refining the estimates of $PRIV_{ijk}$ is controlling for any sources of observed and unobserved heterogeneity at the village level. In this regard, following Dostie and Jayaraman (2006), Javaid et al. (2012), Andrabi et al. (2008), French et al. (2010) and Mani et al. (2013), we estimate a village fixed effects model as outlined in equation (4.2):

$$A_{ijk} = \beta_0 + \beta_1 PRIV_{ijk} + \beta_2 X'_{ijk} + \beta_3 \psi_{ijk} + \phi_k + \varepsilon_{ijk} \tag{4.2}$$

$\phi_k$ is the village fixed effects. Through the village fixed effects, we are able to (a) remove all sources of observed and unobserved heterogeneity at the village-level and (b) address cluster-related issues in the standard errors since common village-level unobservables are also cluster effects (Wooldridge, 2003; Mani et al., 2013).

#### 4.4.2.3 Household Fixed Effects Approach

Equation (4.2) does not address the potential observed and unobserved heterogeneity at the household level. To address this identification challenge, we follow Desai et al. (2008), Vegas and Devercelli (ND), De Haan et al. (2014) and French et al. (2010) by estimating a household/family fixed effects model shown in equation (4.3):

$$A_{ij} = \beta_0 + \beta_1 PRIV_{ij} + \beta_2 X'_{ij} + \psi_j + \varepsilon_{ij} \tag{4.3}$$

$\psi_j$ is the household fixed effects. Similarly, through the household fixed effects, we are able to remove all sources of observed and unobserved heterogeneity at the household level. Each household in our data is considered as a cluster since there are individual children within the household who are genetically linked. We cluster standard errors at the household level (Nichols and Schaffer, 2007; Vegas and Devercelli, ND; Maitra et al., 2016).

#### 4.4.2.4 Assessing the Potential Bias from Unobservables

The OLS, village fixed effects and family fixed effects methods cannot deal with all sources of endogeneity. For instance, even after using the household fixed effects, within-household child-varying factors[7] which play a role in influencing parental education decisions (Behrman et al., 1994; Andrabi et al., 2008; Maitra et al., 2016) are likely to remain in the error term, and may be correlated with attendance to private schools. Put differently, when estimating a household fixed effects model, the estimates might be free from within-household child-specific factors and household unobserved heterogeneity. However, the possible presence of omitted variables mainly originating from within-household child-varying factors that are likely to be correlated with both private school attendance and student achievement means that we should be careful with interpreting our private school effects as being causal.

Acknowledging this limitation, we turn to a methodology proposed by Altonji et al. (2005) to assess the potential size of any bias on the estimated coefficient of the private school variable due to unobservable selectivity.[8] In their paper, Altonji et al. (2005) propose the idea *that selection on observables is the same as selection on unobservables*[9], which is equivalent to the condition that:

$$\frac{Cov(\varepsilon\,,\,PRIV)}{Var(\varepsilon)} = \frac{Cov(\beta_2 X\,,\,PRIV)}{Var(\beta_2 X)} \tag{4.4}$$

where $X$ is a vector of all observable (child, household and village) characteristics, and $\varepsilon$ is the error term potentially correlated with $PRIV$. Intuitively, we can assess the strength of the evidence of private school effect by checking how plausibly large the quantity on the left must be relative to the quantity on the right to explain the whole $\beta_1$ estimate in

[7] *Within-household child-varying factors* include factors such as child ability and/or motivation. These factor influence parental decision to send a child to either private or public schools. However, they are not easy to observe or gather in a typical survey like Uwezo.

[8] This approach has been widely used in the context of problems similar to ours. Altonji et al. (2005) uses the procedure to study the effectiveness of Catholic schools in the USA. Others include Kingdon and Teal (2010) whose study examines the impact of teacher unionization on student achievement in India, Cavalcanti et al. (2010) who study the effect of private school attendance on public university entrance examinations in Brazil and most recently Simumba (2013) who investigates the effect of child labour on children's school attendance in rural Zambia.

[9] This expression entails that the relationship between private attendance and the normalized mean distribution of the index of unobserved variables is the same as the one between private school attandance and observed explanatory variables

the OLS and fixed effects models under the null hypothesis that there is no private school effect (e.g. $\beta_1 = 0$).

The bias from OLS and the fixed effects models is $\frac{Cov(\varepsilon, \widetilde{PRIV})}{Var(\widetilde{PRIV})}$ and this is equivalent to $\frac{Cov(\varepsilon, PRIV)}{Var(\widetilde{PRIV})}$ if $\varepsilon$ and $X$ are orthogonal. The tildes denote the residuals from a regression of $PRIV$ on $X$. This bias can be assessed by the following equation.[10]

$$\frac{Cov(\varepsilon, PRIV)}{Var(\widetilde{PRIV})} = \frac{Cov(\varepsilon\,,\,PRIV)}{Cov(\beta_2 X\,,\,PRIV)}\frac{Var(\beta_2 X)}{Var(\varepsilon)}\frac{Cov(\beta_2 X\,,\,PRIV)}{Var(\beta_2 X)}\frac{Var(\varepsilon)}{Var(\widetilde{PRIV})} \tag{4.5}$$

$$\frac{Cov(\varepsilon, PRIV)}{Var(\widetilde{PRIV})} = \frac{Cov(\beta_2 X\,,\,PRIV)}{Var(\beta_2 X)}\frac{Var(\varepsilon)}{Var(\widetilde{PRIV})} \tag{4.6}$$

where the first equality follows if $\varepsilon$ and $X$ are orthogonal and the second equality follows from the fact that $\frac{Cov(\varepsilon, PRIV)}{Var(\varepsilon)} = \frac{Cov(\beta_2 X\,,PRIV)}{Var(\beta_2 X)}$. When reporting our regression results for OLS and fixed effects models, we will also show the results from applying this method based on equation (4.6).[11]

#### 4.4.2.5 Non-Parametric Estimation: Propensity Score Matching Approach

We further address the endogeneity of $PRIV_{ijk}$ in equation (4.1) by use of a non-parametric matching approach (propensity score matching). We are interested in estimating the effect of private schools on student achievement. This is a clear example of a treatment evaluation study whose main pillars are *individuals* (students), *treatment* (going to private school) and *outcomes* (the tests scores). In the case of a binary treatment like ours, the treatment indicator $T$ can be defined as $T = 1$ if a student attends a private school and $T = 0$ if a student attends a public school. If we define $Y_i$ as the outcome of the intervention, then $Y_i(T_i)$ is the potential outcome for student $i$ where $i = 1, ......N$. Following Roy (1951) and Rubin (1974), the treatment effect for a student $i$ can be written as:

$$\gamma_i = Y_i(1) - Y_i(0) \tag{4.7}$$

[10]The bias is given by $plim\beta_1 = \beta_1 + \frac{Cov(\varepsilon, \widetilde{PRIV})}{Var(\widetilde{PRIV})}$ and it is positive as long as the variable $PRIV$ is not orthogonal to the error term $\varepsilon$.

[11]We are grateful to Prof. Todd Elder of Michigan State University for sharing the Stata routines for estimating the potential size of any bias on the estimated coefficient of the private school variable due to unobservable selectivity.

However, we cannot simultaneously observe $Y_i$ when $Y_i = 1$ and $Y_i = 0$. Since we are interested in estimating the effect of private schools, we can only observe $Y_i(1)$ and not $Y_i(0)$. The latter is called a counterfactual. Propensity score matching overcomes the problem of lack of counterfactual by matching participants (students in private schools) to non-participants (students in public schools) who are observationally similar based on pre-treatment observable characteristics, which we denote as $X$. The assumption here is that conditional on observables, students in private and public schools do not differ systematically along unobservables.

Propensity score matching is founded on two key assumptions: *conditional independence* and *common support (*or *overlap condition)*. Conditional independence means that given a set of observable characteristics of $X$ which are not affected by treatment, potential outcomes are independent of treatment assignment*(Rosenbaum and Rubin, 1983)*. Formally:

$$Y_i(0), Y_i(1) \perp T_i|(X_i) \tag{4.8}$$

The *common support* ensures that for each value of observable characteristics $X$, there is a positive probability of being both in the treated and untreated groups:

$$0 < Pr(T_i = 1|(X_i)) < 1 \tag{4.9}$$

Given that conditional independence assumption holds and assuming that there is overlap between both groups, the PSM estimator for the treatment effect on the treated (ATT) can be written in general as:

$$\gamma_{ATT}^{PSM} = E(\triangle|p(X), T = 1) = E[(Y(1)|p(X),\, T = 1)] - E[(Y(0)|p(X),\, T = 0)] \tag{4.10}$$

To put this in words, the propensity score matching estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

For estimation, we first estimate a model of school choice (private versus public) using a probit model[12]. We then use the *propensity score*[13] from the probit model to match the treated (private school students) and non-treated (public school students) who are observationally similar.

#### 4.4.2.6 Sensitivity Analysis using Rosenbaum Bounds

As we have mentioned, students in private schools (treated group) are matched with those in public schools (control group) on the basis of observables. The underlying assumption is that conditional on observables, private and public school students do not differ systematically along unobservables. While our matching process is based on a rich set of observable child, family and community characteristics collected by Uwezo survey (see table C4.2 in appendix C), we cannot rule out the presence of selection bias resulting from unobservables. There could be a possibility of selection bias into private schools due to unobserved factors and this could happen even in cases where students in the treated group have been well matched to those in the control group. Rosenbaum (2002) has developed a procedure, known as the Rosenbaum bounds, that allows us to assess the sensitivity of our results to the selection on unobservables.[14]

We briefly explain the Rosenbaum bounds procedure drawing on a number of studies (Aakvik, 2001; Bharath et al., 2011; Azam et al., 2015; Becker and Caliendo, 2007) that have applied it. First, assume that student's $i$ probability of receiving treatment (attending a private school) is given by equation (4.11):

$$P_i = P(X_i\,,\,u_i) = P(D_i = 1|X_i\,,\,u_i) = F(\beta X_i + \gamma u_i) \tag{4.11}$$

where $X_i$ are student$i$'s observed characteristics, $u_i$ is the unobserved variable, and $\gamma$ is the effect of $u_i$ on private school enrolment. If our treatment estimates are free

[12]When estimating the propensity score, two choices have to be made. The first one concerns the model to be used for the estimation (which we use probit), and the second one the variables to be included in this model. We control for a comprehensive list of individual, household and village variables that influence household school choice discussed in Chapter 2.

[13]Matching pupils directly can be computationally demanding especially when there are a large number of characteristics of $X$ to control (curse of dimensionality). Rosenbaum and Rubin (1983) demonstrate that matching can be done on a single-index variable, *the propensity score,* which in our case is the probability of attending a private school given the observed characteristics $X$ estimated through the probit model. The *propensity score* considerably reduces the dimensionality problem, as conditioning is on the basis of a scalar rather than a vector. The propensity score, however, must verify the *balancing property*. That is, the function used to compute the propensity score should be such that individuals with a similar propensity to attend a private school display, on average, similar values of $X_i$ (Vandenberghe and Robin, 2004; Caliendo and Kopeinig, 2008; Azam et al., 2015)

[14]This strategy is similar to the one used by Altonji et al. (2005) in the case of OLS and fixed effects models.

from hidden bias, $\gamma$ will be zero and the private school participation probability will be determined solely by $X_i$. However, if there is hidden bias, then it is possible that two students with the same observed characteristics $X$, have different chances of receiving treatment (attending private school).

Suppose we have a matched pair of students $i$ and $j$, and suppose $F$ in equation (4.11) follows a logistic distribution. If both students have identical observed characteristics—as implied by the matching procedure, the odds ratio that the two students receive treatment is then given by:

$$\frac{\frac{P_i}{1-P_i}}{\frac{P_j}{1-P_j}} = \frac{P_i(1-P_i)}{P_j(1-P_j)} = \frac{e^{(\beta X_i + \gamma u_i)}}{e^{(\beta X_j + \gamma u_j)}} = e^{\gamma(u_i - u_j)} \tag{4.12}$$

As can be seen in equation (4.12), both students differ in their odds of receiving treatment by a factor that involves the parameter $\gamma$ and the difference in their unobserved characteristics $u$. So, if there are either no differences in unobserved variables $(u_i - u_j)$ or if unobserved variables have no influence on the probability of participating $(\gamma = 0)$, the odds ratio is one, implying the absence of hidden or unobserved selection bias. Sensitivity analysis now evaluates how changing the values of $\gamma$ and $(u_i - u_j)$ alters inference about the effect of private schools.

Following Rosenbaum (2002), Aakvik (2001) and Becker and Caliendo (2007), we assume for simplicity that the unobserved covariate is a dummy variable with $u_i \in 0, 1$. Rosenbaum (2002) shows that equation (4.12) implies the following bounds on the odds ratio that either of the two matched individuals will receive treatment:

$$\frac{1}{e^{\gamma}} \leq \frac{P_i(1-P_i)}{P_j(1-P_j)} \leq e^{\gamma} \tag{4.13}$$

$\Gamma = e^{\gamma}$ is a measure of the degree of departure from the case that is free of hidden bias (Rosenbaum, 2002). Both matched students $i$ and $j$ have the same probability of participating only if $\Gamma = e^{\gamma} = 1$ and in this case the model will be free of hidden bias. Otherwise, if for example $\Gamma = e^{\gamma} = 2$, students who appear to be similar (in terms of $X$) could differ in their odds of receiving the treatment by as much as a factor of 2.

## 4.5 Estimation Results and Discussion

### 4.5.1 Descriptive Statistics

We have two dependent variables, that is student scores in language and maths. As we discussed in Chapter 2, the Uwezo literacy (language) tests assessed five principal competencies, ranging from letter recognition to comprehension of the paragraph. The numeracy (maths) tests assessed seven principal competencies, ranging from counting and matching numbers to simple division tasks.

To define the dependent variables based on these competencies, we closely follow two recent studies by French et al. (2010) and Wakano (2016). French et al. (2010) estimated the effect of private schools in rural India based on the Annual Status of Education Report (ASER) survey. The Uwezo survey is modeled on the ASER survey. Just like Uwezo survey, the ASER survey collects data at three levels: households, school (one public schools per village) and village levels. Children in both surveys (Uwezo and ASER surveys) are assessed in similar literacy and numeracy competencies. Wakano (2016) used the Uwezo survey to estimate the effects of locally hired teachers on student achievements in Kenya.

In the footsteps of French et al. (2010) and Wakano (2016), we allow scores in language to range from 0 (student could not manage any of the tasks) to 5 (student could manage all tasks up to comprehension level). In other words, if a student did not manage any task, he/she receives a zero and if he/she managed all the tasks (up to comprehension), he/she gets five marks. In the same vein, maths scores range from 0 (student could not manage any of the tasks) to 7 (student could manage all tasks up to division level) (see table 4.1). In the regression analysis, we again follow French et al. (2010) by standardizing the scores described in table 4.1 to the mean of 0 and standard deviation of 1 to make interpretation easy. We do so separately for language and maths scores.

Table 4.1: Student Test Score Outcomes in Language and Maths

| **Language** | **Mark** | **Maths** | **Mark** |
|---|---|---|---|
| Could do nothing | 0 | Could do nothing | 0 |
| Could read letters | 1 | Could count and match numbers | 1 |
| Could read words | 2 | Could identify numbers | 2 |
| Could read a paragraph | 3 | Could discriminate quantities | 3 |
| Could read a story | 4 | Could do addition | 4 |
| Could do comprehension | 5 | Could do subtraction | 5 |
| | | Could to multiplication | 6 |
| | | Could to division | 7 |

*Source*: Own calculation based on Uwezo 2012. Notes: Based on Uwezo (2012), Uwezo (2014) following French et al. (2010) and Wakano (2016).

Before turning to regression results, we show some descriptive statistics. In Chapter 2, we described student learning by analyzing the *share of children achieving a specific competency level* (see table 2.3 and table 2.4). In table 4.2, we show the *overall mean score* for language and maths based on score allocations as described in table 4.1. The mean score for language is 2.72. Looking at table 4.1, this means that the majority of students assessed could manage tasks ranging between reading words and reading a paragraph. Similarly, the mean score for maths is 4.75 meaning that the majority of students could manage tasks ranging between addition and subtraction. In both subjects, private school students do better and are able to handle higher level tasks relative to their counterparts in public schools.

Table 4.2: Student Learning Outcome by School Type

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Whole sample<br>Mean | Public sample<br>Mean | Private sample<br>Mean | Public-Private<br>Mean Dif. |
| Language | 2.72 | 2.62 | 3.47 | -0.84*** |
| Maths | 4.75 | 4.67 | 5.39 | -0.71*** |
| **Sample** | 52,196 | 44,373 | 6,256 | |

*Source*: Own calculations based on Uwezo 2012. Notes: ***1% significance level, **5% significance level and *10% significance level.

In table 4.3, we report the means for child, family and village related variables used in the estimation.[15] We report results for the whole sample, for the public sample and

[15]Some, although not all, of the variables in this table were partly discussed in Chapter 2 (table 2.2). The summaries might differ because the summaries in table 2.2 are based on the whole sample but those in table 4.3 are based the restricted sample of children in grades 2 to 4.

the private sample. In column 4, we show the mean differences between public and private samples. Since we are interested in the effect of private schools relative to public counterparts, our interest here lies mainly in column 2, 3 and 4. As can be seen from these columns, relative to their counterparts from public schools, private school students are more likely to be young, female and with no disability. Similarly, private school students are also more likely to attend tuition classes.

As it can be seen in table 4.3, 15 percent of grade 2 to grade 4 children in the Uwezo survey attend private schools. We know that these students attend private schools based on the response to the question that asked about the type of school a child attends. Table 4.3 further shows that the mean for measured family and village background characteristics are substantially higher for students who attend private schools. For instance, private school learners are more likely to be born of young parents, with higher educational attainments relative to their counterparts in public schools. They also come from homes with a higher index of asset ownership[16] as well as homes that are more likely to have their own water source and toilet facility. In addition, they come from households that are more likely to use electricity as a source of lighting (as opposed to sources such as paraffin) and whose dwelling place is made of bricks and stones (as opposed to materials such as mud and polythene).

[16] We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durables (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock (cattle, donkey, camel, sheep/goat).

Table 4.3: Mean Statistics for Children, Households and Villages

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Whole Sample | Public School | Private School | Public-Private diff |
| **Panel A: Student Characteristics** | | | | |
| Age of student | 9.31 | 9.41 | 8.55 | 0.86*** |
| Student is female | 0.48 | 0.48 | 0.49 | -0.01** |
| Student has some disability | 0.03 | 0.03 | 0.02 | 0.01** |
| Student goes for paid tuition | 0.36 | 0.33 | 0.69 | -0.36*** |
| Student attends private school | 0.15 | 0.00 | 1.00 | – |
| **Panel B: Household Characteristics** | | | | |
| Age of the mother | 35.34 | 35.57 | 34.09 | 1.48*** |
| *Education level of the mother* | | | | |
| None | 0.24 | 0.26 | 0.09 | 0.17*** |
| Has primary education level | 0.54 | 0.56 | 0.47 | 0.09*** |
| Has secondary education level | 0.20 | 0.17 | 0.38 | -0.22*** |
| Has post-secondary education level | 0.02 | 0.01 | 0.06 | -0.05*** |
| *Education level of the father* | | | | |
| None | 0.20 | 0.22 | 0.06 | 0.15*** |
| Has primary education level | 0.47 | 0.50 | 0.37 | 0.13*** |
| Has secondary education level | 0.29 | 0.27 | 0.47 | -0.20*** |
| Has post-secondary education level | 0.04 | 0.02 | 0.10 | -0.08*** |
| Number of household members | 5.87 | 5.95 | 5.32 | 0.63*** |
| Household has source of water at home | 0.21 | 0.17 | 0.39 | -0.22*** |
| Household has toilet/latrine at home | 0.77 | 0.75 | 0.91 | -0.15*** |
| Index of household assets | 0.13 | -0.01 | 1.07 | -1.09*** |
| *Meals taken per day* | | | | |
| Less than three meals | 0.25 | 0.27 | 0.14 | 0.25*** |
| Three meals | 0.75 | 0.73 | 0.86 | -0.12*** |
| *Wall material for dwelling place* | | | | |
| Mud | 0.57 | 0.61 | 0.30 | 0.31*** |
| Polythene and iron | 0.08 | 0.08 | 0.09 | -0.01*** |
| Timber | 0.11 | 0.11 | 0.12 | -0.02*** |
| Bricks and/or Stone | 0.24 | 0.20 | 0.49 | -0.28*** |
| *Regular source of lighting* | | | | |
| Paraffin | 0.74 | 0.79 | 0.50 | 0.29*** |
| Electricity | 0.19 | 0.13 | 0.47 | -0.34*** |
| Other | 0.07 | 0.08 | 0.03 | 0.05*** |
| Time taken to reach at school | 0.52 | 0.53 | 0.42 | 0.11*** |
| **Panel C: Village Characteristics** | | | | |
| Village has electricity | 0.47 | 0.43 | 0.75 | -0.32*** |
| Village has tarmac road | 0.21 | 0.18 | 0.41 | -0.23*** |
| Village has all-weather road | 0.81 | 0.81 | 0.88 | -0.07** |
| Village has a protected water point | 0.43 | 0.42 | 0.49 | -0.07 |
| Village has chief's office | 0.64 | 0.62 | 0.75 | -0.13*** |
| Village has police post | 0.28 | 0.26 | 0.45 | -0.19*** |
| Village has an education committee | 0.31 | 0.32 | 0.31 | -0.01 |
| **Number of children** | **52,709** | **44,754** | **6,343** | |
| **Number of households** | **20,180** | **16,659** | **2,993** | |
| **Number of villages** | **1,296** | **1,098** | **164** | |

*Source*: Own calculations based on Uwezo 2012. Notes: (1) We do not include father's age because of large missing values; (2) We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durable assets (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock assets (cattle, donkey, camel, sheep/goat); and (3) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

It therefore appears that pupils who attend private schools already have disproportionately higher academic potential and access to complementary educational resources relative to their counterparts attending public schools. As noted by Altonji et al. (2005) and Goldberger and Cain (1982), this raises the possibility that part or even all of the gap in student test scores between private and public students as observed in table 4.2 column 2 and 3 may be a reflection of who attends private schools, thus indicating some level of selection. In other words private schools could be attracting students who are already advantaged given their home environments. This provides the motivation for this paper: to estimate the private school premium while addressing such potential selection into private schools based on the methods we have presented in the last section. We report the results in the section that follows.

### 4.5.2 OLS and Fixed Effects Estimates of Private Schools Effects

To put our results into perspective, we first present the OLS regression (equation (4.1)), as a baseline model, followed by the fixed effects regression. Model 1 of table 4.4 and table 4.5 presents estimated OLS results for maths and language respectively. We can see that after accounting for students, household and village characteristics, the results from OLS show that attending a private school relative to a public school is associated, on average, with an increase in maths and language scores of 0.18 and 0.27 score standard deviations respectively.[17]

[17] In the interest of brevity, we do not interpret the coefficients for the child, household and village controls in the three models of table 4.4 and table 4.5. However, as can be seen from the two tables, these characteristics exert a significant influence on student achievement as hypothesized.

Table 4.4: Effect of Private Schools on Student Test Scores in Maths

| | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| | No Fixed Effects (OLS) | | Village Fixed Effects | | Household Fixed Effects | |
| | Coefficient | Standard Error | Coefficient | Standard Error | Coefficient | Standard Error |
| Student attends private school | 0.18*** | (0.01) | 0.20*** | (0.02) | 0.13*** | (0.03) |
| **Student Characteristics** | | | | | | |
| Age of student | 0.09*** | (0.02) | 0.08*** | (0.02) | 0.16*** | (0.02) |
| Age of student squared | -0.00*** | (0.00) | -0.00*** | (0.00) | -0.00*** | (0.00) |
| Student is female | 0.01 | (0.01) | 0.01* | (0.01) | 0.02** | (0.01) |
| Student has some disability | -0.15*** | (0.03) | -0.12*** | (0.03) | -0.15*** | (0.04) |
| Student goes for paid tuition | 0.10*** | (0.01) | 0.10*** | (0.01) | 0.09*** | (0.02) |
| Student's current grade | 0.41*** | (0.01) | 0.41*** | (0.01) | 0.31*** | (0.01) |
| **Household Characteristics** | | | | | | |
| Age of the mother | 0.01** | (0.00) | 0.00 | (0.00) | | |
| Age of the mother squared | -0.00* | (0.00) | -0.00 | (0.00) | | |
| Education level of the mother (ref: None) | | | | | | |
| Has primary education level | 0.04** | (0.02) | 0.04** | (0.02) | | |
| Has secondary education level | 0.10*** | (0.02) | 0.10*** | (0.02) | | |
| Has post-secondary education level | 0.15*** | (0.05) | 0.10** | (0.05) | | |
| Education level of the father (ref: None) | | | | | | |
| Has primary education level | -0.01 | (0.02) | 0.01 | (0.02) | | |
| Has secondary education level | 0.03* | (0.02) | 0.06*** | (0.02) | | |
| Has post-secondary education level | 0.08** | (0.03) | 0.13*** | (0.03) | | |
| Number of household members | -0.01*** | (0.00) | -0.00** | (0.00) | | |
| Household has source of water at home | 0.07*** | (0.01) | 0.04*** | (0.02) | | |
| Household has toilet/latrine at home | 0.02 | (0.01) | 0.03* | (0.02) | | |
| Index of household assets | 0.001 | (0.00) | 0.02* | (0.01) | | |
| Meals taken per day(ref: less than three) | | | | | | |
| Three meals | 0.05*** | (0.01) | 0.02* | (0.01) | | |
| Wall material for dwelling place (ref: Mud ) | | | | | | |
| Polythene and iron | 0.06*** | (0.02) | -0.00 | (0.02) | | |
| Timber | 0.11*** | (0.02) | 0.01 | (0.02) | | |
| Bricks and/or Stone | 0.12*** | (0.01) | 0.03 | (0.02) | | |
| Regular source of lighting (ref: Paraffin) | | | | | | |
| Electricity | 0.07*** | (0.01) | 0.03** | (0.02) | | |
| Other | 0.02 | (0.02) | -0.04 | (0.03) | | |
| Time taken to reach at school | -0.00 | (0.01) | -0.01 | (0.01) | | |
| **Village Characteristics** | | | | | | |
| Village has electricity | -0.01 | (0.01) | | | | |
| Village has tarmac road | 0.00 | (0.01) | | | | |
| Village has all-weather road | -0.05*** | (0.01) | | | | |
| Village has a protected water point | 0.01 | (0.01) | | | | |
| Village has chief's office | 0.01 | (0.01) | | | | |
| Village has police post | -0.03*** | (0.01) | | | | |
| Village has an education committee | 0.01 | (0.01) | | | | |
| Constant | -2.08*** | (0.10) | -1.99*** | (0.10) | -2.06*** | (0.09) |
| Observations (number of students) | 32,689 | | 32,689 | | 32,689 | |
| R Squared | 0.23 | | 0.26 | | 0.42 | |
| Number of villages | 3,876 | | 3,876 | | 3,876 | |
| Number of households | 27,970 | | 27,970 | | 27,970 | |
| Estimated bias based on equation (4.6) | 0.48 | | 0.32 | | -0.10 | |
| Ratio | 0.38 | | 0.63 | | – | |

Notes: (1) Student goes for paid tuition means student attends classes offered beyond the normal scheduled school time; (2) Student's current grade is entered as a continuous variable. Results do not change even when we enter student's current grade as a categorical variable; (3) We do not control for father's age because of large number of missing values; (4) We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durable assets (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock assets (cattle, donkey, camel, sheep/goat); (5) Standard errors are in parenthesis; (6) In the OLS and household fixed effects models, standard errors are clustered at household level. In the village fixed effects model, standard errors are clustered at the village level; (7) Ratio (on the last row) is defined as the ratio of the coefficient on private school and the estimated bias based on equation (4.6). (8) ***1% significance level, **5% significance level and *10% significance level.

Table 4.5: Effect of Private Schools on Student Test Scores in Language

| | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| | No Fixed Effects (OLS) | | Village Fixed Effects | | Household Fixed Effects | |
| | Coefficient | Standard Error | Coefficient | Standard Error | Coefficient | Standard Error |
| Student attends private school | 0.27*** | (0.02) | 0.29*** | (0.02) | 0.21*** | (0.04) |
| **Student Characteristics** | | | | | | |
| Age of student | 0.00 | (0.02) | 0.01 | (0.02) | 0.06*** | (0.02) |
| Age of student squared | 0.00 | (0.00) | 0.00 | (0.00) | -0.00 | (0.00) |
| Student is female | 0.04*** | (0.01) | 0.05*** | (0.01) | 0.05*** | (0.01) |
| Student has some disability | -0.14*** | (0.03) | -0.09*** | (0.03) | -0.12*** | (0.03) |
| Student goes for paid tuition | 0.13*** | (0.01) | 0.12*** | (0.01) | 0.11*** | (0.02) |
| Student's current grade | 0.43*** | (0.01) | 0.42*** | (0.01) | 0.38*** | (0.01) |
| **Household Characteristics** | | | | | | |
| Age of the mother | 0.01*** | (0.00) | 0.01** | (0.00) | | |
| Age of the mother squared | -0.00*** | (0.00) | -0.00 | (0.00) | | |
| Education level of the mother (ref: None) | | | | | | |
| Has primary education level | 0.00 | (0.02) | 0.05*** | (0.02) | | |
| Has secondary education level | 0.10*** | (0.02) | 0.13*** | (0.02) | | |
| Has post-secondary education level | 0.18*** | (0.05) | 0.20*** | (0.05) | | |
| Education level of the father (ref: None) | | | | | | |
| Has primary education level | -0.08*** | (0.02) | -0.00 | (0.02) | | |
| Has secondary education level | 0.01 | (0.02) | 0.08*** | (0.02) | | |
| Has post-secondary education level | 0.05 | (0.03) | 0.12*** | (0.03) | | |
| Number of household members | -0.01*** | (0.00) | -0.01*** | (0.00) | | |
| Household has source of water at home | 0.07*** | (0.01) | 0.02 | (0.02) | | |
| Household has toilet/latrine at home | 0.01 | (0.01) | 0.04** | (0.02) | | |
| Index of household assets | 0.02 | (0.01) | 0.03* | (0.02) | | |
| Meals taken per day(ref: less than three) | | | | | | |
| Three meals | 0.02* | (0.01) | 0.04** | (0.01) | | |
| Wall material for dwelling place (ref: Mud ) | | | | | | |
| Polythene and iron | 0.13*** | (0.02) | 0.02 | (0.02) | | |
| Timber | 0.16*** | (0.02) | 0.07*** | (0.02) | | |
| Bricks and/or Stone | 0.13*** | (0.01) | 0.07*** | (0.02) | | |
| Regular source of lighting (ref: Paraffin) | | | | | | |
| Electricity | 0.13*** | (0.02) | 0.05*** | (0.02) | | |
| Other | 0.09*** | (0.02) | -0.04 | (0.03) | | |
| Time taken to reach at school | 0.01 | (0.01) | -0.00 | (0.01) | | |
| **Village Characteristics** | | | | | | |
| Village has electricity | 0.04*** | (0.01) | | | | |
| Village has tarmac road | 0.05*** | (0.01) | | | | |
| Village has all-weather road | -0.03** | (0.01) | | | | |
| Village has a protected water point | 0.02** | (0.01) | | | | |
| Village has chief's office | 0.00 | (0.01) | | | | |
| Village has police post | 0.02 | (0.01) | | | | |
| Village has an education committee | 0.02 | (0.01) | | | | |
| Constant | -1.92*** | (0.10) | -2.01*** | (0.10) | -1.92*** | (0.08) |
| Observations (number of students) | 32,689 | | 32,689 | | 32,689 | |
| R Squared | 0.27 | | 0.28 | | 0.47 | |
| Number of villages | 3,876 | | 3,876 | | 3,876 | |
| Number of households | 27,970 | | 27,970 | | 27,970 | |
| Estimated bias based on equation (4.6) | 0.74 | | 0.48 | | -0.01 | |
| Ratio | 0.36 | | 0.60 | | – | |

Notes: (1) Student goes for paid tuition means student attends classes offered beyond the normal scheduled school time; (2) Student's current grade is entered as a continuous variable. Results do not change even when we enter student's current grade as a categorical variable; (3) We do not control for father's age because of large number of missing values; (4) We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durable assets (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock assets (cattle, donkey, camel, sheep/goat); (5) Standard errors are in parenthesis; (6) In the OLS and household fixed effects models, standard errors are clustered at household level. In the village fixed effects model, standard errors are clustered at the village level; (7) Ratio (on the last row) is defined as the ratio of the coefficient on private school and the estimated bias based on equation (4.6). (8) ***1% significance level, **5% significance level and *10% significance level.

We are careful not to give the OLS estimates a causal interpretation due to possible endogeneity of private school choice. We begin to address this challenge by estimating a village fixed effects model. The village fixed effects model helps us to remove all sources of village level unobserved and observed heterogeneity common to all children in the village. Through the village fixed effects, we are also able to address cluster-related issues in the standard errors since common village-level unobservables are also cluster effects (Wooldridge, 2003; Mani et al., 2013). Results are shown in model 2 of table 4.4 and table 4.5. We still find a relatively large private school effect, in fact slightly higher than estimates based on OLS. The estimated private school coefficient means that attending a private school relative to a public school is associated, on average, with an increase in maths and language scores of 0.20 and 0.29 standard deviations respectively, an indication that OLS estimates are perhaps biased downwards.

The village fixed effects do not however control for the observed and unobserved heterogeneity at the household level. We explore this through the household fixed effects model which controls for household-level observed and unobserved factors, allowing us to focus on within-household child-specific factors such as gender, age and grade. Model 3 of table 4.4 and table 4.5 presents the results of the family fixed effects model. As can be seen from the tables, after controlling for family-level observed and unobserved factors, we observe a reduction in the size of the private school effects. Nevertheless, there is still a sizable and significant positive effect of private schools on student language and maths test scores. Specifically, we find a private school advantage of 0.13 and 0.21 score standard deviations in maths and language respectively.

As we noted, the household fixed effects are unlikely to control for the *within-household child-varying factors* which are likely to remain in the error term and may be corrected with attendance to private schools. In the last two rows of table 4.4 and table 4.5, we report the estimated bias using Altonji et al. (2005)'s procedure based on equation (4.6).[18] This procedure estimates the potential size of any bias on the estimated coefficient of the private school variable due to unobservable selectivity (see also Cavalcanti et al. (2010) and Kingdon and Teal (2010)).

Like Kingdon and Teal (2010), where the *sign of the private school effect* and the *bias* are *identical*, it means that we have overestimated the true effect. Looking at table 4.4

[18] In an attempt to address the potential omitted-variable bias resulting from *within-household child-varying factors*, we follow Maitra et al. (2016) by estimating an extended version of equation (4.3) given as $A_{ij} = \beta_0 + \beta_1 PRIV_{ij} + \beta_2 X'_{ij} + \psi_j + (\theta_i * \psi_j) + \varepsilon_{ij}$ where $\theta_i$ denoted individual fixed effects. This specification includes unobserved traits varying across different children (in ascending birth order) within the same household. As noted by Maitra et al. (2016), this specification is an improvement of equation (4.3) because it accounts for the unobserved child-invariant and child-varying factors within the household. The results from this improved version of equation ss are practically smilar to those based on the household fixed effects. We do not report these results.

and table 4.5, the estimated coefficient in the OLS regression is 0.18 and 0.27 for maths and language respectively. The estimated bias is positive and its 0.48 and 0.74 for maths and language respectively, which suggests that the OLS regression overestimates the true effect of private schooling on test score. We find similar evidence in the village fixed effects model too. Since the true effect has been over-estimated in the OLS and village fixed effects, we can find the *size of the unobservables necessary to explain away the implied effect from private school attendance.* Following Altonji et al. (2005), we calculate this by dividing the estimated coefficient by the bias (that is the ratio of the estimated coefficient to the bias). For instance, in the case of the OLS results for maths (table 4.4), the ratio of the estimated private school effect coefficient to the bias is 0.38. This implies that the role of unobservables that determine student maths test scores would have to be more than 0.38 times the role of observables for the entire private school effect to be explained away by the unobservables.

On the other hand, where the *sign of the private school effec*t and the *bias* are *not identical*, it means that we have underestimated the true effect. For instance, the estimated coefficient in the household fixed effects is 0.13 and 0.21 for maths and language respectively. The estimated bias is however negative. It is equal to $-0.10$ and $-0.01$ for maths and language respectively, suggesting that the household fixed effects regression underestimates the true effect of private schooling on test score. Since we have under-estimated the true private school effect, there is no need to calculate the *size of the unobservables necessary to explain away the implied effect from private school attendance.*

In summary, we learn the following from the application of Altonji et al. (2005)'s procedure. First, there is evidence of a bias on the estimated coefficient of the private school variable due to unobservable selectivity. This bias however reduces, substantially, as we move from OLS to village fixed effects and to household fixed effects. In the OLS and village fixed effects, the magnitude of bias, as compared to the coefficient, is quite large, suggesting that the OLS and the village fixed effects models may suffer from the problem of selection due to unobservables and hence they are not reliable for obtaining the true effect of private schools on test score. Since the private schooling decision is made at the household level, it is likely that a substantial part of the unobservable component is pertaining to the household. Consistent with this view, when we estimate a household fixed effects model, we find that the estimated coefficient is smaller in magnitude. Moreover, the estimated bias in household fixed effects model is negative and also smaller in magnitude. This in fact indicates that unlike the previous models, household fixed effects model yields a coefficient that is an underestimate of the true effect of private school. Therefore from this analysis we find that household fixed effects regression is a more reliable model that closely captures the true effect of private schooling on test scores.

We can also see that there is a substantial reduction in the size of the bias as we move from OLS to the fixed effects models.

### 4.5.3 Propensity Score Matching Estimates of Private Schools Effects

We now turn our attention to the estimates based on the propensity score matching approach. In the appendix of this chapter, we show different indicators characterizing the level of success of the matching process. Table C4.1 in appendix C shows results for the probit model[19] that produced the propensity scores which were in turn used for matching the treated and non-treated participants. Figure C4.1 in appendix C shows considerable overlap between treated (private school students) group and control (public school students) group.

Table C4.2 in appendix C shows that matching balanced quite well among all the variables affecting household school choice. In column 9 and column 10 of table C4.2, we report the t-tests and p-values of equality between treated (private school students) group and control (public school student) group after matching for each variable. Looking at the t-tests and the p-values, we find that almost all the values are insignificant showing a very successful level of matching. The table further shows that the matching process significantly reduces the standardized bias (SB). A standardized bias of below 5 percent after matching is widely acceptable in most empirical studies (Caliendo and Kopeinig, 2008). In our case, the standardized bias, shown in column 8, for all the variables, is below 5 percent. A physical inspection of figure C4.2 and C4.3 further confirms that indeed matching significantly reduces standardized bias (SB).

Since a number of matching algorithms are considered (nearest neighbor matching, kernel matching, radius matching and caliper matching),[20] the match quality across these algorithms deserves attention. In this regard, table 4.6 provides information related to the quality of matching for the different matching algorithms based on the following indicators: pseudo R2, LR chi2 values, p-value, mean bias and variance among others. Generally, all the algorithms perform exceptionally well in terms of matching as shown by zero level of pseudo R2 and very high levels of p-values, which in most cases equal to

[19] The probit model of school choice (private versus public) is specified as follows: $Prob(Pi = 1) = F(Z\prime b)$.

[20] For a detailed exposition of these matching algorithms, we refer readers to Caliendo and Kopeinig (2008), Rosenbaum (2002) and Dehejia and Wahba (2002).

Table 4.6: Propensity Score Matching Quality Test (Before and After Matching)

| | Nearest Neighbor Matching ($\sigma = 0.00001$) | | 4-Nearest Neighbor Matching ($\sigma = 0.00001$) | | 5-Nearest Neighbor Matching ($\sigma = 0.00001$) | | Kernel Matching ($\sigma = 0.00001$) | | Radius Matching ($\sigma = 0.00001$) | | Caliper Matching ($\sigma = 0.00001$) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Before | After | Before | After | Before | After | Before | After | Before | After | Before | After |
| Pseudo R-squared | 0.21 | 0.01 | 0.21 | 0.01 | 0.21 | 0.00 | 0.20 | 0.01 | 0.21 | 0.00 | 0.21 | 0.01 |
| LR ch2 | 4466.0 | 49.23 | 4466.0 | 33.36 | 4466.0 | 32.06 | 4259.4 | 12.84 | 4466.0 | 32.20 | 4466.0 | 49.23 |
| p-values | 0.00 | 0.31 | 0.00 | 0.95 | 0.00 | 0.99 | 0.00 | 0.94 | 0.00 | 0.92 | 0.00 | 0.31 |
| Mean bias | 28.2 | 2.9 | 28.2 | 2.4 | 28.2 | 1.4 | 29.7 | 1.6 | 28.2 | 2.4 | 28.2 | 2.9 |
| Medbias | 26.9 | 2.2 | 26.9 | 1.8 | 26.9 | 1.4 | 24.5 | 1.4 | 26.9 | 2.0 | 26.9 | 2.2 |
| ASB | 129.3 | 25.9 | 129.3 | 21.4 | 129.3 | 20.9 | 126.5 | 8.7 | 129.3 | 21.0 | 129.3 | 25.9 |
| R | 1.26 | 1.35 | 1.26 | 1.29 | 1.26 | 1.29 | 1.22 | 1.14 | 1.26 | 1.03 | 1.26 | 1.35 |
| Variance | 80 | 30 | 80 | 20 | 80 | 30 | 83 | 0 | 80 | 30 | 80 | 30 |

Notes: (1) *'Before'* means before matching. *'After'* means after matching; (2) We include the following variables in the probit regression when estimating the propensity score: child variables (gender, age, aged squared, whether the child attends for extra-tuition classes and child's grade), mother's age and mother's age squared, mothers education, father's education, household size, dummy variable for whether the household has a toilet, dummy variable for whether the household has a water facility, time taken to reach school, dummy variable for whether the household owns the following assets (TV, radio, car, computer, mobile phone, bicycle, motorbike, cart, cattle, donkey, camel, sheep/goat), number of meals per day, type of household dwelling unit, regular source of lighting for the household and village characteristics (whether a village has chief's camp, a shopping center, electricity connection, tarmac road, all-weather road, education committee, protected water point and whether a village is rural); (3) The probit results are shown in table C4.1 in appendix C; (4) Standard errors are in parentheses and; (5) ***1% significance level, **5% significance level and *10% significance level.

one, after matching.[21]

Table 4.7 shows comparable private school effects from the different matching algorithms.[22] Estimates from different matching algorithms are within the same range. In maths, we find a private school advantage ranging from 0.14 score standard deviations based on nearest neighbor matching (with replacement) to 0.17 score standard deviations based on Kernel matching. In language, we find a private school advantage between 0.26 score standard deviations based on almost all matching algorithms to 0.27 based on neighbor matching (with replacement) and caliper matching.

Lastly, we assess the extent to which estimates from propensity score matching are influenced by hidden (unobserved) bias. As discussed in section 4.4.1.6, if there are unobservables that influence both student assignment into private schools and student test score performance, then a bias might arise and this is likely to undermine the robustness of the estimates we present in table 4.7. Similar to the procedure by Altonji et al. (2005), our interest here is to determine how strongly an unmeasured bias must influence the selection process to undermine the implications of the estimates (Azam et al., 2015; Rosenbaum and Rubin, 1983; Rosenbaum, 2002). If there is a positive selection on unobservables, our estimated private school effects overestimate the true effects (Azam et al., 2015; Rosenbaum and Rubin, 1983) because students who perform better are likely to sort into private schools.

In table 4.8, we show the upper bound on the p-value of the null hypothesis of no private school effect for different levels of $\Gamma$ (gamma). Recall that our estimates in table 4.7 show that private schools are positively correlated with both language and maths student test scores. In this case, the assumption that we have under-estimated the true private school effects (e.g lower bound sig-) does not apply and therefore, as shown in table 4.8,

[21] Nevertheless, the nearest neighbor and caliper matching algorithms are characterized by relatively low levels of p-value.

[22] In each matching algorithm, we impose a caliper width of 0.00001 which is much lower than what most studies use. Imposing caliper widths helps avoid bad matches and hence helps to further deal with selection issues (Caliendo and Kopeinig, 2008). While there is no empirical evidence on the optimal caliper width (Austin, 2008), the choice of caliper width depends on the extent of variance-bias trade off the researcher wants to achieve (Heckman et al., 1997; Faries et al., 2010) and the sample size (Smith, 2000). Low levels of caliper width result in the matching of more similar subjects, leading to improved comparability of groups which translates to less biased estimates. However, it may also result in the formation of fewer matched pairs, thus decreasing the precision, due to high variance, of the estimated treatment effects. In many studies, including those in education, researchers use calipers of pre-determined width (ad hoc) that are generally independent of the distribution of the propensity score. In medical literature, caliper width of 0.6 and 0.2 of the logit of the standard deviation of the logit of the propensity is predominantly used (Austin, 2008).

Table 4.7: Effect of Private Schools on Student Test Scores

| | (1) | (2) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| | Nearest Neighbor Matching ($\sigma = 0.00001$) | 4-Nearest Neighbor Matching ($\sigma = 0.00001$) | 5-Nearest Neighbor Matching ($\sigma = 0.00001$) | Kernel Matching ($\sigma = 0.00001$) | Radius Matching ($\sigma = 0.00001$) | Caliper Matching ($\sigma = 0.00001$) |
| Maths | 0.14*** | 0.15*** | 0.15*** | 0.17*** | 0.15*** | 0.15*** |
| | (0.032) | (0.029) | (0.029) | (0.017) | (0.029) | (0.033) |
| Language | 0.27*** | 0.26*** | 0.26*** | 0.26*** | 0.26*** | 0.27*** |
| | (0.032) | (0.030) | (0.029) | (0.018) | (0.029) | (0.032) |
| Untreated | 26,598 | 26,598 | 26,598 | 26,598 | 26,598 | 26,598 |
| Treated | 3,428 | 3,428 | 3,428 | 3,428 | 3,428 | 3,428 |
| Total | 30,026 | 30,026 | 30,026 | 30,026 | 30,026 | 30,026 |

Notes: (1) We include the following variables in the probit regression when estimating the propensity score: child variables (gender, age, aged squared, whether the child attends for extra-tuition classes and child's grade), mother's age and mother's age squared, mothers education, father's education, household size, dummy variable for whether the household has a toilet, dummy variable for whether the household has a water facility, time taken to reach school, dummy variable for whether the household owns the following assets (TV, radio, car, computer, mobile phone, bicycle, motorbike, cart, cattle, donkey, camel, sheep/goat), number of meals per day, type of household dwelling unit, regular source of lighting for the household and village characteristics (whether a village has chief's camp, a shopping center, electricity connection, tarmac road, all-weather road, education committee, protected water point and whether a village is rural); (2) The probit results are shown in table C4.1 in appendix C; (3) Untreated are the number of students in the untreated group (number of public school students). Treated are the number of treated students that are on the common support; (4) Standard errors are in parentheses and; (5) ***1% significance level, **5% significance level and *10% significance level.

we only consider the upper bound sig+ (p-value). If the p-values remain significant (for instance, less than 0.1) for reasonably large values of gamma, then our private school effects are robust to hidden unobservables (Azam et al., 2015).

The results in table 4.8 show that the positive effect of private schools on maths test scores withstands even at relatively high values of selection on unobservables. In other words, we can reject the null hypothesis of zero private school effect on maths test scores even in the presence of relatively high values of selection on unobservables. In the case of language, the effect of private schools disappears even under low levels of unobserved selectivity. For instance, we fail to reject the null hypothesis of zero private school effect on language test scores even with observationally similar students who differ in their relative odds of attending private school by a factor of 1.2 (see Rosenbaum and Rubin (1983) for a detailed theoretical discussion and Azam et al. (2015) for empirical application).

Table 4.8: Sensitivity Analysis of PSM estimates, Rosenbaum Bounds

| | Maths | Language |
|---|---|---|
| Gamma (Γ) | upper bound sig+ (p-value) | upper bound sig+ (p-value) |
| 1 | 0.0000 | 0.0000 |
| 1.1 | 0.0000 | 0.0000 |
| 1.2 | 0.0000 | 1.0000 |
| 1.3 | 0.0000 | 1.0000 |
| 1.4 | 0.0000 | 1.0000 |
| 1.5 | 0.0000 | 1.0000 |

### 4.5.4 Comparison of Estimates from the Different Estimation Approaches

Finally, we bring together estimates based on different methods as shown in table 4.9. For propensity score matching, we choose the 5-Nearest Neighbor Matching because this matching algorithm performs best relative to others on the basis of the matching quality indicators presented in table 4.6. Each of this method has its strengths and weakness. It is for this reason that we try multiple methods to get a sense of the range of the private school premium in Kenya. As it can be seen in table 4.9, we see that in maths, the premium ranges from 0.13 to 0.20 score standard deviation, using the household and village fixed effects model, respectively. In the case of language, it ranges from 0.20 to 0.29 score standard deviation, using the household and village fixed effects model, respectively.

Results from the Altonji et al. (2005) procedure show that the magnitude of bias, as compared to the private school coefficient, is quite large in the OLS and village fixed effects suggesting that these models may suffer from the problem of selection due to unobservables. The OLS and village fixed effects in fact overestimate the true private school effect. The propensity score matching procedure is based on an assumption that conditional on observables, private and public school students do not differ systematically along unobservables. Sensitivity analysis based on Rosenbaum (2002) however shows that the estimates based on propensity score matching, especially for language, are not free from the hidden bias and therefore do not entirely meet this assumption. Perhaps this explains why the estimates based on propensity score matching are quite close to those in OLS.

Table 4.9: Effect of Private School on Student Test Scores: Different Estimation Approaches

| | (1)<br>OLS<br>Model | (2)<br>Village Fixed<br>Effects Model | (3)<br>Household Fixed<br>Effects Model | (4)<br>PSM 5-Nearest<br>Neighbor |
|---|---|---|---|---|
| Maths | 0.18*** | 0.20*** | 0.13*** | 0.15*** |
| | (0.01) | (0.02) | (0.03) | (0.020) |
| Language | 0.27*** | 0.29*** | 0.21*** | 0.26*** |
| | (0.02) | (0.02) | (0.04) | (0.021) |
| Observations | 27,970 | 27,970 | 27,970 | 29,209 |

Notes: Standard errors are in parentheses, ***1% significance level, **5% significance level and *10% significance level.

Since private school choice takes place at the household level, it is likely that a substantial part of the unobservables are accounted for by the household fixed effects model. It is for this reason that the household fixed effects model yields smaller coefficients of the private school effect. Also, the estimated bias based on the household fixed effects models are negative and also smaller in magnitude, indicating that unlike the other models, household fixed effects models yield coefficients that are an underestimate of the true effect of private school. Put together, true private schools effects lie within the range we provide above. However, the household fixed effects regressions are more reliable and closely capture the true effect of private schooling on student learning.

## 4.6 Conclusion

In this chapter, we use a rich household survey data to quantify the relative contribution of private schools on cognitive achievement of lower primary (grade 2 to 4) school children in Kenya. We are not aware of any study that focuses on the importance of private schools on cognitive development of lower primary children in Kenya. We investigate private school effect by carefully accounting for the endogenous selection into schools through different estimation methods including OLS, fixed effects and propensity score matching. We find that the private school premium lies within the range of 0.13 to 0.20 score standard deviation in maths and 0.21 to 0.29 score standard deviation in language. Our results should be interpreted in the context of the limitations of estimation methods used.

One of the challenges facing any study that estimates the effect of private schools is the extent to which the researcher is able to account for the endogenous nature of school choice. The extent to which the researcher is able to deal with such challenge depends on the quality and nature of data at his or her disposal. In this study, we are fortunate to use the Uwezo household survey that is quite rich in terms of variables related to children, their households and the communities where households are located. With this survey, we have been able to use a number of estimation techniques that account for the endogeneity of school choice. Results from Altonji et al. (2005) shows that the size of the bias on the estimated coefficient of the private school variable due to unobservable selectivity, especially based on the household fixed effects model, is quite small. This therefore makes one confident that the range of the size of the private school premium we present could be close to the true effect.

Our work points to the relative contribution of private schools on literacy (language) and numeracy (maths) skill acquisition among children mainly in lower primary grades in Kenya. It underscores the need to integrate, into public schools, pedagogical techniques and organizational structures of private schools. However, in a country like Kenya that is experiencing dramatic increases in private school provision, confirming the relative importance of private schools is just one step. The next step involves investigating why private schools do better than public schools even with no discernible differences in the quality of infrastructure relative to public schools. This question is beyond the scope of this dissertation mainly due to lack of data to address it. In the concluding chapter however, we draw on some previous work in Kenya and argue that factors related to teachers effort and behavior, which we find important in explaining student variation in chapter 3, are perhaps potential candidates explaining the private-public performance differences. Our arguments remain largely anecdotal and call for further inquiry into this issue subject to data availability.

Given the resource constrains facing households and that attending a private school in Kenya is associated with some costs, the next chapter investigates which child within the household get the chance to be admitted to private schools.

# Chapter 5

# Birth Order and Gender Effects on Intra-household Schooling Choices and Education Attainments

## 5.1 Introduction

In chapter 4, we found that private schools are associated with better learning achievements. Interestingly, private schools, including not-for-profit-private schools, unlike public schools, are not free of charge. In Kenya, there is evidence that within households, some children may be sent to private schools while other in public schools. In the Uwezo survey, 15 percent of the households exhibit such within-household variation in school type choice (see table 5.1). This raises the question of whether in a household for which resources are scarce, parents are likely to send some of their children to private schools and others in public schools. This question relates to the literature on the role of the family in promoting the human capital formation of children (Cunha et al., 2006). According to this literature, most schooling decisions are made within the family. However, research on family characteristics that influence children's education outcomes is still inconclusive and has not been fully explored (Tenikue and Verheyden, 2010; Black et al., 2005).

A number of family characteristics have been found to influence children's education outcomes. These include sibling features such as birth order (De Haan et al., 2014; Price, 2008; Booth and Kee, 2009; Conley and Glauber, 2006; Tenikue and Verheyden, 2010, 2007; Kristensen and Bjerkedal, 2007; Harkonen, 2014; Ejrnaes and Portner, 2004), birth spacing (De Haan, 2010; Black et al., 2005), family size (Black et al., 2005; De Haan, 2010) and gender of the child (Sahoo, 2016; Maitra et al., 2016). In particular, the role that birth order plays in influencing child outcomes has dominated the economic literature. This stems from interesting findings in the psychology and sociology literature (Zajonc, 1976; Zajonc and Markus, 1976; Zajonc, 1983) which shows that child outcomes are higher for first born children. This finding is attributed to different factors including the intellectual environment within the household (Zajonc, 1976; Zajonc and Markus, 1976) and family resources (Blake, 1981; Downey, 2001) both of which are hypothesized to diminish with each additional child in the family.

Unlike literature in psychology and sociology, economic literature, both theoretical and empirical, does not demonstrate a universal first-born advantage. While literature in developed countries points to a first-born advantage in terms of education outcomes (Black et al., 2005; De Haan, 2010), evidence from developing countries generally finds a first-born disadvantage, that is, birth order effects are positively related to education outcomes (De Haan et al., 2014; Basu and Van, 1998; Tenikue and Verheyden, 2007, 2010; Ejrnaes and Portner, 2004). Birth order effects on child outcomes are therefore still the subject of further research. Another family characteristic that has received a fair amount of theoretical attention is the gender of the child. Generally, most studies in developing countries document the existence of a gender bias in favor of boys in terms of education and other social outcomes (Maitra et al., 2014, 2016; Sahoo, 2016).

This chapter contributes to this literature by investigating the effect of two important family characteristics, *gender* and *birth order*, on *intra-household investments in*, and *educational outcomes of*, children in Kenya. Following Caceres-Delpiano (2006), we measure *intra-household education investments in children* by household decisions to enrol children in private schools.[1] We define *educational outcomes* by two variables: *completed years of education* and *relative grade progression.* In Kenya, we are only aware of the study by Tenikue and Verheyden (2010) that empirically examined the effect of birth order on educational attainments in twelve countries in sub-Sahara Africa, Kenya included. This study does not however explicitly make a distinction between variables that measure child investments (such as, enrolment of children in private schools) and those that measure child outcomes (completed years of education and relative grade attainment) in examining birth order effects.

An obvious obstacle here is the endogeneity of gender, birth order and even family size, Following Tenikue and Verheyden (2010), Moshoeshoe (2016), Maitra et al. (2016), Black et al. (2005), Sahoo (2016) and De Haan et al. (2014), we apply the family fixed effects

[1] Recall that private schools in Kenya are not free. As we noted in the Chapter 4, even in low cost private schools, parents pay tuition fees at an average of less than 10 US Dollars per month against (Piper et al., 2014; Piper and Mugenda, 2010; Piper et al., 2015). This compares with an avarage household income/consumption of 34 US Dollars per adult equivalent per month nationally (GoK, 2013).

model which allows us to remove all sources of such common household level unobserved heterogeneity.

Here is the summary of our results. Although we do not find an intra-household gender preference in terms of investments in children's education, as measured by household enrolment of children in private schools, there is a female advantage in terms of completed years of education and relative grade progression. Relative to their male siblings, female siblings complete 0.138 more years of education. Female siblings also progress through school faster, accumulating 0.025 more years of education relative to their male siblings. Regarding birth order, our results show significant negative effects of birth order on private school enrolment, completed years of education and relative grade progression. Our results are robust to different robustness checks including correction of selectivity bias due to non-enrolment of children and further attempts to measure birth order effects more accurately. Lastly, we find that household wealth plays a significant role in propagating the birth order but not the gender effects we observe.

The rest of the chapter is organized follows. In section 5.2, we review the theoretical and empirical evidence of gender and birth order effects. Next, we lay out our empirical model which will be used to test for the theoretical predictions. We then provide a descriptive summary of our data (in section 5.4) after which we present the empirical results and finally conclude.

## 5.2 Who is the Most Favoured Child? Theoretical and Empirical Evidence

One of the earliest theories originating from the psychology literature is the confluence model. According to this model, a child's intellectual ability is determined by the sum of the intellectual level in his or her family. As more children are born in the household, the average intellectual environment declines(Zajonc, 1976; Zajonc and Markus, 1976). As a result, first-born children are advantaged since they are born in a household with a higher average intellectual environment. Last-borns enter the household when the average intellectual level is at its lowest. The model therefore predicts a negative correlation between birth order and outcomes such as educational attainments.

The confluence model further predicts that first-borns also develop skills by tutoring younger siblings, thus earning skills that help them excel in academic related outcomes. Such tutoring effect explains the model's predictions that *only children* are likely to do worse in outcomes (such as academic achievements) than *first-borns in large families* because the former do not have anyone to tutor (Zajonc and Markus, 1976). The model further posits that being born in a household with long, rather than short, spacing between siblings reduces the first-born advantage (Zajonc, 1983).

Away from psychology and closer to economic literature is the resource dilution hypothesis. According to this theory, all forms of parental resources, such as time and finances, are generally limited (Jaeger, 2009; Downey, 2001). In particular, as the size of the family enlarges, *per capita family* economic and material resources which cannot be shared by siblings decline (Downey, 2001). Like the confluence model, this model predicts that an increase in family size leads to poorer child outcomes. Closely related to the resource dilution hypothesis is the quantity-quality theory by Becker (1960) whose key feature is the interaction of child quality and quantity in the household budget constraint. According to this model, when there are capital market imperfections and parents have many children (like in developing countries), they can, for a given income, invest less in each child than if they have fewer children. The model predicts a negative relationship between sibling size and child outcomes.

There exists a number of studies that have looked at the empirical evidence of the above theoretical predictions. We start with empirical evidence from developed countries. Much of the evidence in developed countries is generally in line with the theoretical predictions that birth order negatively affects schooling outcomes (Price, 2008; Black et al., 2005; Booth and Kee, 2009; De Haan, 2010; Harkonen, 2014; Kristensen and Bjerkedal, 2007). A study by Black et al. (2005) makes use of survey data from Norway to estimate the effects of birth order on children's education attainments. They estimate a household fixed-effects model and find that birth order is negatively and significantly related to child education. They do not find evidence that the results are driven by parental resources (measured by mother's level of education) and household residential location (rural/urban). They also show that birth order effects do not significantly differ by gender.

Booth and Kee (2009) use the 13th wave of the British Household Panel Survey to estimate the effects of family size and birth order on children's educational attainment. They control for parental household income, parental age at birth and a number of household level attributes. They find that children from larger households have lower levels of education. In line with Black et al. (2005), they find negative birth order effects on children's educational attainment. Using data from the American Time Use Survey in the US, Price (2008) estimates the relationship between birth order and parental time use. He finds that first born children receive significantly more quality time from their parents relative to later-born children.

De Haan (2010) estimates the effect of birth order on education attainments of children in USA and Norway using the Wisconsin Longitudinal Study data and the Brabant Survey data, respectively. To address the potential endogeneity resulting from the possible correlation between birth order and number of sibling, they follow Black et al. (2005) by estimating birth order by household size. Like Black et al. (2005), their results reveal a negative and significant effect of birth order on child education. The authors further find that the age gap between children does not affect the effect of birth order. In addition, the negative effect does not differ between children from higher or lower educated parents. Other studies based in developed countries that find similar negative birth order effects on educational attainment include Harkonen (2014) for Germany and Conley and Glauber (2006)and Kristensen and Bjerkedal (2007) for USA.

Unlike developed countries, much of the evidence in developing countries finds a first-born disadvantage in terms of education outcomes, mainly due to high poverty and low education levels in developing countries (De Haan et al., 2014). High poverty levels in developing countries force households to invest less in the human capital of first-born children (Ejrnaes and Portner, 2004; Basu and Van, 1998; Tenikue and Verheyden, 2010, 2007), for example. The income from older children contributes to family resources, allowing young children to go to school thus explaining the positive birth order effects on child schooling.

Empirical evidence seems to support the above resource constraint hypothesis. Tenikue and Verheyden (2010) estimate a household fixed effects model to examine the impact of birth order on educational attainment using the demographic and health survey data for 12 sub-Saharan Africa countries including Kenya. Educational attainment is measured by the number of completed years of education (for the children in their sample as at the time of the survey). In line with the resource constraint hypothesis, they find positive birth order effects (for example, a first-born disadvantage) in poor households while the opposite holds for richer households. An earlier study by Tenikue and Verheyden (2007) also applied a family fixed effects model to examine the impact of birth order on educational attainment using the Cameroon Household Survey of 2001. This study finds a first-born disadvantage among poor households which however disappears in wealthier households indicating that wealth has the potential to reverse the first-born advantage.

Empirical evidence further points to other factors for the positive birth order effects in developing countries apart from resource constraints. De Haan et al. (2014) estimate the causal effect of birth order on the probability of school enrolment and child labor using nationally representative data from Ecuador. Their estimates, based on family fixed effects, show that earlier born (early order) children are less likely to enrol in school but more likely to participate in child labor relative to later born (later order) children. Analyzing the mechanisms driving their results, De Haan et al. (2014) find that earlier born children receive less quality time from their mothers and more so, are breast feed for a shorter time. The evidence presented in their paper also shows that birth order effects are particularly large among poor households.

Another sibling characteristic that has received theoretical attention is the gender of the child. Generally, most studies in developing countries document the existence of gender bias in favor of boys. For instance, in Ghana, a study by Garg and Morduch (1998) found that children are better off in terms of measured health indicators if they have sisters and no brothers. Another study, by Gupta (1987) based in rural, India shows that although there is a preference for boys in terms of food allocation, clothing, and education and medical expenses, parents also discriminate selectively against some of their daughters. In particular, in households where there is more than one daughter, younger daughters are worse off relative to their older sisters.

In another study from India, Sahoo (2016) explores the role of gender on intra-household schooling choices between private and government schools. He estimates a household fixed effects model on a three-period longitudinal data set based on rural households from Uttar Pradesh and finds that girls are less likely to be enrolled in private schools by 6 percentage points. Similarly, Maitra et al. (2016) examines the role of gender in private school choice using two nationally representative data sets from household surveys conducted in India in 2005 and 2012. They find that female siblings are significantly disadvantaged in both survey years. They find a significant female disadvantage in both surveys (4 percentage points in 2005 and 6 percentage point in 2012) which varies across sub-samples and years.

This paper uses the case study of Kenya to contribute to this literature by empirically testing the prediction of the theoretical models we have reviewed with regard to gender and birth order. Apart from Tenikue and Verheyden (2007), we are not aware of any other study that has explored the gender and birth order effects on intra-household schooling choices and education attainment in Kenya.

## 5.3 The Theoretical and Empirical Model

In terms of the theoretical framework, our study is grounded in the theories we reviewed in the last section, namely the *Confluence Model* (CM) and *Resource Dilution Hypothesis* (RDH) as well as other economic models including *quantity-quality theory* by Becker

(1960) and the *liquidity model* by Tenikue and Verheyden (2010). We particularly seek to test the prediction of these models in the context of Kenya.

In terms of the empirical model, we are interested in estimating the effect of *gender* (being female) and *birth order* on three variables related to children in the households, namely, *private school enrolment, completed years of education* and *relative grade progression.* Following Maitra et al. (2016), Tenikue and Verheyden (2010), Sahoo (2016), De Haan et al. (2014) and Black et al. (2005), we estimate the following household fixed effects model by OLS as outlined in 5.1:

$$y_{ij} = \beta_0 + \beta_1 GIRL_{ij} + \beta_2 second_{ij} + \beta_3 third_{ij} + \beta_4 fourth_{ij} + \beta_5 fifth_{ij} + \beta_6 X'_{ij} + \psi_j + \varepsilon_{ij} \tag{5.1}$$

where $y_{ij}$ represents the three outcomes of interest: (a) type of school (equals to one if private) that child $i$ from household $j$ is currently enrolled; (b) child $i$'s completed years of education; and lastly (c) child $i$'s relative grade progression (which we defined and discussed in Chapter 2). Each of the measures of $y_{ij}$ depends on: (a) the child's gender, where $GIRL_{ij}$ is a dummy variable for gender being a girl; (b) child's order of birth, where $second_{ij}$, $third_{ij}$, $fourth_{ij}$ and $fifth_{ij}$ denote the second-born, third-born, fourth-born and fifth-born child, respectively (first-born being the base category); and (c) a vector of other child characteristics $X_{ij}$ (age, a dummy variable for whether the child goes for paid up tuition and a dummy variable for whether a child has some form of disability).

As mentioned, an estimation bias may arise from the potential endogeneity of the child's gender and family size. We are able to deal with such endogeneity and remove all sources of unobserved heterogeneity common to all children in the family through the family fixed effects, denoted $\psi_j$. Finally, $\varepsilon_{ij}$ is the error term.

We interpret the estimated coefficients on the dummies $second_{ij}$, $third_{ij}$, $fourth_{ij}$ and $fifth_{ij}$ as the effect of being the second, third, fourth and fifth child relative to the first child (the first child being the reference category). Our birth order variable is likely to be correlated (positively) with the age of the child since children in our sample were observed when they were still in school. Others like De Haan et al. (2014), Moshoeshoe (2016) and Tenikue and Verheyden (2010) have solved this challenge by including dummies for child's age in the regressions. We apply this same strategy. We also include two additional child level variables: a variable indicating whether a child goes for paid tuition and whether the child has some form of disability. Many studies focusing on developing countries do not account for these variables which may be correlated with our measured outcomes variables.

Each household in our data is considered a cluster since there are individual children within the household who are genetically linked. We cluster standard errors within the household fixed effects in order to derive homoscedastic idiosyncratic error given such clustering (Nichols and Schaffer, 2007; Maitra et al., 2016).

## 5.4 Descriptive Statistics

The Uwezo survey does not allow us to distinguish between biological and non-biological children of the household. We thus treat all children as though they are biological children of the family. We are of the opinion that this assumption will not have a huge implication on our estimates because as explained in chapter 2, information was collected from children *who regularly live* in the household. These children, whether biological or not, by virtue of being regular inhabitants of the household, directly influence intra-household decisions including those related to schooling.[2]

Like Caceres-Delpiano (2006), our sample is limited to children in the household aged 6 to 16 years who are the target group in the Uwezo household assessments. First, we exclude younger children (less than 6 years) because compulsory primary schooling in Kenya begins at age 6. The upper age limit is right-censored since Uwezo targets children of maximum age of 16. Focusing on children aged between 6 to 16 years has an advantage. For instance, the incidence of children below 16 years moving out of the household (to look for a job or otherwise) is low, an aspect that minimizes potential measurement errors in our birth order measures.

Since are exploiting within-family variations in the fixed effects models, it is a requirement that we restrict the sample to include only families with a minimum of two children (Black et al., 2005; Sahoo, 2016; Tenikue and Verheyden, 2010; Maitra et al., 2016; De Haan et al., 2014).[3] We further limit the sample size to households with a maximum of five children. This restriction ensures we have included families that are not likely to have more children. Limiting the sample to households with five children does not have a huge implication on our estimates since fewer than 1.5 percent of households in our sample have more than five children aged 6-16 years. Following De Haan et al. (2014), we drop households with multiple births (twins) because it is not clear how birth

[2]In India, a very recent study by Maitra et al. (2016) examined the effect of gender and birth order on intra-household private school choice. The authors compare estimates based on a sample of only biological children and estimates based on a sample extended to all children who were in the household at the time of the survey. The results between the two samples are similar.

[3]By imposing this restriction, we lose about 39.2 percent of the 72,216 households in the sample.

order can be assigned in such cases.[4] We also exclude households and/or children with missing data on key variables such as age.

After imposing all these restrictions, we are left with 96,920 children and 31,568 households. We construct indicators of birth order for the children based on their reported year of birth. In this case, birth order equals 1, 2, 3, 4 and 5 for the first, second, third, fourth and fifth born children aged 6 to 16 years, respectively. According to De Haan (2010), the most accurate measure of birth order is one based on households where all children of the mother are still alive and live at home at the moment of the survey. Although our data does not allow us to know if there are children staying away from the household at the time of the survey and if some of the children were not alive, we provide some evidence in the robustness test section to allay fears about the accuracy of our measure of birth order.

We are interested in three dependent variables. The first is a dummy variable that equals *1 if the child attends a private school* and *0 if the child attends a public school.* Following Tenikue and Verheyden (2010), we define our second dependent variable as the child's highest *number of completed years of education* as at the time of the survey. The third dependent variable is the *relative grade progression,* which as explained in chapter 2, is the number of years of schooling a child had completed as at the time of the survey, divided by the child's potential years of schooling (see also Mani et al. (2013)). Relative grade progression is defined accounting for the fact that official primary school starting age in Kenya is 6.[5] In this case, all children of age 6 and below are assumed to have accumulated zero years of education. As a result, this dependent variable has a small sample size.

Since private schooling is not free in Kenya, we consider private school enrolment as a measure of parental investment in children's education allowing us to accurately test economic theories such as the resource dilution hypothesis (Caceres-Delpiano, 2006). We associate the next two dependent variables (completed years of education and relative grade progression) as measures of child well-being (education outcomes), that result from inputs such as parental resource allocation (Caceres-Delpiano, 2006).

Table 5.1 shows selected descriptive statistics for the whole sample, for households that send their children to public schools and for households that send their children to private schools. A few variables in the table were already presented in chapter 2. The mean statistics for these variables will however differ slightly from those presented in chapter 2 because the analytical sample in this chapter excludes households with: (i) one

[4]Uwezo did not directly ask if the household had twins or not. If two or more children in the household have the same age, we assume that such children are twins. We lose about 5.3 percent of the 72,216 households in the sample.

[5]Relative grade progression is calculated as $[\frac{Completed\, years\, of\, education}{(Age-6)}]$. The number 6 in the denominator denotes the official age of starting school in Kenya.

child, (ii) more than five children and (ii) with twins.

Table 5.1: Mean Statistics for Children and Households

| | (1) Whole Sample | (2) Public School | (3) Private School | (4) Public-Private diff |
|---|---|---|---|---|
| **Panel A: Dependent Variables** | | | | |
| Never enrolled | 0.12 | – | – | – |
| Dropped out | 0.01 | – | – | – |
| Enrolled | 0.87 | – | – | – |
| Enrolled in private school | 0.14 | – | – | – |
| Completed years of education | 3.43 | 3.50 | 2.95 | 0.56*** |
| Relative grade progression | 0.64 | 0.64 | 0.65 | -0.01*** |
| **Panel B: Child Characteristics** | | | | |
| Age of the child (in years) | 10.87 | 11.24 | 10.29 | 0.95*** |
| Child is female | 0.48 | 0.49 | 0.49 | 0.00 |
| Child attends tuition classes | 0.39 | 0.44 | 0.61 | -0.18*** |
| Child has some form of disability | 0.03 | 0.03 | 0.02 | 0.01*** |
| Child is first-born | 0.38 | 0.41 | 0.36 | 0.05*** |
| Child is second-born | 0.36 | 0.36 | 0.40 | -0.04*** |
| Child is third-born | 0.18 | 0.17 | 0.18 | -0.01*** |
| Child is fourth-born | 0.07 | 0.05 | 0.06 | 0.00 |
| Child is fifth-born | 0.02 | 0.01 | 0.01 | 0.00 |
| **Panel C: Household Characteristics** | | | | |
| Household is in a rural area | 0.78 | 0.79 | 0.60 | 0.18*** |
| Household wealth index (normalized to 0-1 range) | 0.40 | 0.41 | 0.52 | -0.11*** |
| Household belongs to the upper wealth index | 0.26 | 0.25 | 0.51 | -0.27*** |
| Age of mother (in years) | 36.77 | 37.09 | 35.58 | 1.51*** |
| Years of education of the mother | 5.53 | 5.74 | 6.88 | -1.13*** |
| Number of children aged 6 to 16 years in the family | 2.76 | 2.77 | 2.61 | 0.16*** |
| Within household variation in school choice | 0.15 | – | – | – |
| **Number of children** | **96,920** | **74,245** | **9,407** | |
| **Number of households** | **31,568** | **22, 423** | **3,330** | |

Source: Own calculations based on Uwezo 2012. Notes: (1) Our sample is restricted to households with 2-5 children aged 6-16; (2) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school; (2) Completed years of education is number of years of education the child had completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\,years\,of\,education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) The household wealth index is constructed using the principal component analysis (PCA) based on household ownership of durable and livestock assets, type of material used to construct the wall of the dwelling unit, type of lighting regularly used by the household, number of meals taken per day and household sanitation status (for details of specific variables included in the index please refer to chapter 2 ); (6) We normalize the family wealth index to the range of 0 to 1 and classified household whose index lies 0.5 and above as rich while the rest were classified as poor. Refer to chapter 2 for more details and; (7) By mother being a teen at birth of the oldest child (in years) means the mother gave birth her first born child when she was 18 years or less.

Panel A (column 1) shows the results for our three dependent variables for the children. As can be seen from the table, about 12 percent of children have never been enrolled while about 1 percent have dropped out of school.[6] The majority of children, 87 percent are enrolled and of these 14 percent are enrolled in private schools. The average completed years of education of those who are enrolled is 3.43. If children in our sample enter schools on time (at age 6) and accumulate every year without repeating, we expect the relative

[6]Later, we address concerns that such non-enrolment might be a source of selection bias through the Heckman-type selection model since a decision to enroll in a private or a public school is only observed after a decision either to enrol in school or not to enrol has been taken.

grade progression to be equal to 1, showing an efficient education system. As can be seen from table 5.1, our average relative grade is 0.64 (less than 1 by 37 percentage points), meaning that children in our sample accumulate 0.64 grades per year of schooling. This reinforces one of our concerns in chapter 1 and 2 about the late entry and/or relatively high rate of repetition among Kenyan children.

Column 2 and 3 show that children in public schools have slightly more years of education (probably because they are older). However, children in public schools have slightly lower relative grade progression level meaning that they are more likely to start school late and/or repeat classes relative to their counterparts in private schools.

Looking at child demographic characteristics in panel B (column 1), we find that children are on average 10.87 years old and just below half of them, 48 percent, are female. Less than half of the children, 39 percent, reported that they attend paid tuition classes. A relatively small proportion of children, about 3 percent, were reported to have some form of physical disability. Column 2 and 3 show that relative to their counterparts in public schools, private school students are more likely to be young, female and with no disability. The share of first and second born in the sample is 38 and 36 percent, respectively. The share of third and fourth born children is, respectively, 18 percent and 7 percent. The fifth born are least represented at 2 percent.

In terms of household characteristics, shown in panel C (column 1), we find that the majority of households, 78 percent, are in rural areas. The average wealth index (0-1 range) is 0.40, meaning that the majority of households belong to the lower part of the wealth index and can therefore be classified as poor. Only 26 percent of households can be classified as rich, that is, those whose household wealth index is is 0.5 and above (see discussion in Chapter 2). The mean age of the mother is 36.77 years. On average, mothers of children in our sample have 5.53 years of education. There are, on average, 3 children, aged 6-16 years. Lastly, 15 percent of the households exhibit such within-household variation in school type choice where some children attend public schools while others attend private schools even when they are from the same household.

Panel C (column 1 and 2) further shows that households that send children to private schools are more likely to be: smaller in size, based in urban areas, wealthier and with more young and more educated mothers. Thus, it seems, as we pointed out in previous chapters, that children who attend private schools already have disproportionately higher academic potential and access to complementary educational resources. They are more likely to attend private schools, accumulate more years of education and progress faster through schooling. We use family fixed effects models to address such potential source of endogeneity.

## 5.5 Results and Discussion

### 5.5.1 Gender and Birth Order Effects

The dependent variables *completed years of education* and *relative grade progression* are continuous variables and therefore the estimation strategy used is the standard OLS with fixed effects. For private enrolment, the dependent variable is binary, indicating whether the child is enrolled in private (equals to 1) or not (equals to 0). Ideally, we should use the conventional probit or logit that bound the maximum likelihood estimated probabilities on the unit interval (Horrace and Oaxaca, 2006). However, results estimated by probit or logit can be inconsistent when fixed effects are included (Baltagi, 2008; Wooldridge, 2003). We therefore use the Linear Probability Model (LPM) which is generally acceptable when using fixed effects in the context of a dummy dependent variable (Horrace and Oaxaca, 2006).

The LPM, however, comes with two potential challenges. First, its predicted probabilities are not bounded on the unit interval (for example, they can lie outside the 0 to 1 range) and second is the challenge of heteroscedasticity. To deal with heteroscedasticity, we use the robust standard errors, which are clustered at the household level. Regarding the first challenge, Horrace and Oaxaca (2006) show that this bias increases with an increase in the relative share of predicted probabilities falling outside the unit interval. They argue that if no predicted probabilities, or just a few predicted probabilities, lie outside the unit interval, then the LPM is expected to be unbiased and consistent. In our case, the proportion of LPM predicted probabilities that lie outside the unit interval is, in fact, zero.

In table 5.2, we present the OLS and household fixed effects regression results for the effects of gender and birth order on the three dependent variables.[7] Throughout this chapter, we refer to the results in table 5.2 as our *headline results/regression.* Since parents of first-born children are more likely to be younger than those of fourth or fifth born children, we include in the OLS regression the mother's age to control for such cohort effects for the parents (Black et al., 2005). In addition, we include mother's education, and a full set of dummies for the number of children in the family, which control for the correlation between birth order and family size.

[7]In the interest of brevity we only report estimates of our variables of interest (gender and birth order) throughout this paper.

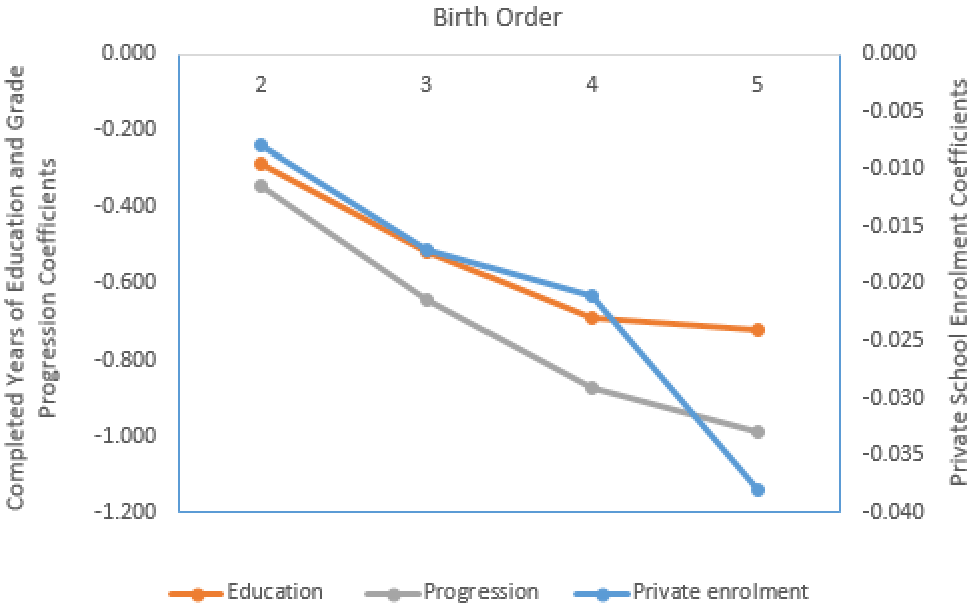
Table 5.2: Effects of Gender and Birth Order on Private School Enrolment, Completed Years of Education and Relative Grade Progression

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Private School enrolment | | Completed Years of Education | | Relative Grade Progression | |
| | OLS | Fixed Effects | OLS | Fixed Effects | OLS | Fixed Effects |
| Female | -0.002 | 0.001 | 0.146*** | 0.138*** | 0.028*** | 0.025*** |
| | (0.002) | (0.002) | (0.008) | (0.009) | (0.002) | (0.002) |
| Second born | -0.009*** | -0.008** | -0.087*** | -0.205*** | -0.019*** | -0.061*** |
| | (0.003) | (0.003) | (0.011) | (0.015) | (0.002) | (0.004) |
| Third born | -0.020*** | -0.013** | -0.165*** | -0.403*** | -0.048*** | -0.124*** |
| | (0.005) | (0.005) | (0.018) | (0.026) | (0.004) | (0.006) |
| Fourth child | -0.028*** | -0.017** | -0.188*** | -0.541*** | -0.079*** | -0.183*** |
| | (0.007) | (0.008) | (0.026) | (0.038) | (0.007) | (0.010) |
| Fifth born | -0.050*** | -0.032*** | -0.120*** | -0.594*** | -0.138*** | -0.271*** |
| | (0.012) | (0.012) | (0.039) | (0.055) | (0.018) | (0.019) |
| Family Size | | | | | | |
| Three children | -0.016*** | | -0.028** | | -0.006** | |
| | (0.004) | | (0.013) | | (0.003) | |
| Four children | -0.022*** | | -0.020 | | 0.004 | |
| | (0.004) | | (0.019) | | (0.003) | |
| Five children | -0.018*** | | -0.076** | | 0.008 | |
| | (0.007) | | (0.030) | | (0.005) | |
| Constant | 0.322*** | 0.328*** | -5.510*** | -3.979*** | -0.412*** | -0.020 |
| | (0.028) | (0.017) | (0.093) | (0.085) | (0.030) | (0.026) |
| Observations | 83,652 | 83,652 | 84,622 | 84,622 | 80,389 | 80,389 |
| R-squared | 0.035 | 0.039 | 0.747 | 0.823 | 0.128 | 0.119 |
| No. of households | 37,282 | | 37,432 | | 36,272 | |

*Notes*: (1) The OLS and fixed effects regressions include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not. In addition, the OLS regression includes mother's level of education and mother's age (to control for parental cohort effects), dummies for the family size; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education the child had completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Looking at the results in table 5.2, the OLS estimates in column 1 shows that being a female child does not have an effect on the probability of being enrolled in a private school. Results in columns 3 and 5 show that relative to their male siblings, female siblings are more likely to complete more years of education and progress faster through school. With regards to birth order, the results reveal a clear pattern of a negative and significant effects of birth order on all the dependent variables which increases in absolute terms with birth order. In figure 5.1, we show the effects of birth on all the measured outcomes based on the household fixed effects model (based on columns 2, 4 and 6 of table 5.2).

Figure 5.1: Effects of Gender and Birth Order on Private School Enrolment, Completed Years of Education and Relative Grade Progression based on Household fixed effects model




We refrain from giving OLS estimates a causal interpretation because of the possible bias that may arise from unobserved household characteristics. We therefore turn to the household fixed effects estimates that address these identification problems (columns 2, 4 and 6). The results generally show a similar pattern as those in OLS. There is no gender effect on our measure of intra-household investment in education (private enrolment). However, relative to their male siblings, female siblings complete 0.138 more years of education. In addition, they are more likely to progress through school faster, accumulating 0.025 more years of education per year of schooling relative to their male counterparts.

The female advantage we observe in terms of *completed years of education* and *relative grade progression* is in contrast with literature generally reported from developing countries (Garg and Morduch, 1998; Gupta, 1987; Maitra et al., 2016; Sahoo, 2016). It is, however, in line with global trends which show that more girls are getting educated and the gender gap in education has narrowed considerably (King and Winthrop, 2015). In Kenya, for example, the Uwezo surveys have consistently shown that over time, more girls than boys are enroling and progressing faster through school (Uwezo, 2012, 2014).

Turning to birth order effects in the fixed effects model, we find a significant negative association between birth order and the three dependent variables. Relative to the first-born, all other later-born children are less likely to be enrolled in private schools and are likely to complete less years of education. First-born children also make more progress than all later all other later-born children. For example, the second and fifth-born children are less likely to be enrolled in a private school by 0.8 percentage points and 3.2 percentage points, respectively, relative to their first-born sibling. Similarly, the second and fifth-born children are likely to complete 0.205 and 0.594 less years of education, respectively, relative to their first-born sibling. Furthermore, we find that first-born children progress through school much faster than their younger siblings. Our results show that the second-born is likely to accumulate 0.061 less years of education per year of schooling relative to his/her first-born counterpart and this disadvantage increases to 0.271 less years of education in the case of the fifth-born.

Surprisingly, the first-born advantage we find in terms of private school attendance advantage, completed years of education and relative grade progression are generally in contrast with the findings in developing countries (as for instance Black et al. (2005); De Haan (2010); Tenikue and Verheyden (2010); Ejrnaes and Portner (2004)). The results are however in agreement with evidence in developed countries, for instance USA (Price, 2008; Black et al., 2005; Booth and Kee, 2009; De Haan, 2010; Harkonen, 2014; Kristensen and Bjerkedal, 2007; Conley and Glauber, 2006), Norway (Black et al., 2005; De Haan, 2010), UK (Booth and Kee, 2009) and Germany (Harkonen, 2014). Our results on private school enrolment are however consistent with Sahoo (2016) who documents a negative birth order effect on private school choice in India.

There are a number of reasons for the potential negative birth order effects we find. The first-borns, as posited by the confluence model, enjoy a higher intellectual environment which declines with entry of additional children (Zajonc and Markus, 1976; Zajonc, 1976). First-born children are also born into a family when limitations on the available parental resources such as finances and time are not thinly spread among many children (Blake, 1981; Downey, 2001; Becker, 1960). Their cognitive ability and development is therefore more likely to be malleable at childhood, leading to better future outcomes (Cunha and Heckman, 2007). In a developing country context like Kenya, parents can also favor the eldest child because these children are more likely to start earning income earlier, thus supplementing the family income. Although limited by data, we try to investigate if some of these factors are driving our results in section 5.6.

### 5.5.2 Robustness Checks

In this section, we carry out a number of robustness checks to determine the validity of our results presented in the headline regressions in table 5.2. Our robustness checks are based on the household fixed effects estimates.

School choice, whether to go to private school or not, is only observed if the child is enrolled in school. As we show in table 5.1, about 11 percent of children are not enrolled in school.[8] Non-enrolment can be a potential source of selectivity bias. Next, we check whether our estimates in table 5.1 compares with those based on a model with selection correction. As observed by Maitra et al. (2016), the standard Heckman-type selection model is not suitable for a household fixed-effects. In this regard, we closely follow Maitra et al. (2016) by estimating a selection equation defined in terms of the decision to enrol a child in school or not as shown in equation (5.2).

$$\begin{aligned} enrol^{*}_{ijk} = \beta_0 + \beta_1 GIRL_{ijk} + \beta_2 second_{ijk} + \beta_3 third_{ijk} + \beta_4 forth_{ijk} + \beta_5 fifth_{ijk} \\ + \beta_6 X^{'}_{ijk} + \beta\psi_{ijk} + \beta_8\phi_{ijk} + \mu_{ijk} \end{aligned} \quad (5.2)$$

where $enrol^{*}_{ijk}$ is the propensity to attend school (enrol) for student $i$ in household $j$ located in village $k$. Since this propensity is not observable, we only observe $enrol_{ij}$ when the child is enrolled e.g. $enrol_{ij} = 1$ if $enrol_{ij} > 0$ otherwise if the child is not enrolled then, $enrol_{ij} = 0$ if $enrol_{ij} \leq 0$. We let the propensity to enrol depend on: (a) the child's gender, where $GIRL_{ij}$ is a dummy for female child, (b) child's order of birth where as before, $second_{ij}$, $third_{ij}$, $fourth_{ij}$ and $fifth_{ij}$ denote the second-born, third-born, fourth-born and fifth-born child, respectively (first-born being the base category), (c) a vector of other child characteristics, $X_{ij}$ (age, a dummy variable for whether the child goes for paid up tuition or not, and a dummy variable for whether a child has some form of disability or not), (d) family characteristics, $\psi_{ijk}$, (e) village characteristics, $\phi_{ijk}$. $\mu_{ijk}$ is a random error.

Like Maitra et al. (2016), we estimate the selection equation equation (5.2) using a probit model after which we compute the inverse Mill's ratio, denoted as $\lambda_{ij}$ for each sample child.[9] At the second stage, we include the inverse Mill's ratio $\lambda_{ij}$ in equation (5.1) and estimate a household fixed effects selectivity corrected model as shown in Equation (5.3):

$$y_{ij} = \beta_0 + \beta_1 GIRL_{ij} + \beta_2 second_{ij} + \beta_3 third_{ij} + \beta_4 forth_{ij} + \beta_5 fifth_{ij} + \beta_6 X^{'}_{ij} + \psi_j + \lambda_{ij} + \varepsilon_{ij} \quad (5.3)$$

[8] We do not know the underlining factors leading to their decision not to enrol.

[9] Recall that in equation (5.2) we are estimating a probit model and so we do not account for household fixed effects for reasons we have already explained.

Like Maitra et al. (2016), we knowlegde that this process of correction for selection may not be ideal, we simply want to test the robustness of our results. Table D5.1 in appendix D shows the results of the selection equation for child enrolment based on equation (5.2).[10] In table 5.3, we present the selectivity corrected gender and birth order effects estimated from the household fixed effects model (equation (5.3)). The estimates do not differ from those presented in our headline regressions in table 5.2. We find no significant differences between female and male children in terms of private enrolment. However, there is a female advantage in terms of completed years of education and relative grade progression. Similarly, we find a significant negative association between birth order and the three dependent variables.

Table 5.3: Effects of Gender and Birth Order using Household Fixed Effects Selectivity Corrected Model

| | (1) | (2) | (3) |
|---|---|---|---|
| | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | 0.001 | 0.156*** | 0.027*** |
| | (0.002) | (0.011) | (0.003) |
| Second born | -0.011*** | -0.317*** | -0.060*** |
| | (0.004) | (0.019) | (0.005) |
| Third born | -0.021*** | -0.620*** | -0.122*** |
| | (0.006) | (0.034) | (0.008) |
| Fourth child | -0.023** | -0.907*** | -0.185*** |
| | (0.009) | (0.050) | (0.013) |
| Fifth born | -0.042*** | -1.198*** | -0.278*** |
| | (0.014) | (0.071) | (0.024) |
| Mills Ratio ($\lambda_{ij}$) | -0.100*** | 0.938*** | -0.014 |
| | (0.015) | (0.068) | (0.036) |
| Constant | 0.533*** | -6.899*** | 0.002 |
| | (0.037) | (0.172) | (0.063) |
| Observations | 55,943 | 56,510 | 48,418 |
| R-squared | 0.041 | 0.803 | 0.121 |
| Number of households | 22,221 | 22,289 | 21,588 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Our sample is based on children aged 6 to16 years. The upper age is right censored

[10] As can be seen from the table, the child, household and community/village characteristics we control for exert a significant influence on enrolment probability.

since Uwezo targets children of the maximum age of 16. One of the assumptions we make is that all children are biologically born by the parents in the household.[11] It is possible that our *observed oldest child* might not be the *actual oldest living child* of the household. Our next robustness check addresses these concerns. According to a report by Kenya National Bureau of Statistics (KNBS) based on 2009 Kenya Demographic Health Survey (DHS), almost one-third of women (32%) in Kenya are married by age 18. The survey further reveals that the median age at first marriage is 20 for women in the age bracket 25–49, and that age at marriage greatly increases with education where women with no education are likely to marry at age 17.5 while those with secondary school education are likely to marry at age 22.4 (KNBS, 2014).

Based on this, we check the robustness of our results by estimating the gender and birth order effects on two samples. The first sample comprise households whose mothers had their *first-born* child when they were teenagers, for example at 18 years of age. In this sample, the mother's age ranges from 17 years to 34 years while the mean age is 28 years. The second sample constitutes households where mothers were 34 years or younger as at the time of the survey. We think that in these two samples, the first child was more likely to be less than 16 years in 2012 (the year when the survey was conducted), thus allowing us to estimate birth order effects in a more accurate manner. Results based on these two restricted sample are shown in table 5.4. In both cases, our estimates of gender and birth order do not deviate from those in the headline regression.

One might be concerned that family size is likely to be correlated with birth order and that this might confound our birth order estimates. Although the use of household fixed effects model helps to deal with such biases, we follow Black et al. (2005) and De Haan (2010) by estimating the effects of birth order effects by household size that controls for potential endogeneity induced by household size. Results are shown in table 5.5. The results for gender are consistent with our headline findings: irrespective of the family size, there is no female advantage in terms private school enrolment but we find a female advantage in terms of completed years of education and relative grade progression. Similarly, there is no gender preference in terms of private school enrolment. We still find negative birth order effects on all the three dependent variables. However, the relationship is insignificant in the case of private school enrolment especially among large families.

[11]We also assume that there is a low probability that there are older children living outside the household.

Table 5.4: Effects of Gender and Birth Order by Mother's Age

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Households whose mothers had their first-borns at 18 years** | | | **Households whose mothers were 34 years or less in 2012** | | |
| Variables | Private School enrolment | Completed Years of Education | Relative Grade Progression | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.002 | 0.136*** | 0.023*** | -0.002 | 0.133*** | 0.025*** |
| | (0.003) | (0.018) | (0.004) | (0.003) | (0.014) | (0.004) |
| Second born | -0.015*** | -0.221*** | -0.078*** | -0.016*** | -0.249*** | -0.075*** |
| | (0.006) | (0.030) | (0.007) | (0.005) | (0.023) | (0.006) |
| Third born | -0.024** | -0.455*** | -0.153*** | -0.023** | -0.471*** | -0.157*** |
| | (0.010) | (0.052) | (0.013) | (0.009) | (0.041) | (0.011) |
| Fourth child | -0.034** | -0.594*** | -0.242*** | -0.026* | -0.623*** | -0.253*** |
| | (0.015) | (0.074) | (0.020) | (0.014) | (0.061) | (0.017) |
| Fifth born | -0.081*** | -0.605*** | -0.322*** | -0.065*** | -0.645*** | -0.332*** |
| | (0.022) | (0.111) | (0.043) | (0.022) | (0.094) | (0.039) |
| Constant | 0.348*** | -3.714*** | -0.089* | 0.353*** | -3.771*** | -0.072 |
| | (0.033) | (0.163) | (0.052) | (0.028) | (0.134) | (0.044) |
| Observations | 22,313 | 22,600 | 21,335 | 33,745 | 34,152 | 31,880 |
| R-squared | 0.052 | 0.820 | 0.135 | 0.049 | 0.824 | 0.138 |
| Number of households | 9,815 | 9,862 | 9,805 | 15,441 | 15,512 | 15,375 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\,years\,of\,education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Table 5.5: Effects of Gender and Birth Order by Household Size

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Completed Years of Education** | | | | **Relative Grade Progression** | | | | **Private School enrolment** | | | |
| | Two child family | Three child family | Four child family | Five child family | Two child family | Three child family | Four child family | Five child family | Two child family | Three child family | Four child family | Five child family |
| Female | 0.138*** | 0.142*** | 0.143*** | 0.123*** | 0.030*** | 0.023*** | 0.026*** | 0.016** | -0.005 | 0.004 | 0.002 | 0.005 |
| | (0.018) | (0.015) | (0.019) | (0.029) | (0.005) | (0.004) | (0.004) | (0.007) | (0.004) | (0.004) | (0.004) | (0.007) |
| Second-born | -0.166*** | -0.205*** | -0.253*** | -0.268*** | -0.074*** | -0.048*** | -0.066*** | -0.054*** | -0.012** | -0.014*** | -0.006 | -0.006 |
| | (0.027) | (0.025) | (0.037) | (0.068) | (0.007) | (0.006) | (0.008) | (0.013) | (0.005) | (0.005) | (0.007) | (0.011) |
| Third-born | | -0.516*** | -0.653*** | -0.761*** | | -0.139*** | -0.138*** | -0.125*** | | -0.001 | -0.006 | -0.015 |
| | | (0.044) | (0.059) | (0.106) | | (0.011) | (0.014) | (0.023) | | (0.007) | (0.009) | (0.015) |
| Fourth-born | | | -1.116*** | -1.242*** | | | -0.271*** | -0.200*** | | | 0.021* | -0.007 |
| | | | (0.084) | (0.142) | | | (0.020) | (0.032) | | | (0.012) | (0.020) |
| Fifth-born | | | | -1.659*** | | | | -0.352*** | | | | 0.002 |
| | | | | (0.179) | | | | (0.042) | | | | (0.026) |
| Constant | -4.121*** | -3.536*** | -2.069*** | -1.549*** | 0.008 | 0.019 | 0.346*** | 0.427*** | 0.336*** | 0.255*** | 0.243*** | 0.153* |
| | (0.160) | (0.159) | (0.236) | (0.426) | (0.051) | (0.047) | (0.068) | (0.123) | (0.033) | (0.033) | (0.046) | (0.091) |
| Observations | 31,184 | 28,935 | 17,505 | 6,998 | 29,426 | 27,589 | 16,695 | 6,679 | 30,842 | 28,610 | 17,292 | 6,908 |
| R-squared | 0.935 | 0.827 | 0.826 | 0.833 | 0.768 | 0.129 | 0.128 | 0.142 | 0.018 | 0.009 | 0.006 | 0.005 |
| No. of households | 15,391 | 11,490 | 5,346 | 1,768 | 15,391 | 11,448 | 5,335 | 1,767 | 15,391 | 1,838 | 5,326 | 1,761 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

### 5.5.3 Heterogeneous Effects of Gender and Birth Order

We are using a large, nationally representative survey with data collected from almost all regions of Kenya. Kenya reflects large inter-regional variation in human development. This is reflected in cultural and social practices as well as geography, and economics of the different regions. In this section, we test to see if the results in our headline regression reflect this heterogeneity. The regressions will be based on the household fixed effects models.

#### 5.5.3.1 Gender and Birth Order Effects by Family Size

We begin by exploring differences in the effects of gender and birth order by household size. Table 5.5 has already been explored as part of the robustness tests. We use it once more to show if there are heterogeneous effects in gender and birth order effects by family size. The results on gender are consistent with our headline results: in all the different family sizes, there is no significant differences between female and male children in terms of private enrolment. However, there is a female advantage in terms of completed years of education and relative grade progression.

It is more revealing to analyze birth order effects in table 5.5 by column (*within families)* and by row *(across families)*. Column 1 to 4 shows the effects of gender and birth order on *years of schooling completed.* Reading results by column, we see significant negative birth order effects irrespective of the family size. Reading results by row, we also find that birth order effects increase *across* the family sizes as we move from a family of two to five children. Put differently, the disadvantage of being the second, third and fourth-born increases with an increase in the family size. For example, the *second-born in a family of two children* completes 0.166 fewer years of education relative to the first-born sibling while the counterpart *second born in a family of five* completes 0.268 fewer years of education relative to the first-born sibling (row 2). These results generally support the theoretical predictions of the confluence (Zajonc and Markus, 1976; Zajonc, 1976), resource hypothesis (Downey, 2001) and quantity-quality (Becker, 1960) models which predict a negative relationship between child outcomes and family size.

Similarly, results in column 5 to 8 (read by column) shows significant negative birth order effects on *relative grade progression* irrespective of the family size in line with theoretical predictions. However, results (read by row) shows birth order effects on *relative grade progression* reduce *across* family sizes. The disadvantage (gap) of being the second, third and fourth-born, *relative to the first-born*, reduces with an increase in the family sizes (see column 5 to 8). For example, *relative to the first-born,* a *second-born child in a* *family of two children* accumulates 0.074 fewer years of education while the *same second-born in a five-child family* accumulates 0.054 fewer years of education. This result seems to be in line with the *tutoring effect* of the confluence model (Zajonc and Markus, 1976; Zajonc, 1976) which posits that large families can narrow latter-born disadvantage in child outcomes. We think that latter-born siblings in large families are likely to progress faster through school for two potential reasons: they are likely to *start school on time* by accompanying their older siblings who are already in school and are also likely to develop skills by tutoring their younger siblings or being tutored by older siblings.

Next, we test for the equality of the gender and birth order coefficients *across family sizes*. To do so, we follow De Haan et al. (2014) and Moshoeshoe (2016) by estimating a fully interacted model where every variable in the family fixed effects model, not just gender and birth order, is interacted with family size. In the next sub-section, we briefly explain the intuition behind fully interacted models. Results are reported in table 5.6. The coefficient of the interaction between gender and family size is insignificant in all the outcomes variables. This means that an increase in family size is not associated with a female advantage in terms of private school enrollment, completed years of education and relative grade progression.

The interaction term between birth order and private school enrolment variable is insignificant showing the absence of significant differences in the effects of birth order on private school enrolments across family sizes. The interaction terms between birth order and family size are negative and significant in the completed years of education regression confirming results in table 5.6 that the effects of birth order on completed years of education get larger as the size of the family increases. However, birth order interaction terms with relative grade progression are generally positive and significant again confirming results in table 5.5 that birth order effects on relative grade progression get smaller as the size of the family increases.

Table 5.6: Effects of Gender and Birth Order: Fully Interacted Models with Family Size

| | (1) | (2) | (3) |
|---|---|---|---|
| | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.004 | 0.147*** | 0.036*** |
| | (0.006) | (0.031) | (0.008) |
| Second born | -0.018* | -0.092* | -0.071*** |
| | (0.011) | (0.052) | (0.013) |
| Third born | -0.017 | -0.303*** | -0.222*** |
| | (0.021) | (0.101) | (0.024) |
| Fourth child | -0.011 | -0.511*** | -0.461*** |
| | (0.043) | (0.196) | (0.056) |
| Fifth born | 0.043* | -1.614*** | -0.360*** |
| | (0.023) | (0.111) | (0.029) |
| Female* family Size | 0.001 | -0.002 | -0.003 |
| | (0.002) | (0.010) | (0.002) |
| Second-born* family Size | 0.004 | -0.038** | 0.003 |
| | (0.003) | (0.017) | (0.004) |
| Third-born* family Size | 0.005 | -0.083*** | 0.022*** |
| | (0.006) | (0.031) | (0.007) |
| Forth-born* family Size | 0.008 | -0.137*** | 0.052*** |
| | (0.011) | (0.051) | (0.014) |
| Fifth-born* family Size | – | – | – |
| | – | – | – |
| Constant | 0.275*** | -3.279*** | 0.113*** |
| | (0.020) | (0.097) | (0.029) |
| Observations | 83,652 | 84,622 | 80,389 |
| R-squared | 0.040 | 0.824 | 0.123 |
| Number of households | 36,329 | 36,501 | 36,272 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

#### 5.5.3.2 Gender and Birth Order Effects by Location

Family size may matter more or less depending on whether the family is located in a rural or urban area. In a country like Kenya, a large household may be a source of labour on the farm, hence more beneficial in rural than urban areas. Also, urban areas in Kenya have a more education opportunities, especially high concentration of private schools than rural areas (Piper and Mugenda, 2010; Piper et al., 2014). For these reasons, we check for heterogeneity in gender and birth order effects by location (rural versus urban) and further test if our results in the main regression are an artefact of household location. We estimate our household fixed effects model by location whose results are shown in table 5.7. The results on gender, in both rural and urban areas, are consistent with our headline regressions table 5.2: we do not find significant differences between female and male children in terms of private enrolment in both rural and urban locations but there is a female advantage in terms of completed years of education and relative grade progression.

Interestingly, we find significant negative birth order effects on private school enrolment in the rural sample but none in the urban sample (column 1 and 4). As pointed out in the previous chapter, private schools are the main source of education in urban areas. For some families in urban informal settlements (especially in Nairobi), the choice is sometimes not between a government primary school and a non-formal private school, but between the non-formal private school and no school at all (Piper et al., 2014). With such near universal access to private schools in urban areas, there are no incentives for intra-household discrimination among siblings thus explaining the lack of significant birth order effects on private school enrolment in urban areas. On the other hand, private schools are not as prevalent in rural areas as they are in urban areas. The few private schools in rural areas are likely to charge higher fees thus inducing intra-household discrimination among children in favor of older siblings in terms of their access.

Table 5.7 further shows that birth order effects are different between rural and urban areas in terms of completed years of education (column 2 and 5) and relative grade progression (column 3 and 6). In particular, there is strong latter-sibling disadvantage in terms of completed years of education in rural households. For instance, a fifth-born child in a rural household is likely to complete 0.721 fewer years of education relative to their first-born sibling while a fifth-born child in an urban household is likely to complete 0.327 fewer years of education relative to their first-born sibling. Here, the disadvantage facing the fifth-born, relative to her first-born counterpart, in a rural household, is higher than that of a fifth-born in an urban household.

Table 5.7: Effects of Gender and Birth Order by Rural and Urban

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Rural Areas** | | | **Urban Areas** | | |
| Variables | Private School enrolment | Completed Years of Education | Relative Grade Progression | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.001 | 0.164*** | 0.031*** | 0.004 | 0.074*** | 0.009** |
| | (0.002) | (0.011) | (0.003) | (0.005) | (0.020) | (0.005) |
| Second born | -0.008** | -0.216*** | -0.060*** | -0.007 | -0.174*** | -0.060*** |
| | (0.003) | (0.018) | (0.004) | (0.008) | (0.033) | (0.008) |
| Third born | -0.015*** | -0.441*** | -0.126*** | -0.002 | -0.314*** | -0.119*** |
| | (0.006) | (0.031) | (0.008) | (0.014) | (0.057) | (0.014) |
| Fourth child | -0.019** | -0.620*** | -0.185*** | -0.015 | -0.335*** | -0.182*** |
| | (0.009) | (0.045) | (0.011) | (0.021) | (0.083) | (0.021) |
| Fifth born | -0.036*** | -0.721*** | -0.280*** | -0.016 | -0.327*** | -0.295*** |
| | (0.013) | (0.063) | (0.022) | (0.032) | (0.126) | (0.043) |
| Constant | 0.301*** | -3.796*** | 0.025 | 0.459*** | -4.401*** | -0.073 |
| | (0.019) | (0.100) | (0.031) | (0.046) | (0.177) | (0.057) |
| Observations | 60,841 | 61,563 | 58,535 | 17,020 | 17,172 | 16,280 |
| R-squared | 0.041 | 0.820 | 0.115 | 0.035 | 0.839 | 0.132 |
| No. of households | 26,178 | 26,305 | 26,131 | 7,574 | 7,599 | 7,559 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Similarly, to formally test for the equality of the effects of gender and birth order between rural and urban areas, we estimate a fully interacted model by interacting every variable with the rural location dummy.[12] Results are shown in table 5.8. Since this is a fully interacted family fixed effects model with *a rural dummy*, the coefficients on gender (female) and birth order dummies in table 5.8 are for urban areas. Notice that the coefficients in the table are identical to those for urban areas presented in table 5.7 (columns 4, 5 and 6). Second, the interaction terms in table 5.8 capture the difference between rural and urban location on each of the model parameters (Gordon, 2015). A significant interaction term on the variable means that the effect of the variable on the measured dependent variable is significant between rural and urban. The interaction terms therefore provide a formal test of equality of gender and birth order effects between rural and urban areas (see Gordon (2015), Gujarati (1970a) and Gujarati (1970b) for theoretical foundations of fully interacted models and De Haan et al. (2014) and Moshoeshoe (2016) for empirical application).

[12]By a fully interacted model, the rural location dummy is interacted with our variables of interest (gender and birth order dummies) as well as all other variables (e.g. age, disability and tuition attendance status) in the family fixed effects model. In doing so, we allow all the parameters of the model including the intercept to vary by location (Gujarati, 1970b,a; Gordon, 2015). Two most recent studies that have investigated heterogeneity in birth order effects using fully interacted family fixed effects models are De Haan et al. (2014) and Moshoeshoe (2016).

Table 5.8: Effects of Gender and Birth Order: Fully Interacted Models with Rural Dummy

| | (1) Private School enrolment | (2) Completed Years of Education | (3) Relative Grade Progression |
|---|---|---|---|
| Female | 0.004 | 0.074*** | 0.009 |
| | (0.006) | (0.027) | (0.006) |
| Second born | -0.007 | -0.174*** | -0.060*** |
| | (0.010) | (0.043) | (0.011) |
| Third born | -0.002 | -0.314*** | -0.119*** |
| | (0.019) | (0.075) | (0.019) |
| Fourth child | -0.015 | -0.335*** | -0.182*** |
| | (0.028) | (0.110) | (0.029) |
| Fifth born | -0.016 | -0.327* | -0.295*** |
| | (0.043) | (0.167) | (0.058) |
| Female*rural | -0.005 | 0.090*** | 0.021*** |
| | (0.007) | (0.030) | (0.007) |
| Second-born*rural | -0.001 | -0.042 | 0.000 |
| | (0.011) | (0.049) | (0.012) |
| Third-born*rural | -0.013* | -0.127* | -0.007 |
| | (0.007) | (0.086) | (0.021) |
| Forth-born*rural | -0.005** | -0.285** | -0.003 |
| | (0.002) | (0.125) | (0.033) |
| Fifth-born*rural | -0.020** | -0.394** | 0.015 |
| | (0.010) | (0.187) | (0.065) |
| Constant | 0.336*** | -3.928*** | 0.004 |
| | (0.018) | (0.087) | (0.027) |
| Observations | 77,861 | 78,735 | 74,815 |
| R-squared | 0.791 | 0.909 | 0.676 |
| No. of households | 36,329 | 36,501 | 36,272 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\,years\,of\,education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

As can be seen in table 5.8, the interaction term between female dummy and rural dummy is significant only in the completed years of education regression ((column 2). This means that there is a strong female advantage in terms of completed years of education in rural than urban areas. However, there is no evidence of significant female advantage in terms of private school enrolment and relative grade progression between rural and urban areas. The interaction terms between birth order and rural dummy are negative and statistically significant in the private school enrolment and completed years of education regression. This means there are stronger negative birth order effects in terms of private school enrolment and completed years of education in rural than urban areas.

## 5.6 Possible Explanation for the Gender and Birth Order Effects

We now examine the possible explanation for the gender and birth order effects observed. In particular, our data allows us to test if the effects are propagated through the resource hypothesis or birth-spacing (or child-spacing) channel. All the estimates in this section are based on the family fixed effects model.

### 5.6.1 Gender, Birth Order Effects and Household Wealth

We begin by testing to see if the effects of gender and birth order are propagated through household wealth. In order to do this, we use the family wealth index constructed in chapter 2.[13] A number of studies have used a similar index to test the mechanisms through which birth order effects are propagated. A study by Tenikue and Verheyden (2010) uses a similar wealth index based on the Demographic and Health Survey data to examine birth order effects between siblings in rich and poor families in terms of schooling and child labor in 12 sub-Saharan Africa countries. They find that the education levels of earlier born children are lower than their later born siblings in poor households, whereas earlier-born children are more educated in richer ones.

There are a number of reasons why latter-born children do worse. The resource hypothesis (Downey, 2001) and quantity-quality (Becker, 1960) models argue that investment in children increases at higher levels of economic status. They argue that as the size of the family increases, per capita familial resources reduce thus reducing investment in children. If constraints on household resources are to some extent responsible for the negative effect of birth order as predicted by theoretical models, we might expect the negative effect of birth order to *be attenuated or even reversed* among rich households. Evidence in developing countries further shows that girls are likely to suffer more in resource constrained households (Garg and Morduch, 1998; Gupta, 1987). Therefore, we might expect a girl preference in rich households.

[13]Recall that in the previous chapter, we used this same family wealth index to assess the effect of private schools among poor and rich households.

Table 5.9: Effects of Gender and Birth Order by Household Wealth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Households Classified as Poor** | | | **Households Classified as Rich** | | |
| | Private School enrolment | Completed Years of Education | Relative Grade Progression | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.001 | 0.141*** | 0.026*** | 0.003 | 0.123*** | 0.022*** |
| | (0.002) | (0.014) | (0.003) | (0.006) | (0.024) | (0.006) |
| Second-born | -0.001 | -0.239*** | -0.065*** | -0.023** | -0.137*** | -0.048*** |
| | (0.004) | (0.023) | (0.006) | (0.010) | (0.038) | (0.010) |
| Third-born | 0.000 | -0.512*** | -0.132*** | -0.038** | -0.219*** | -0.096*** |
| | (0.007) | (0.040) | (0.010) | (0.018) | (0.067) | (0.017) |
| Fourth-born | -0.001 | -0.719*** | -0.193*** | -0.034 | -0.307*** | -0.153*** |
| | (0.011) | (0.058) | (0.015) | (0.027) | (0.098) | (0.027) |
| Fifth-born | -0.001 | -0.859*** | -0.282*** | -0.088** | -0.208 | -0.237*** |
| | (0.017) | (0.083) | (0.030) | (0.039) | (0.143) | (0.057) |
| Constant | 0.241*** | -3.314*** | -0.025 | 0.519*** | -5.238*** | -0.022 |
| | (0.023) | (0.130) | (0.042) | (0.057) | (0.213) | (0.069) |
| Observations | 62,055 | 62,843 | 59,798 | 21,597 | 21,779 | 20,591 |
| R-squared | 0.772 | 0.903 | 0.671 | 0.800 | 0.923 | 0.634 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

In table 5.9, we present the gender and birth order estimates for poor and rich households.[14] As can be seen from table 5.9, the results on the effect of gender on measured outcomes is similar to those in the headline regression- whether in poor or rich households, we find no presence of female advantage in terms of private school enrolments but there is a female advantage in terms of completed years of education and relative grade progression.

However, we see that among poor households (column 1), there are no significant birth order effects on private school enrolment. However, in rich households (column 4), young siblings are significantly less likely to attend private schools. For instance, a fifth-born child in a poor family has equal chance of attending a private school (relative to her eldest sibling) (column 1) while her counterpart in a rich family is 8.8 percentage point less likely to attend a private school (relative to her eldest sibling) (column 4). The results suggest that family wealth *intensifies* rather than *attenuates* the negative effect of birth order on private enrolment. This is surprising result that is contrary to our expectation. This is because attending a private school in Kenya involves some costs and if our measure of

[14]Following De Haan et al. (2014), we normalized the family wealth index to the range of 0 and 1 and classified households with a wealth index of 0.5 and above as rich and vice versa. We have confirmed that the results do not significantly change even when we use the family wealth index in its original form without normalization.

household wealth is accurate, we expect *family wealth* to *lessen* (or even reverse) rather than *worsen* the latter-born disadvantage in terms of private school access. We return to explain this peculiar result shortly.

In line with our theoretical predictions, table 5.9 shows that higher family wealth *attenuates* the negative effect of birth order on completed years of education and relative grade progression. The effects of birth order on the number of completed years of schooling are two times larger among poor households relative to rich households (columns 2 and 5). Similarly, birth order effects on relative grade progression are relatively higher among poor households relative to rich households (columns 3 and 6).

In table 5.10, we show results from a fully interacted family fixed effects model with a dummy variable indicating that the family is rich. The interaction terms between female dummy and a dummy variable for the rich household are insignificant in all the regressions. This means that family wealth does not have a gender effect (female advantage) in terms of private school enrolment, completed years of schooling and relative grade progression. The interaction of birth order effects and a dummy variable for the rich household are largely significant in all the dependent variables. The interaction terms with private school enrolments are negative (column 1) confirming results in table 5.9 that family wealth indeed *intensifies* rather than *attenuates* the negative effect of birth order on *private enrolment.* The interaction terms with completed years of education and relative grade progression (column 2 and 3) are positive showing that family wealth *attenuates* the negative effect of birth order on *completed years of education* and *relative grade progression*.

One might be concerned that our results are an artifact of our classification of poor and rich households. For instance, we normalized the family wealth to a range of 0 to 1 and classified households whose index was 0.5 and above as rich. Our results might be an artifact of such a cut-off point. To allay such fears, following De Haan et al. (2014), we allow the wealth index, in its continuous form, to be fully interacted with the gender, birth order dummies and all control variables. Results are shown in table D 5.2 in appendix D. Generally, the results do not deviate from those in table 5.9. As can be seen in table D 5.2, the interaction terms between female dummy and family wealth are largely insignificant.[15] On the other hand, the interaction term with birth order dummies are largely significant and further show that wealth *amplifies* the effects of birth order on private school enrolment and *attenuates* birth order effects on completed years of education and relative grade progression.

[15]Nonetheless, the interaction term between female dummy and family wealth is significant but only at 5 percent in the completed years of education regression showing that family wealth increases female advantage in terms of completed years of education.

Table 5.10: Effects of Gender and Birth Order: Fully Interacted Models with Rich Family Dummy

| | (1) | (2) | (3) |
|---|---|---|---|
| | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.001 | 0.141*** | 0.026*** |
| | (0.002) | (0.014) | (0.003) |
| Second-born | -0.001 | -0.239*** | -0.065*** |
| | (0.004) | (0.023) | (0.006) |
| Third-born | 0.000 | -0.512*** | -0.132*** |
| | (0.007) | (0.041) | (0.010) |
| Fourth-born | -0.001 | -0.719*** | -0.193*** |
| | (0.011) | (0.059) | (0.015) |
| Fifth-born | -0.001 | -0.859*** | -0.282*** |
| | (0.017) | (0.084) | (0.030) |
| Female*Rich household | 0.003 | -0.018 | -0.004 |
| | (0.007) | (0.027) | (0.007) |
| Second born*Rich household | -0.022** | 0.101** | 0.017 |
| | (0.011) | (0.044) | (0.011) |
| Third born*Rich household | -0.039** | 0.293*** | 0.036* |
| | (0.019) | (0.078) | (0.019) |
| Fourth child*Rich household | -0.033 | 0.412*** | 0.040* |
| | (0.028) | (0.113) | (0.020) |
| Fifth born*Rich household | -0.087** | 0.651*** | 0.044 |
| | (0.042) | (0.164) | (0.063) |
| Constant | 0.313*** | -3.809*** | -0.024 |
| | (0.017) | (0.084) | (0.026) |
| Observations | 83,652 | 84,622 | 80,389 |
| R-squared | 0.045 | 0.827 | 0.119 |
| No. of Households | 36,329 | 36,501 | 36,272 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\, years\, of\, education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

As promised, we return to the results in column 1 and 2 of table 5.9. Contrary to our expectation, there are no birth order effects among poor households and negative birth order effects among rich households. We maintain that attending a private school involves some costs and therefore *family wealth* should *lessen* rather than *worsen* the latter-born disadvantage in terms of private school access. To disentangle these results, we show the effects of birth order on private school enrolment by *region (rural and urban)* and *household wealth (poor and rich)* as shown in table 5.11. Recall that we attributed the lack of birth order effects in urban areas in table 5.7 (column 4) to the near universal access to private schools in urban areas. We further argued that the scarcity of private schools in rural areas could be driving up their prices thus inducing households to discriminate against some children in terms of private school access (see Table 5.7 column 1).

Table 5.11: Effects of Gender and Birth Order by Region and Household Wealth

| | Private School enrolment | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | **Urban Areas** | | **Rural Areas** | |
| | Rich Household | Poor Household | Rich Household | Poor Household |
| Female | -0.001 | 0.008 | 0.002 | -0.001 |
| | (0.011) | (0.008) | (0.007) | (0.003) |
| Second born | -0.004 | -0.007 | -0.037*** | 0.000 |
| | (0.018) | (0.012) | (0.012) | (0.005) |
| Third born | 0.011 | -0.004 | -0.069*** | 0.002 |
| | (0.034) | (0.022) | (0.021) | (0.008) |
| Fourth child | 0.017 | -0.020 | -0.071** | 0.001 |
| | (0.050) | (0.031) | (0.032) | (0.012) |
| Fifth born | 0.033 | -0.030 | -0.163*** | 0.002 |
| | (0.075) | (0.050) | (0.045) | (0.018) |
| Constant | 0.542*** | 0.350*** | 0.501*** | 0.235*** |
| | (0.104) | (0.069) | (0.070) | (0.026) |
| Observations | 8,022 | 8,998 | 12,436 | 48,405 |
| R-squared | 0.804 | 0.784 | 0.790 | 0.769 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Looking in column 1 and 2 of table 5.11, we see no birth order effects among both rich and poor houses in urban areas, consistent with results in table 5.7 (column 4). This is also consistent with our hypothesis that the near universal access to private schools in urban areas could have indeed eroded incentives for households to discriminate against some children in terms of their access. It therefore follows that the *negative birth order effects* we see in column 4 of table 5.9 among *rich households* is mainly driven by *rural* *rich households*. Column 3 of table 5.11 confirms this assertion: we see a significant negative association between birth order and private enrolment among children from rich households in rural areas. In column 4 of table 5.11, we do not see evidence of birth order effects among rural poor. This lack of birth order effects among rural poor combined with the lack of birth order effects among the urban poor in columns 2 of the same table means that the general lack of birth order effects on private school enrolments in table 5.9 (column 1) is being driven by both rural and urban poor households.

We can now speculate what is driving the peculiar results in column 1 and 4 of table 5.9. The near universal access of private schools in urban areas means that all children, from both rich and poor households, have a higher chance of accessing them. On the other hand, we think that the few private schools in rural areas seem to be accessible only by rich households. However, these households seem to be constrained due to the relatively high fees charged by these private schools and as a result, it is the first-borns who are favored. For the rural poor households, we think that these rural private schools/academies are almost non-accessible to them mainly due to affordability. Put differently, for the rural poor, it is not a question of intra-household discriminating against some children in terms of access to private schools but rather a general lack of access to private schools in rural areas due to costs.

The general lack of access to private schools by children from poor rural household can be seen in table D 5.3 in appendix D. In this table, we estimate the probability of private school enrolment (using a probit model) while accounting for among others, the interaction between a rural dummy and a dummy denoting whether a child is from a poor household. As it can be seen from the table, results show that children from rural poor households are indeed less likely to be enrolled in private schools.

In summary, private schools are highly concentrated in urban areas and as a result, they are accessible to all children, regardless of economic status. In rural areas, private schools are scarce and hence charging high fees. The high cost of attending private schools in rural areas seems to have, locked out the poor households and induced an intra-household child-discrimination among the rural households working in favour of first-born children.

## 5.7 Conclusion

In this chapter, we examine the effect of gender and birth order on intra-household education investment in children and the resultant educational outcomes in Kenya. We measure intra-household education investment in children by the household's decision to enrol children in private schools and educational outcomes by two variables: completed years of education and relative grade progression. We use the Uwezo survey and implement the household fixed effects models that control for potential endogeneity of gender, birth order, family size and the household level unobserved heterogeneity. We find no intra-household gender preference in terms of whether or not to enrol a child in private school. However, there is a consistent female advantage in terms of completed years of education and relative school progression. Regarding birth order effects, the results reveal a clear pattern of significant negative effects of birth order on private school enrolment, completed years of education and relative school progression.

The female advantage we find (in terms of *completed years of education* and *relative grade progression)* is generally not in consistent with literature reported from developing countries but in line with global trends which show that more girls are getting educated and the gender gap in education has narrowed considerably. Similarly, the first-born advantage we find seems to be in line with the findings in developed countries but not developing countries. Nevertheless, these results generally support the theoretical predictions of the confluence, resource hypothesis and quantity-quality models which predict a first-born advantage. Our results are robust to different robustness checks including correction of selectivity bias originating from non-enrolment of children and further attempts to measure birth order effects more accurately. We check the heterogeneity of the gender and birth order effects and find that these effects significantly differ by family size and by location of the family (rural or urban).

We end the discussion by testing for the drivers of our observed gender and birth order effects. We find evidence to support the hypothesis that our birth order effects (but not gender effects) are driven household wealth. Following De Haan (2010) and Moshoeshoe (2016), we also check if the gender and birth order effects are driven by child spacing. However, we do not report these results since the coefficients for the interaction of gender and birth order with average child spacing are effectively zero.

# Chapter 6

# Summary and Conclusions

## 6.1 Summary of Findings

The government of Kenya (like that of several sub-Saharan countries) has done well to make primary education free. Unfortunately, little attention has been paid to the quality of that education which has suffered. This thesis takes a deeper look at the available data and analyzes children's learning in Kenya. It then looks at the role teachers, private schools and the family in promoting children learning, each presented in a distinct essay. Building on the literature which emphasizes on the importance of the teacher input in student learning, the first essay explores the influence of teacher subject and pedagogical knowledge and teacher effort (in terms of teacher effective instruction time and classroom practices) on grade 4 language and maths test scores.

Regression results indicate that teacher subject knowledge and pedagogical skill matter for student achievements. A one standard deviation increase in the teacher's knowledge in language (maths) increases student test scores by 0.075 (0.126) score standard deviations in language (maths). Teachers who spend more time on instruction and can keep students engaged during the lesson are associated with higher student test scores. For instance, an additional hour of teacher effective instruction time increases student achievement by 0.051 and 0.059 score standard deviations in language and maths, respectively. There is evidence that a number of classroom teaching practices have an effect on student test scores although the effect differs between language and maths. For instance, the practice of reviewing and assigning homework increases student test scores in language by 0.383 standard deviations while it reduces test scores in maths by 0.377 standard deviations. While the practice of using local language to illustrate learning reduces student achievement in language by 0.161 standard deviations, it has no effect on maths.

The second essay examines the effect of private schools on literacy (language) and numeracy (maths) skill acquisition among children mainly drawn from lower primary grades in Kenya. We use the Uwezo survey, which, unlike the SDI survey, allows us to apply a number of approaches that deal with the endogenous nature of private school choice. We find a large effect of private schooling on test scores across all estimation techniques. In maths, we find a private school premium ranging from 0.13 to 0.20 score standard deviations, based on the household and village fixed effects models, respectively. In the case of language, the premium ranges from 0.20 to 0.29 score standard deviations, based on the household and village fixed effects models, respectively.

In the third essay, we shift our focus to analyze the role of the family in promoting human capital development of children in Kenya. Specifically, we investigate the effect of two important family characteristics - gender and birth order - on intra-household investments in, and educational outcomes of, children in Kenya aged. Our measure of intra-household education investment in children is the household's decision to enrol children in private schools. Educational outcomes by two variables: completed years of education and relative grade progression. We do not find a female advantage in terms of private school enrolment. However, we find a consistent female advantage in terms of completed years of education and relative grade progression. Our results show a significant negative birth order effects on the three dependent variables. We find that first-born children are more likely to be enrolled in private schools and complete more years of education. Furthermore, first-born children also progress through school much faster than their younger siblings. There is evidence to suggest that household wealth is driving the birth order (and not gender) effects we observe.

## 6.2 Limitations of the Study and Potential Areas for further Research

There are important limitations in this study that are unavoidable to mention. We present them by essay (chapter). In the first essay (chapter 3), we show that student scores in maths and language are driven by teacher human capital and teacher effort. However, the estimates we present are not causal. We could not apply some techniques known in the literature that deal with selection issues due to data limitations. For instance, we could not estimate a *school fixed effects model* (and by extension current techniques trending in the literature such as *within-teacher within-student variation*) primarily because there is no within school variation in the variables capturing teacher human capital and effort as only one teacher, *in our sample of 222 school was observed in class and assessed in* *the teacher tests.* Our results however do not deviate from those found in other studies that use these methods that deal with selections into schools. Nevertheless, establishing the causality of teacher knowledge and effort on student test scores to facilitate proper policy interventions remains a potential area for further research, but highly dependent on credible data.

There are a number of options for the next round of the SDI survey. For instance, the team should consider *observing and testing at least two or more teachers from different streams (e.g 4A and 4B) and/or from different grades (e.g grade 3 and grade 4) within a given school.* This will create a variation in the measures of teacher human capital and effort and allow estimation of a school fixed effects model. Efforts to undertake classroom observations and teacher tests from schools where students are taught by the same teacher in both subjects will particularly allow the application of within-teacher within-student variation approaches. This will allow a causal interpretation of the teacher knowledge and effort within a cross-sectional set-up (see studies by Metzler and Woessmann (2012); Shepherd (2013); Shepherd et al. (2015)).

All our measures of classroom practices are binary indicators. They simply indicate whether or not the teacher observed in the classroom engaged in the specific practice. For instance, in analyzing the effect of the practice of challenging students intellectually by asking them questions, we just know that the teacher simply posed questions to students. We have no knowledge about the nature of questions that teachers posed and the type of learners questions were directed to. Similarly, we simply know that the teacher had a lesson plan and a scheme of work (judged by the surveyors to be well prepared) but we are not entirely sure about the quality of these teaching tools. This certainly constrains the credibility of our estimates. Taking this work forward, we recommend that the next round of SDI survey should collect more details on these important pedagogical indicators. We know from past studies that classroom environments in Kenya are mainly characterized by teacher initiated questions and that boys are more likely to be asked questions than girls (Hardman et al., 2009; MoEHRD, 1999). The SDI classroom observation module should build on this previous work by collecting details information such as: type of questions asked, the initiators of the questions (between teachers and students), the gender of the students the questions are targeted to, among others.

In the second essay, we find that private schools are positively associated with student test score achievements. Analyzing the effectiveness of private schools in Kenya comes with a number challenges. For instance, private schools are quite heterogeneous. They mainly comprise highly fragmented non-formal schools (mainly located in informal settlements) and formal private academies (in middle and high-income urban areas).

Heterogeneity is also reflected in the mode of funding. We have government supported private and self-reliant private schools. As noted by Ashley et al. (2014), empirical work that does not account for these heterogeneities risks misrepresenting the private school effect. For example, in India, a study by Chakrabarti and Peterson (2008) finds that the effects of private aided schools are different from those of private unaided schools. Unfortunately, the manner in which our data was collected does not allow us to account for this heterogeneity. Our estimates should therefore be interpreted in the context of these limitation. Going forward, it would be useful to estimate the separate effects for aided and unaided private schools as well as formal and non-formal private schools. All this is however dependent on the availability of data.

An equally important question is why private schools perform better than public schools. We do not address this question because it is beyond the scope of our work and secondly, we do not have adequate data to answer it. However, researchers in Kenya argue that this public-private performance gap has little to do with resources. There is an overwhelming evidence which shows that most of the recent well performing private schools[1] are characterized by poor school infrastructure and learning facilities and lack well trained teachers (Tooley et al., 2008; Heyneman and Stern, 2014; Tooley and Longfield, 2015; Edwards Jr. et al., 2015; Piper and Mugenda, 2010; Oketch et al., 2010, 2012; Piper et al., 2015).[2] Not only are public school teachers more qualified (in terms of experience and level of training), they are also paid better than those in low-cost primary schools. A study carried out by Tooley and Dixon (2005) reported that public school teachers in Nairobi earn an average monthly salary that is almost three times more that that of private school counterparts. Bold et al. (2012) reported that average salaries for civil service teachers in 2009 were roughly 261 US dollars relative to 56 US dollars paid to teachers hired informally by local school management committees.

However, we know that the Kenyan public education school system faces a number of challenges mainly related to teacher effort. Many public schools are characterized by high rates of teacher absenteeism and even worse, teachers who do report to classes even when in school. Table 3.3 in chapter 3 shows that a public school teacher is almost 14 percent points more likely to be absent from class relative to his/her counterpart in a private school. A survey by Gideon (2014) based on two Coastal Counties of Kenya (Kilifi and Kwale) finds that public school teachers in these Counties do not show up for nearly a quarter of their weekly lessons, leaving the learners on their own. According to the the

[1] That is the *non-formal schools* in urban informal settlements as well as the *formal private academies* located in medium income urban locations.

[2] Table 2.2 (b) in Chapter 2 shows no discernible differences in the quality of infrastructure between private and the public schools in the SDI survey.

Global Monitoring Report (Education for All 2000-2015), on a typical day, more than 40,000 of the 200,000 public primary school teachers stay out of classes (UNESCO, 2015). It is therefore possible that factors related to teacher effort could be potential candidates that can explain the public-private performance gap in Kenya. We identify this as a potential area for future research which of course hinges on availability of data.

In the third essay (Chapter 3), we analyze the gender and birth order effects on children outcomes but make several assumptions, purely because of data limitations. To mention a few, we assume that all children are biological children of the family with whom they live at the time of the survey since there was no question in Uwezo survey distinguishing between biological and non-biological household children. We construct indicators of birth order and average child spacing based on their reported year of birth. Unfortunately, Uwezo does not allow us to know if there are children who were staying outside the household at the time of the survey and if some of the children were not alive. In addition, Uwezo did not directly ask if the household had twins or not. If two or more children in the household have the same age, we assume that such children are twins. Efforts by the Uwezo team to include questions that clarify children's biological relationship with parents and among other information related to siblings will provide an avenue to improve on this work.

We test for the mechanisms through which the gender and birth order effects we observe are propagated. The results show that the observed negative birth order effects are driven by household wealth. As it is a common practice in the literature, we construct family wealth based on a wide range of household socioeconomic characteristics. We do not rule out possible measurement errors in our measure of family wealth which may have implications on our results. Efforts to collect data on household income or expenditure, two conventional measures of household living standards will provide an avenue to further investigate the role of family wealth in the gender and birth order effects we present. In addition, the extent to which we examine the drivers for the our observed gender and birth order effects are transmitted is constrained by data. More generally, subject to data availability, research is needed to test many other possible drivers for the gender and birth order effects.

## 6.3 Policy Implications

Our finding that student scores are driven by teacher knowlegde, pedagogy, effective instruction time and teacher classroom practices suggest that intervention at the level of teacher knowledge and effort as policy instruments may improve tests scores. First, there is need to institute innovative policies and strategies, including at the school level, to encourage teacher attendance both in school and in class. Schools should also find ways to substitute for absent teachers. There is need for re-fresher courses for teachers on courses related to their subject content to increase their subject knowlegde as well as courses aimed at enhancing the teacher's capacity in classroom management including how to effectively use classroom instructional time.

The finding that private schools are associated with better student achievements has clear implications for policymakers. Expanding access to private schools provides an opportunity to deal with the challenge of declining quality of education in Kenya. Following Bold et al. (2013b), we foresee two policy approaches. The first policy option includes implementing *the school voucher system*, a strategy that combines private provision of education with public finance, a common practice in the USA and Latin America. The school voucher system involves the government giving parents funds to pay for their children education in private schools (see Angrist et al. (2002)). The second policy option involves integrating, into the current public education school system, pedagogical techniques and organizational structures of private schools (see Bold et al. (2013b)).

There are also implications for policymakers from the finding that latter-born children, especially in poor and large households, lag behind in terms of education outcomes. This call for efforts to sensitize the population on the importance of family planning. There is also need to institute interventions such as cash transfer and other financial assistance to large and poor families. Given that its is latter-born children who are most disadvantaged, such support systems should be designed to improve the conditions of latter-born children.

# Bibliography


Aakvik, A. (2001). Bounding a matching estimator: the case of a norwegian training program. *Oxford bulletin of economics and statistics*, 63(1):115–143.

Aaronson, D., Barrow, L., and Sander, W. (2007). Teachers and student achievement in the chicago public high schools. *Journal of labor Economics*, 25(1):95–135.

Ackers, J. and Hardman, F. (2001). Classroom interaction in kenyan primary schools. *Compare*, 31(2):245–261.

Alcazar, L., Rogers, F. H., Chaudhury, N., Hammer, J., Kremer, M., and Muralidharan, K. (2006). Why are teachers absent? probing service delivery in peruvian primary schools. *International Journal of Educational Research*, 45(3):117–136.

Altinok, N. and Kingdon, G. (2012). New evidence on class size effects: A pupil fixed effects approach. *Oxford Bulletin of Economics and Statistics*, 74(2):203–234.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2000). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. Technical report, National bureau of economic research.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of Political Economy*, 113(01):151–184.

Andrabi, T., Das, J., and Khwaja, A. I. (2008). A dime a day: The possibilities and limits of private schooling in pakistan. *Comparative Education Review*, 52(3):329–355.

Angrist, J., Bettinger, E., Bloom, E., King, E., and Kremer, M. (2002). Vouchers for private schooling in colombia: Evidence from a randomized natural experiment. *The American Economic Review*, 92(05):1535–1558.

ASER (2014). Annual status of education report (rural) 2014. Technical report, New Delhi, India: ASER.

Ashley, L. D., Mcloughlin, C., Aslam, M., Engel, J., Wales, J., Rawal, S., Batley, R., Kingdon, G., and Nicolai, S. (2014). The role and impact of private schools in developing countries: A rigorous review of the evidence. final report. education rigorous literature review. Technical report, Department for International Development.

Aslam, M. and Kingdon, G. (2011). What can teachers do to raise pupil achievement? *Economics of Education Review*, 30(3):559–574.

Austin, P. C. (2008). A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003. *Statistics in medicine*, 27(12):2037–2049.

Azam, M., Kingdon, G., and Wu, K. B. (2015). Impact of private secondary schooling on cognitive skills: evidence from india. *Education Economics*, pages 1–16.

Azam, M. and Kingdon, G. G. (2015). Assessing teacher quality in india. *Journal of Development Economics*, 117:74–83.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Bank, W. (2014). Laying the foundation for a robust health care system in kenya: Kenya public expenditure review. Technical report, Nairobi, Kenya: World Bank.

Basu, K. and Van, P. H. (1998). The economics of child labor. *American economic review*, pages 412–427.

Becker, G. S. (1960). An economic analysis of fertility. In *Demographic and economic change in developed countries*, pages 209–240. Columbia University Press.

Becker, S. O. and Caliendo, M. (2007). Mhbounds-sensitivity analysis for average treatment effects.

Behrman, J. R., Rosenzweig, M. R., and Taubman, P. (1994). Endowments and the allocation of schooling in the family and in the marriage market: the twins experiment. *Journal of Political Economy*, pages 1131–1174.

Bharath, S. T., Dahiya, S., Saunders, A., and Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Financial Studies*, 24(4):1141–1203.

Bietenbeck, J.-C. (2011). Teaching practices and student achievement: evidence from timss. *Yayımlanmamış yüksek lisans tezi. CEMFI*, (114).

Black, S. E., Devereux, P. J., and Salvanes, K. G. (2005). The more the merrier? the effect of family size and birth order on children's education. *The Quarterly Journal of Economics*, pages 669–700.

Blake, J. (1981). Family size and the quality of children. *Demography*, 18(4):421–442.

Bold, T., Kimenyi, M., Mwabu, G., and Sandefur, J. (2011a). The high return to private schooling in a low-income country. *Center for Global Development Working Paper*, (279).

Bold, T., Kimenyi, M., Mwabu, G., and Sandefur, J. (2011b). Why did abolishing fees not increase net enrollment in kenyan public schools?. *Center for Global Development, Working Paper*, (271).

Bold, T., Kimenyi, M., Mwabu, G., and Sandefur, J. (2013a). The high return to low-cost private schooling in a developing country. *London: International Growth Centre (IGC) London School of Economics*.

Bold, T., Kimenyi, M., Mwabu, G., Sandefur, J., et al. (2010). Does abolishing fees reduce school quality? evidence from kenya. *Centre for the Study of African Economics (CSAE) Working Paper WPS/2011-04*.

Bold, T., Kimenyi, M., Mwabu, G., and Welcome, P. D.-C. (2012). Interventions & institutions experimental evidence on scaling up education reforms in kenya. *URL www. iies. su. se/polopoly_ fs/1.101632*, 1348137980.

Bold, T., Kimenyi, M. S., and Sandefur, J. (2013b). Public and private provision of education in kenya. *Journal of African Economies*, 22(suppl 2):ii39–ii56.

Booth, A. L. and Kee, H. J. (2009). Birth order matters: the effect of family size and birth order on educational attainment. *Journal of Population Economics*, 22(2):367–397.

Boyd, D., Grossman, P., Lankford, H., Loeb, S., and Wyckoff, J. (2006). How changes in entry requirements alter the teacher workforce and affect student achievement. *Education*, 1(2):176–216.

Bruns, B. and Luque, J. (2014). *Great teachers: How to raise student learning in Latin America and the Caribbean*. World Bank Publications.

Bruns, B. and Rakotomalala, R. (2003). *Achieving universal primary education by 2015: A chance for every child*, volume 1. World Bank Publications.

Bryk, A. S. and Raudenbush, S. W. (1992). *Hierarchical linear models: applications and data analysis methods.* Sage Publications, Inc.

Caceres-Delpiano, J. (2006). The impacts of family size on investment in child quality. *Journal of Human Resources*, 41(4):738–754.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1):31–72.

Case, A. and Deaton, A. (1999). School inputs and educational outcomes in south africa. *Quarterly journal of economics*, pages 1047–1084.

Cavalcanti, T., Guimaraes, J., and Sampaio, B. (2010). Barriers to skill acquisition in brazil: Public and private school students performance in a public university entrance exam. *The Quarterly Review of Economics and Finance*, 50(4):395–407.

Cavatassi, R., Davis, B., Lipper, L., et al. (2004). Estimating poverty over time and space: construction of a time-variant poverty index for costa rica. *Rome: Food and Agriculture Organization*.

Chakrabarti, R. and Peterson, P. E. (2008). School choice international: Exploring public-private partnerships. *MIT Press (BK)*.

Chaudhury, N., Hammer, J., Kremer, M., Muralidharan, K., and Rogers, F. H. (2006). Missing in action: teacher and health worker absence in developing countries. *The Journal of Economic Perspectives*, 20(1):91–116.

Clotfelter, C. T., Ladd, H. F., and Vigdor, J. L. (2006). Teacher-student matching and the assessment of teacher effectiveness. *Journal of Human Resources*, 41(4):778–820.

Clotfelter, C. T., Ladd, H. F., and Vigdor, J. L. (2007). Teacher credentials and student achievement: Longitudinal analysis with student fixed effects. *Economics of Education Review*, 26(6):673–682.

Conley, D. and Glauber, R. (2006). Parental educational investment and childrens academic risk estimates of the impact of sibship size and birth order from exogenous variation in fertility. *Journal of human resources*, 41(4):722–737.

Corder, S. P. (1982). *Error analysis and interlanguage*, volume 198. Oxford University Press.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. Technical report, National Bureau of Economic Research.

Cunha, F., Heckman, J. J., Lochner, L., and Masterov, D. V. (2006). Interpreting the evidence on life cycle skill formation. *Handbook of the Economics of Education*, 1:697–812.

Danielson, C. (1996). A framework for teaching. *Alexandria, VA: Association for Supervision and Curriculum Development*.

De Haan, M. (2010). Birth order, family size and educational attainment. *Economics of Education Review*, 29(4):576–588.

De Haan, M., Plug, E., and Rosero, J. (2014). Birth order and human capital development evidence from ecuador. *Journal of Human Resources*, 49(2):359–392.

Dee, T. S. (2005). A teacher like me: Does race, ethnicity, or gender matter? *American Economic Review*, pages 158–165.

Dehejia, R. H. and Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, 84(1):151–161.

Desai, S., Dubey, A., Joshi, B., Sen, M., Sheriff, A., and Vanneman, R. (2008). India human development survey. *College Park, Maryland: University of Maryland*.

Desai, S., Dubey, A., Vanneman, R., Banerji, R., et al. (2009). Private schooling in india: A new educational landscape. In *India Policy Forum*, volume 5, pages 1–38. National Council of Applied Economic Research.

Dieterle, S., Guarino, C. M., Reckase, M. D., and Wooldridge, J. M. (2015). How do principals assign students to teachers? finding evidence in administrative data and the implications for value added. *Journal of Policy Analysis and Management*, 34(1):32–58.

Dixon, P. (2012). Why the denial? low-cost private schools in developing countries and their contributions to education. *Econ Journal Watch*, 9(3).

Dixon, P. and Tooley, J. (2012). A case study of private schools in kibera: an update. *Educational Management Administration & Leadership*, page 1741143212456908.

Dobbie, W. and Fryer Jr, R. G. (2011). Getting beneath the veil of effective schools: Evidence from new york city. Technical report, National Bureau of Economic Research.

Dostie, B. and Jayaraman, R. (2006). Determinants of school enrollment in indian villages. *Economic Development and Cultural Change*, 54(2):405–421.

Downey, D. B. (2001). Number of siblings and intellectual development: The resource dilution explanation. *American Psychologist*, 56(6-7):497.

Echaune, M., Ndiku, J, M., and Sang, A. (2015). Parental involvement in homework and primary school academic performance in kenya. *Journal of Education and Practice*, 6(9).

Edwards Jr., D. B., Klees, S., and Wildish, J. (2015). Dynamics of low-fee private schools in kenya: Governmental legitimation,school-community dependence,and resource uncertainty. Technical report, Teachers College Record, forthcoming.

Ejrnaes, M. and Portner, C. C. (2004). Birth order and the intrahousehold allocation of time and education. *Review of Economics and Statistics*, 86(4):1008–1019.

Evans, W. N. and Schwab, R. M. (1995). Finishing high school and starting college: Do catholic schools make a difference? *The Quarterly Journal of Economics*, pages 941–974.

Faries, D. E., Obenchain, R., Haro, J. M., and Leon, A. C. (2010). *Analysis of observational health care data using SAS.* SAS Institute.

Fehrler, S., Michaelowa, K., and Wechtler, A. (2009). The effectiveness of inputs in primary education: insights from recent student surveys for sub-saharan africa. *The Journal of Development Studies*, 45(9):1545–1578.

Fielding, A. (2010). Module 8: Multilevel modelling in practice: Research questions, data preparation and analysis. *LEMMA VLE, University of Bristol, Centre for Multilevel Modelling. Retrieved December*, 16:2014.

Filmer, D. (2005). Gender and wealth disparities in schooling: Evidence from 44 countries. *International Journal of Educational Research*, 43(6):351–369.

Filmer, D., Molina, E., and Stacy, B. (2015). What goes on inside the classroom in africa? assessing the relationship between what teachers know, what happened in the classroom, and student performance.

Filmer, D. and Pritchett, L. H. (2001). Estimating wealth effects without expenditure data or tears. an application to educational enrollments in states of india. *Demography*, 38(1):115–132.

Filmer, D., Scott, K., et al. (2008). *Assessing asset indices*, volume 4605. World Bank Publications.

French, R. (2008). Schooling participation and pupil achievement in india. Technical report, Department of Quantitative Social Science. London, Institute of Education, University of London.

French, R., Kingdon, G., et al. (2010). The relative effectiveness of private and government schools in rural india: Evidence from aser data. *London: Institute of Education.*

Garg, A. and Morduch, J. (1998). Sibling rivalry and the gender gap: Evidence from child health outcomes in ghana. *Journal of Population Economics*, 11(4):471–493.

Gelman, A. and Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Gideon, W. (2014). Titled missing in action: Where are the teachers? Technical report, Breakthrough Foundation, Nairobi Kenya.

Glewwe, P. (2002). Schools and skills in developing countries: Education policies and socioeconomic outcomes. *Journal of economic literature*, 40(2):436–482.

Glewwe, P. and Jacoby, H. (1994). Student achievement and schooling choice in low-income countries: Evidence from ghana. *Journal of Human Resources*, pages 843–864.

Glewwe, P. and Kremer, M. (2006). Schools, teachers, and education outcomes in developing countries. *Handbook of the Economics of Education*, 2:945–1017.

Glewwe, P. W., Hanushek, E. A., Humpage, S. D., and Ravina, R. (2011). School resources and educational outcomes in developing countries: A review of the literature from 1990 to 2010. Technical report, National Bureau of Economic Research.

Goe, L., Bell, C., and Little, O. (2008). Approaches to evaluating teacher effectiveness: A research synthesis. *National Comprehensive Center for Teacher Quality*.

GoK (2013). Exploring kenyas inequality: Pulling apart or pooling together? Technical report, Nairobi: Government Printer.

GoK (2015). Economic survey. Technical report, Nairobi: Government Printer.

Goldberger, A. S. and Cain, G. G. (1982). The causal analysis of cognitive outcomes in the coleman, hoffer and kilgore report. *Sociology of education*, 55(2):103–122.

Goldhaber, D. D. and Eide, E. R. (2003). Methodological thoughts on measuring the impact of private sector competition on the educational marketplace. *Educational Evaluation and Policy Analysis*, 25(2):217–232.

Gordon, R. A. (2015). *Regression Analysis for the Social Sciences*. New York: Routlegde.

Govinda, R. and Varghese, N. V. (1993). Quality of primary schooling in india: A case study of madhya pradesh. Technical report, Paris 07 SP, France: UNESCO.

Gujarati, D. (1970a). Use of dummy variables in testing for equality between sets of coefficients in linear regressions: A generalization. *The American Statistician*, 24(5):18–22.

Gujarati, D. (1970b). Use of dummy variables in testing for equality between sets of coefficients in two linear regressions: a note. *The American Statistician*, 24(1):50–52.

Gupta, M. D. (1987). Selective discrimination against female children in rural punjab, india. *Population and development review*, pages 77–100.

Hammersley, M., Kozma, T., Reid, I., Yogev, A., Shapira, R., Halsey, A., Heath, A., and Ridge, J. (1981). Origins and destinations. *British Journal of the Sociology of Education*, 2(1):91–5.

Hanushek, E. A. (2006). School resources. *Handbook of the Economics of Education*, 2:865–908.

Hanushek, E. A. (2008). Incentives for efficiency and equity in the school system. *Perspektiven der Wirtschaftspolitik*, 9(s1):5–27.

Hanushek, E. A. and Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of economic literature*, pages 607–668.

Hanushek, E. A. and Woessmann, L. (2012). Do better schools lead to more growth? cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, 17(4):267–321.

Hardman, F., Abd-Kadir, J., Agg, C., Migwi, J., Ndambuku, J., and Smith, F. (2009). Changing pedagogical practice in kenyan primary schools: the impact of school-based training. *Comparative Education*, 45(1):65–86.

Harkonen, J. (2014). Birth order effects on educational attainment and educational transitions in west germany. *European sociological review*, 30(2):166–179.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Heyneman, S. P. and Stern, J. M. (2014). Low cost private schools for the poor: What public policy is appropriate? *International Journal of Educational Development*, 35:3–15.

Hidalgo Cabrillana, A. and Lopez-Mayan, C. (2015). Teaching styles and achievement: student and teacher perspectives. *Available at SSRN 2569020*.

Horrace, W. C. and Oaxaca, R. L. (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters*, 90(3):321–327.

Hox, J. (2010). *Multilevel analysis: Techniques and applications*. Routledge.

Jacob, B. A. and Lefgren, L. (2005). Principals as agents: Subjective performance measurement in education. Technical report, National Bureau of Economic Research.

Jaeger, M. M. (2009). Sibship size and educational attainment. a joint test of the confluence model and the resource dilution hypothesis. *Research in social stratification and mobility*, 27(1):1–12.

Javaid, K., Musaddiq, T., and Sultan, A. (2012). Prying the private school effect: an empirical analysis of learning outcomes of public and private schools in pakistan. Technical report, Lahore: University of Management Sciences (LUMS), Department of Economics.

Jones, S., Schipper, Y., Ruto, S., and Rajani, R. (2014). Can your child read and count? measuring learning outcomes in east africa. *Journal of African economies*, 23(5):643–672.

Kane, T. J., Taylor, E. S., Tyler, J. H., and Wooten, A. L. (2011). Identifying effective classroom practices using student achievement data. *Journal of Human Resources*, 46(3):587–613.

King, E. and Winthrop, R. (2015). Today's challenges for girl's education. Technical report, Brookings Institute Working Paper No. 90.

Kingdon, G. and Teal, F. (2010). Teacher unions, teacher pay and student performance in india: A pupil fixed effects approach. *Journal of Development Economics*, 91(2):278–288.

Kingdon, G. G. (2006). Teacher characteristics and student performance in india: A pupil fixed effects approach.

KIPPRA (2016). Kenya economic report 2016: Fiscal decentralization in support of devolution. Technical report, Kenya Institute for Public Policy Research and Analysis (KIPPRA), Nairobi, Kenya.

KNBS (2009). The 2009 kenya population and housing census. Technical report, Kenya National Bureau of Statistics, Nairobi, Kenya.

KNBS (2014). 2014 demographic and health survey key findings. Technical report, Kenya National Bureau of Statistics, Nairobi, Kenya.

Kristensen, P. and Bjerkedal, T. (2007). Explaining the relation between birth order and intelligence. *Science*, 316(5832):1717–1717.

Kukla-Acevedo, S. (2009). Do teacher characteristics matter? new results on the effects of teacher preparation on student achievement. *Economics of Education Review*, 28(1):49–57.

Larbi, G., Adelabu, M., Rose, P., Jawara, D., Nwaorgu, O., and Vyas, S. (2004). Non-state providers of basic services. *Country Studies, Nigeria. Birmingham: University of Birmingham*.

Lavy, V. (2010). Do differences in schools' instruction time explain international achievement gaps? evidence from developed and developing countries. Technical report, National Bureau of Economic Research.

Lavy, V. (2011). What makes an effective teacher? quasi-experimental evidence. Technical report, National Bureau of Economic Research.

Lavy, V. (2012). Expanding school resources and increasing time on task: effects of a policy experiment in israel on student academic achievement and behavior. Technical report, National Bureau of Economic Research.

Lochner, L. (2011). Non-production benefits of education: Crime, health, and good citizenship. Technical report, National Bureau of Economic Research.

Maitra, P., Pal, S., and Sharma, A. (2014). What explains the gender gap in private school enrolment? recent evidence from india. *Recent Evidence from India (October 31, 2014)*.

Maitra, P., Pal, S., and Sharma, A. (2016). Absence of altruism? female disadvantage in private school enrollment in india. *World Development*, 85:105–125.

Makori, A., Chepwarwa, J., Jepkenei, E., and Jacob, P. (2015). Admission into public secondary schools in kenya:understanding parental preferential limitations. *Journal of Educational and Social Research*, 5:3–12.

Mani, S., Hoddinott, J., and Strauss, J. (2013). Determinants of schooling: Empirical evidence from rural ethiopia. *Journal of African Economies*, 22(5):693–731.

Martin, G. H. and Pimhidzai, O. (2013). Education and health services in kenya: Data for results and accountability.

McEwan, P. J. (2002). Public subsidies for private schooling: A comparative analysis of argentina and chile. *Journal of Comparative Policy Analysis*, 4(2):189–216.

McEwan, P. J. and Carnoy, M. (2000). The effectiveness and efficiency of private schools in chile's voucher system. *Educational evaluation and policy analysis*, 22(3):213–239.

McLaughlin, B. (2013). *Second language acquisition in childhood: Volume 2: School-age Children*. Psychology Press.

Metzler, J. and Woessmann, L. (2012). The impact of teacher subject knowledge on student achievement: Evidence from within-teacher within-student variation. *Journal of Development Economics*, 99(2):486–496.

Mincer, J. (1970). The distribution of labor incomes: a survey with special reference to the human capital approach. *Journal of Economic Literature*, 8(1):1–26.

Mincer, J. (1974). Schooling, experience, and earnings. human behavior & social institutions no. 2.

MoEHRD (1999). Classroom interaction in kenyan primary schools: A national primary baseline special study. Technical report, Nairobi, Kenya: Ministry of Education and Human Resource Development.

Monk, D. H. (1994). Subject area preparation of secondary mathematics and science teachers and student achievement. *Economics of education review*, 13(2):125–145.

Moshoeshoe, R. (2016). Birth order effects on educational attainment and child labour: Evidence from lesotho. Technical report, Economic Research Southern Africa (ERSA), Working paper 621.

Newhouse, D. and Beegle, K. (2006). The effect of school type on academic achievement evidence from indonesia. *Journal of Human Resources*, 41(3):529–557.

Ngware, M. W., Oketch, M., and Mutisya, M. (2014). Does teaching style explain differences in learner achievement in low and high performing schools in kenya? *International Journal of Educational Development*, 36:3–12.

Nichols, A. and Schaffer, M. (2007). Clustered errors in stata. In *United Kingdom Stata Users' Group Meeting*.

Nishimura, M. and Yamano, T. (2013). Emerging private education in africa: determinants of school choice in rural kenya. *World Development*, 43:266–275.

Oketch, M., Mutisya, M., Ngware, M., and Ezeh, A. C. (2010). Why are there proportionately more poor pupils enrolled in non-state schools in urban kenya in spite of fpe policy? *International Journal of Educational Development*, 30(1):23–32.

Oketch, M., Mutisya, M., and Sagwe, J. (2012). Do poverty dynamics explain the shift to an informal private schooling system in the wake of free public primary education in nairobi slums? *London Review of Education*, 10(1):3–17.

Oketch, M. and Ngware, M. (2010). Free primary education still excludes the poorest of the poor in urban kenya. *Development in Practice*, 20(4-5):603–610.

Oketch, M. and Somerset, A. (2010). Free primary education and after in kenya: Enrolment impact, quality effects, and the transition to secondary school.

Olembo, J. O. (1985). Financing primary school buildings in kenya. Technical report, Nairobi: Transafrica Press.

Onsomu, E., Nzomo, J., and Obiero, C. (2005). The sacmeq ii project in kenya: A study of the conditions of schooling and the quality of education. Technical report, ResearchTriangle Park. NC, USA: RTI International.

Orazem, P. F. and King, E. M. (2007). Schooling in developing countries: The roles of supply, demand and government policy. *Handbook of development economics*, 4:3475–3559.

Pal, S. (2010). Public infrastructure, location of private schools and primary school attainment in an emerging economy. *Economics of Education Review*, 29(5):783–794.

Piper, B. and Mugenda, A. (2012). The primary math and reading (primr) initiative:baseline report. Technical report, RTI International,Research Triangle Park, NC, USA.

Piper, B. and Mugenda, O. (2010). The primary math and reading (primr) initiative: Baseline report. Technical report, Kenya National ExaminationsCouncil, Nairobi.

Piper, B., Schroeder, L., and Trudell, B. (2015). Oral reading fluency and comprehension in kenya: reading acquisition in a multilingual environment. *Journal of Research in Reading*.

Piper, B., Zuilkowski, S. S., and Mugenda, A. (2014). Improving reading outcomes in kenya: First-year effects of the primr initiative. *International Journal of Educational Development*, 37:11–21.

Pontefract, C. and Hardman, F. (2005). The discourse of classroom interaction in kenyan primary schools. *Comparative education*, 41(1):87–106.

Price, J. (2008). Parent-child quality time does birth order matter? *Journal of Human Resources*, 43(1):240–265.

Pritchet, L. and Banerji, R. (2013). Schooling is not education! using assessment to change the politics of non-learning. Technical report, Center for Global Development Washington, D.C.

Psacharopoulos, G. (1987). Public versus private schools in developing countries: evidence from colombia and tanzania. *International Journal of Educational Development*, 7(1):59–67.

Psacharopoulos, G. and Patrinos, H. A. (2004). Returns to investment in education: a further update. *Education economics*, 12(2):111–134.

Riddell, A. (2003). The introduction of free primary education in sub-saharan africa. *Background paper prepared for the Education for All Global Monitoring Report*, 4.

Rivkin, S. G., Hanushek, E. A., and Kain, J. F. (2005). Teachers, schools, and academic achievement. *Econometrica*, pages 417–458.

Rockoff, J. E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. *American Economic Review*, pages 247–252.

Rockoff, J. E., Staiger, D. O., Kane, T. J., and Taylor, E. S. (2010). Information and employee evaluation: Evidence from a randomized intervention in public schools. Technical report, National Bureau of Economic Research.

Rosenbaum, P. R. (2002). Observational studies. Technical report, 2nd ed. New York: Springer.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2):135–146.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology*, 66(5):688.

Sahoo, S. (2016). Intra-household gender disparity in school choice: Evidence from private schooling in india. *Journal of Development Studies (forthcoming).*

Schwerdt, G. and Wuppermann, A. C. (2011). Is traditional teaching really all that bad? a within-student between-subject approach. *Economics of Education Review*, 30(2):365–379.

Shepherd, D. (2013). The impact of teacher subject knowledge on learner performance in south africa: A within-pupil across-subject approach. In *International Workshop on Applied Economics of Education, Cantanzaro*, pages 1–32.

Shepherd, D. et al. (2015). Learn to teach, teach to learn: A within-pupil across-subject approach to estimating the impact of teacher subject knowledge on south african grade 6 performance. Technical report.

Simumba, J. (2013). Child labour and schooling: Evidence from rural zambia. Technical report, Zambia Institute for Policy Analysis and Research Discussion Paper.

Smith, J. (2000). A critical survey of empirical methods for evaluating active labor market policies. Technical report, Research Report, Department of Economics, University of Western Ontario.

Spence, M. and Lewis, M. A. (2009). *Health and growth.* World Bank Publications.

Spernes, K. (2011). I buy paraffin so he can read in the evening–a study from kenya about parental involvement in school. *International Journal About Parents in Education*, 5(1).

Stallings, J. (1977). *Learning to Look: A Handbook on Classroom Observation and Teaching Models.* Belmont, CA: Wadsworth Publishing.

Stallings, J. and Knight, S. (2003). Using the stallings observation system to investigate: Time on task in four countries. Technical report, Unpublished paper for the International Time on Task Project, World Bank, Washington, DC.

Stock, J. H. (2010). The other transformation in econometric practice: Robust tools for inference. *The journal of economic perspectives*, 24(2):83–94.

Swanson, R. C., Cattaneo, A., Bradley, E., Chunharas, S., Atun, R., Abbas, K. M., Katsaliaki, K., Mustafee, N., Meier, B. M., and Best, A. (2012). Rethinking health systems strengthening: key systems thinking tools and strategies for transformational change. *Health Policy and Planning*, 27(suppl 4):iv54–iv61.

Tenikue, M. and Verheyden, B. (2007). Birth order, child labor and schooling: Evidence from cameroon.

Tenikue, M. and Verheyden, B. (2010). Birth order and schooling: Theory and evidence from twelve sub-saharan countries. *Journal of African Economies*, 19(4):459–495.

Thapa, A. (2015). Public and private school performance in nepal: an analysis using the slc examination. *Education Economics*, 23(1):47–62.

Todd, P. E. and Wolpin, K. I. (2003). On the specification and estimation of the production function for cognitive achievement*. *The Economic Journal*, 113(485):F3–F33.

Tooley, J. (2013). Challenging educational injustice: Grassroots privatisation in south asia and sub-saharan africa. *Oxford Review of Education*, 39(4):446–463.

Tooley, J., Bao, Y., Dixon, P., and Merrifield, J. (2011). School choice and academic performance: Some evidence from developing countries. *Journal of School Choice*, 5(1):1–39.

Tooley, J. and Dixon, P. (2005). *Private education is good for the poor: A study of private schools serving the poor in low-income countries*. Cato Institute Washington, DC.

Tooley, J., Dixon, P., and Stanfield, J. (2008). Impact of free primary education in kenya a case study of private schools in kibera. *Educational Management Administration & Leadership*, 36(4):449–469.

Tooley, J. and Longfield, D. (2015). The role and impact of private schools in developing countries: A response to the dfid-commissioned rigorous.

Trudell, B. and Piper, B. (2013). Whatever the law says: Language policy implementation and early-grade literacy achievement in kenya. *Current Issues in Language Planning*, 1(15).

UN (2015). The millennium development goals report 2015. Technical report, New York:United Nations.

UNESCO (2000). The dakar framework for action- education for all: Meeting our collective commitments. Technical report, Paris:UNESCO.

UNESCO (2015). Education for all 2000-2015: Global monitoring report. Technical report, Paris 07 SP, France: UNESCO.

Uwezo (2012). Are our children learning? annual learning assessment report 2012. Technical report, Twaweza East Africa,Dar es Salaam, Tanzania.

Uwezo (2014). Are our children learning? annual learning assessment report- the state of education in kenya in 2015 and beyond. Technical report, Twaweza East Africa, Nairobi, Kenya.

Uwezo (2015). Are our children learning? five stories on the state of education in uganda in 2015 and beyond. Technical report, Twaweza East Africa, Kampala, Uganda.

Van Klaveren, C. (2011). Lecturing style teaching and student performance. *Economics of Education Review*, 30(4):729–739.

Vandenberghe, V. and Robin, S. (2004). Evaluating the effectiveness of private education across countries: a comparison of methods. *Labour economics*, 11(4):487–506.

Vegas, E. and Devercelli, A. (ND). The world banks new tool to inform policy when scaling-up ecd. Technical report, Education Unit, Human Development Department, World Bank, Washington dc, usa.

Vyas, S. and Kumaranayake, L. (2006). Constructing socio-economic status indices: how to use principal components analysis. *Health policy and planning*, 21(6):459–468.

Wakano, A. (2016). The effect of ratio between pta teachers and government employed teachers on education outcomes in kenya primary schools. Technical report, Graduate School of Economics and Osaka School of International Public Policy.

Wasanga, P. M., Ogle, A. M., and Wambua, R. M. (2010). Report on monitoring of learner achievement for class 3 in literacy and numeracy. Technical report, Nairobi: Kenya National Examinations Council. World Bank.

West, M. R. and Wobmann, L. (2006). Which school systems sort weaker students into smaller classes? international evidence. *European Journal of Political Economy*, 22(4):944–968.

Wittenberg, M. and Leibbrandt, M. (2017). Measuring inequality by asset indices: A general approach with application to south africa. *Review of Income and Wealth.*

Wooldridge, J. M. (2003). Cluster-sample methods in applied econometrics. *The American Economic Review*, 93(2):133–138.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

World-Bank (2009). Abolishing school fees in africa: Lessons from ethiopia, ghana, kenya, malawi and mozambique. Technical report, Washington DC, US: World Bank.

World-Bank (2016). World development indicators. Technical report, Washington DC, US: World Bank.

Zajonc, R. B. (1976). Family configuration and intelligence. *Science*, 192(4236):227–236.

Zajonc, R. B. (1983). Validating the confluence model. *Psychological Bulletin*, 93(3):457.

Zajonc, R. B. and Markus, G. B. (1976). Birth order and intellectual development. In *Social psychology in transition*, pages 157–177. Springer.

Zakharov, A., Carnoy, M., and Loyalka, P. (2014). Which teaching practices improve student performance on high-stakes exams? evidence from russia. *International Journal of Educational Development*, 36:13–21.

# Appendixes

## Appendix A: Appendix for Chapter 2

We would like to provide a short note on the SDI survey sample. The SDI survey team aimed to observe a grade 4 language or maths lesson in all the sampled schools. Classroom observation for language and maths however took place in only 276 schools. In 2 schools, a science and creative arts subjects were observed respectively. In the remaining 28 schools, classroom observation did not take place because teachers were absent from class. We include them in the *absence from class* indicator. Of the 276 teachers who were observed, 222 teachers participated in the teacher test assessment while 54 did not. In this section, we investigate whether these dynamics introduce any systematic patterns or biases in the data. Table A2.1 shows the means for selected school, class and student characteristics for the following samples: (a) full sample of 306 schools (b) sample of 222 schools where teachers were observed and assessed, (c) sample of 54 schools where teachers were observed and not assessed and (d) 28 schools where classroom observation did not take place. A comparison of these means reveals no evidence of large differences among the different samples.

Second, we investigate whether there is evidence of systematic patterns with respect to the 54 teachers who participated in the observation and not teachers tests. One way is to compare them with their 222 counterparts who participated in both. For these two samples, we have information regarding teachers classroom practices as well as other characteristics except for teacher scores. Table A2.2 shows among others, descriptive statistics for the measures of how teachers spend their time in class and their classroom practices for the 222 and 54 samples (details about these characteristics are provided in the next Chapter). In general, we do not find any significant differences between the two samples. Of interest to us is that both teachers seem to be identical in terms of how they spent their time in class.

Table A2.1: SDI Survey Summary Statistics for different Samples

| | Full Sample (N=306) | Observed Sample (N=222) | Observed & not Tested Sample (N=54) | Not Observed Sample (N=28) |
|---|---|---|---|---|
| **School Characteristics** | | | | |
| Rural | 0.68 | 0.68 | 0.61 | 0.79 |
| Public | 0.78 | 0.77 | 0.76 | 0.86 |
| Class size | 33.67 | 32.28 | 36.63 | 38.39 |
| Pupil per teacher | 31.27 | 31.13 | 31.28 | 31.85 |
| School located near tarmac road | 0.34 | 0.32 | 0.46 | 0.21 |
| **Minimum Teaching Resources** | | | | |
| Classroom has a blackboard (percent) | 0.99 | 0.99 | 1.00 | 0.96 |
| Classroom has a piece of chalk (percent) | 0.92 | 0.97 | 1.00 | 0.43 |
| Share of pupil with a pencil (percent) | 0.98 | 0.98 | 0.98 | 0.97 |
| Share of pupil with an exercise book | 0.99 | 0.99 | 0.98 | 0.97 |
| Average number of students per textbook (maths) | 2.62 | 2.61 | 2.58 | 2.72 |
| Average number of students per textbook (English) | 3.64 | 3.64 | 3.07 | 4.73 |
| **Infrastructure Availability (percent)** | | | | |
| School has toilets | 1.00 | 1.00 | 0.98 | 1.00 |
| School toilets are designated for boys and girls | 0.97 | 0.97 | 0.98 | 0.96 |
| School toilets are private (have doors) | 0.93 | 0.94 | 0.93 | 0.89 |
| School toilets are accessible | 0.95 | 0.95 | 0.94 | 0.93 |
| School toilets are clean | 0.71 | 0.70 | 0.69 | 0.79 |
| Sufficient light for reading from the back of the classroom | 0.85 | 0.86 | 0.83 | 0.82 |
| **Students Characteristics** | | | | |
| Number of students | 2,953 | 2,142 | 520 | 271 |
| Female | 0.50 | 0.50 | 0.47 | 0.51 |
| Age | 10.43 | 10.45 | 10.22 | 10.64 |
| Had breakfast | 0.87 | 0.86 | 0.90 | 0.89 |
| English | 79.74 | 79.03 | 83.10 | 79.60 |
| Maths | 60.28 | 60.28 | 59.90 | 61.36 |
| Non verbal reasoning | 58.88 | 58.87 | 60.38 | 56.27 |

*Source*: Own computation from Uwezo 2012. ***significance<1 percent, **significance<5 percent, *significance<10 percent

Table A2.2: Teacher Classroom Practices and Teacher Characteristics: Comparison of the 222 and 54 School Samples

| | Observed Sample (N=222) | Observed & not Tested (N=54) | Mean Difference |
|---|---|---|---|
| Effective Instruction Time | 2hrs 59min | 3hr 01min | 2min |
| Percent of student off-task | 9.13 | 11.44 | -2.31 |
| **Teacher classroom practices** | | | |
| Teacher had a well planned lesson plan | 0.85 | 0.89 | -0.04 |
| Teacher had a well planned scheme of work | 0.79 | 0.93 | -0.13** |
| Teacher called children by name | 0.87 | 0.87 | 0.00 |
| Teacher gave feedback of praise and moral encouragement | 0.85 | 0.85 | 0.00 |
| Teacher gave student feedback that was scolding at a mistake | 0.79 | 0.91 | -0.12** |
| Teacher hit or slapped children | 0.98 | 0.94 | 0.03 |
| Teacher introduced the lesson | 0.89 | 0.98 | -0.09 |
| Teacher summarized the lesson | 0.65 | 0.69 | -0.04 |
| Teacher challenged students (through questions) | 0.43 | 0.46 | -0.03 |
| Teacher used local language and local information | 0.33 | 0.28 | 0.06 |
| Teacher reviewed homework | 0.38 | 0.37 | 0.01 |
| Teacher assigned homework | 0.68 | 0.71 | -0.03 |
| **Other teacher characteristics** | | | |
| Female | 0.41 | 0.56 | -0.15** |
| Experience ( in years) | 13.17 | 14.46 | -1.38 |
| Teacher has post-secondary education+ | 0.72 | 0.56 | 0.17** |

*Source*: Own computation from Uwezo 2012. ***significance<1 percent, **significance<5 percent, *significance<10 percent

# Appendix B: Appendix for Chapter 3

Table B3.1: Indicators for Constructing Village level Wealth Index

| No. | Individual or household characteristic |
|---|---|
| 1 | Average number of years of education per adult (person aged 18 years and above). |
| 2 | Percent of people in the village aged 6 years & above who got a service from the following in the last one month of the census survey: |
| | (a) Radio |
| | (b) TV |
| | (c) Mobile phone |
| | (d) Computer |
| 3 | Percent of households in the village who own the following assets: |
| | (a) Radio |
| | (b) TV |
| | (c) Mobile phone |
| | (d) Computer |
| | (e) Bicycle |
| | (f) Motorcycle |
| | (g) Car |
| | (h) Refrigerator |
| 4 | Percent of households in the village whose main water source is: |
| | (a) Pond, dam, lake, rain, jabia and water vendor |
| | (b) Unprotected well, unprotected spring, stream/river and borehole |
| | (c) Protected well and protected spring |
| | (d) Piped into dwelling place |
| | (e) Piped outside the dwelling place |
| 5 | Percent of households in the village whose dwelling materials ( walls) is made up of: |
| | (a) Stones |
| | (b) Bricks/block |
| | (c) Mud/wood |
| | (d) Mud/cement |
| | (e) Wood only |
| | (f) Corrugated iron sheets |
| | (g) Other materials (grass and tin) |
| 6 | Percent of households in the village whose main source of lighting is: |
| | (a) Electricity and solar |
| | (b) Pressure and gas lamp |
| | (c) Lantern and |
| | (d) Fuel wood |
| 7 | Percent of households in the village who own the following livestock: |
| | (a) Cattle |
| | (b) Sheep |
| | (c) Goat |
| | (d) Camel |
| | (e) Chicken |

## Table B3.2: Teacher Human Capital, Teacher Effort and Student Language Test Scores

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Teacher subject knowledge | 0.053* | 0.079** | 0.103*** | 0.080** | 0.075** |
| | (0.027) | (0.032) | (0.029) | (0.031) | (0.031) |
| Teacher pedagogical knowledge | 0.001 | -0.038 | -0.033 | -0.011 | -0.007 |
| | (0.043) | (0.042) | (0.043) | (0.048) | (0.053) |
| Effective instruction time (in hours) | 0.051* | 0.045* | 0.071*** | 0.056** | 0.051** |
| | (0.026) | (0.023) | (0.022) | (0.024) | (0.023) |
| Percent of student off-task (average) | -0.005 | -0.018*** | -0.018*** | -0.029*** | -0.030*** |
| | (0.007) | (0.006) | (0.006) | (0.008) | (0.008) |
| **Teacher Classroom Practices** | | | | | |
| Teacher reviews and assigns homework | | 0.181* | 0.353*** | 0.451*** | 0.383*** |
| | | (0.097) | (0.094) | (0.113) | (0.135) |
| Teacher uses local language to illustrate learning | | -0.243*** | -0.177** | -0.171* | -0.161** |
| | | (0.089) | (0.084) | (0.094) | (0.081) |
| Teacher challenges students by asking questions | | -0.121 | -0.189*** | -0.225*** | -0.190** |
| | | (0.079) | (0.062) | (0.073) | (0.074) |
| Teacher keeps a lesson plan and scheme of work | | -0.251* | -0.296** | -0.242* | -0.263* |
| | | (0.139) | (0.126) | (0.132) | (0.112) |
| Teacher instills discipline in students | | -0.392*** | -0.329*** | -0.365*** | -0.298*** |
| | | (0.113) | (0.108) | (0.100) | (0.101) |
| **Teacher Controls** | | | | | |
| Teacher is female | | | 0.201** | 0.136 | 0.078 |
| | | | (0.084) | (0.099) | (0.097) |
| Teacher experience (in years) | | | 0.035** | 0.035** | 0.035** |
| | | | (0.017) | (0.016) | (0.015) |
| Teacher experience squared (in years) | | | -0.001** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) |
| Teacher is on contract (Ref: government) | | | -0.457*** | -0.220 | -0.250 |
| | | | (0.137) | (0.162) | (0.172) |
| Teacher's highest education level is a diploma or a degree (Ref: Secondary) | | | 0.054 | 0.055 | 0.105 |
| | | | (0.094) | (0.093) | (0.088) |
| Teacher has ECD or primary certificate in teaching (Ref: Diploma or degree) | | | -0.075 | -0.183 | -0.175 |
| | | | (0.087) | (0.121) | (0.137) |
| **School and Classroom Controls** | | | | | |
| School is public | | | | -0.311* | -0.334** |
| | | | | (0.156) | (0.117) |
| School is rural | | | | -0.166 | -0.186 |
| | | | | (0.146) | (0.179) |
| School is located next to tarmac road | | | | 0.046 | 0.157 |
| | | | | (0.138) | (0.140) |
| Number of pupils per teacher | | | | 0.007 | 0.006 |
| | | | | (0.006) | (0.005) |
| Index of school infrastructure | | | | 0.026 | 0.026 |
| | | | | (0.024) | (0.022) |
| Class size | | | | -0.009*** | -0.009*** |
| | | | | (0.003) | (0.003) |
| Index of classroom instructional inputs | | | | 0.031 | 0.070 |
| | | | | (0.070) | (0.072) |
| **Student Controls** | | | | | |
| Student age (in years) | | | | | -0.171 |
| | | | | | (0.226) |
| Student age squared (in years) | | | | | 0.001 |
| | | | | | (0.011) |
| Student is female | | | | | 0.090** |
| | | | | | (0.042) |
| Student had breakfast | | | | | 0.055 |
| | | | | | (0.079) |
| Student score in maths | | | | | 0.016*** |
| | | | | | (0.003) |
| Student non-verbal reasoning score | | | | | 0.004*** |
| | | | | | (0.001) |
| **Village Controls (**Village level wealth index) | 0.027 | 0.019 | -0.036 | -0.033 | -0.032 |
| | (0.035) | (0.034) | (0.028) | (0.026) | (0.028) |
| Constant | -0.123 | 0.491*** | 0.257 | 0.538** | 0.783 |
| | (0.111) | (0.176) | (0.208) | (0.224) | (1.239) |
| Division Fixed Effects | Y | Y | Y | Y | Y |
| Observations | 1,077 | 1,077 | 1,077 | 1,077 | 1,077 |
| R-squared | 0.376 | 0.396 | 0.407 | 0.413 | 0.495 |

Notes: (1) The estimates are based on 113 schools; (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class) and assessed in the teacher tests; (3) The index of school infrastructure is based on the following items, given equal weight: (a) toilets that were judged as designated for boys and girls, accessible, private and clean, (b) electricity and (c) sufficient light for reading from the back of the class; (4) Index of classroom instructional inputs is based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book (language), (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls and other materials (other than children's work such as flips charts) displayed on the walls; (5) Standard errors are in parenthesis and are clustered at the class level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

Table B3.3: Teacher Human Capital, Teacher Effort and Student Maths Test Scores

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Teacher subject knowledge | 0.173*** | 0.172*** | 0.175*** | 0.166*** | 0.126*** |
| | (0.055) | (0.051) | (0.057) | (0.046) | (0.045) |
| Teacher pedagogical knowledge | 0.039 | 0.005 | -0.023 | 0.111*** | 0.112*** |
| | (0.053) | (0.051) | (0.045) | (0.038) | (0.035) |
| Effective instruction time (in hours) | 0.150*** | 0.137*** | 0.199*** | 0.087** | 0.059* |
| | (0.039) | (0.041) | (0.038) | (0.034) | (0.030) |
| Percent of student off-task (average) | -0.018** | -0.020*** | -0.010 | -0.005 | -0.002 |
| | (0.008) | (0.007) | (0.008) | (0.006) | (0.005) |
| **Teacher Classroom Practices** | | | | | |
| Teacher reviews and assigns homework | | -0.208* | -0.217* | -0.463*** | -0.377*** |
| | | (0.113) | (0.114) | (0.087) | (0.084) |
| Teacher uses local language to illustrate learning | | -0.262** | -0.162 | -0.106 | -0.073 |
| | | (0.129) | (0.135) | (0.089) | (0.096) |
| Teacher challenges students by asking questions | | 0.211 | 0.219 | 0.348*** | 0.273*** |
| | | (0.150) | (0.134) | (0.114) | (0.102) |
| Teacher keeps a lesson plan and scheme of work | | 0.012 | -0.038 | -0.243* | -0.248* |
| | | (0.152) | (0.163) | (0.120) | (0.115) |
| Teacher instills discipline in students | | 0.037 | 0.111 | 0.338** | 0.217 |
| | | (0.178) | (0.174) | (0.156) | (0.156) |
| **Teacher Controls** | | | | | |
| Teacher is female | | | -0.267** | -0.091 | -0.165* |
| | | | (0.134) | (0.091) | (0.085) |
| Teacher experience (in years) | | | -0.065*** | -0.078*** | -0.082*** |
| | | | (0.018) | (0.016) | (0.016) |
| Teacher experience squared (in years) | | | 0.002*** | 0.002*** | 0.002*** |
| | | | (0.001) | (0.000) | (0.000) |
| Teacher is on contract (Ref: government) | | | 0.019 | 0.243* | 0.247* |
| | | | (0.185) | (0.133) | (0.131) |
| Teacher's highest education level is a diploma or a degree (Ref: Secondary) | | | 0.284* | -0.041 | -0.008 |
| | | | (0.155) | (0.132) | (0.129) |
| Teacher has ECD or primary certificate in teaching (Ref: Diploma or degree) | | | -0.096 | 0.080 | 0.090 |
| | | | (0.160) | (0.118) | (0.103) |
| **School and Classroom Controls** | | | | | |
| School is public | | | | -0.692*** | -0.696*** |
| | | | | (0.191) | (0.182) |
| School is rural | | | | 0.077 | 0.058 |
| | | | | (0.117) | (0.111) |
| School is located next to tarmac road | | | | 0.152 | 0.150 |
| | | | | (0.182) | (0.178) |
| Number of pupils per teacher | | | | -0.003 | 0.000 |
| | | | | (0.007) | (0.006) |
| Index of school infrastructure | | | | -0.175*** | -0.159*** |
| | | | | (0.035) | (0.034) |
| Class size | | | | -0.001 | 0.001 |
| | | | | (0.004) | (0.004) |
| Index of classroom instructional inputs | | | | 0.121*** | 0.062* |
| | | | | (0.039) | (0.036) |
| **Student Controls** | | | | | |
| Student age (in years) | | | | | -0.229 |
| | | | | | (0.140) |
| Student age squared (in years) | | | | | 0.011* |
| | | | | | (0.006) |
| Student is female | | | | | -0.114* |
| | | | | | (0.060) |
| Student had breakfast | | | | | 0.136* |
| | | | | | (0.080) |
| Student score in language | | | | | 0.273*** |
| | | | | | (0.043) |
| Student non-verbal reasoning score | | | | | 0.004*** |
| | | | | | (0.002) |
| **Village Controls (**Village level wealth index) | 0.142*** | 0.152*** | 0.129*** | 0.025 | 0.019 |
| | (0.035) | (0.036) | (0.040) | (0.035) | (0.033) |
| Constant | -0.139 | -0.023 | -0.104 | 1.112*** | 1.783** |
| | (0.133) | (0.182) | (0.215) | (0.362) | (0.811) |
| Division Fixed Effects | Y | Y | Y | Y | Y |
| Observations | 1,034 | 1,034 | 1,034 | 1,034 | 1,034 |
| R-squared | 0.302 | 0.313 | 0.332 | 0.370 | 0.430 |

Notes: (1) The estimates are based on 109 schools. (2) The measures of teacher human capital and teacher effort are based on the single teacher who was observed (teaching a language class) and assessed in the teacher tests; (3) The index of school infrastructure is based on the following items, given equal weight: (a) toilets that were judged as designated for boys and girls, accessible, private and clean, (b) electricity and (c) sufficient light for reading from the back of the class; (4) Index of classroom instructional inputs is based on the following items, given equal weight: (a) proportion of students with pens and exercise books, (b) number of students per text book (maths), (c) whether the classroom had the following: piece of chalk, a black board, a corner library, children's work displayed on the walls and other materials (other than children's work such as flips charts) displayed on the walls; (5) Standard errors are in parenthesis and are clustered at the class level and (6) ***1 percent significance level, **5 percent significance level and *10 percent significance level.

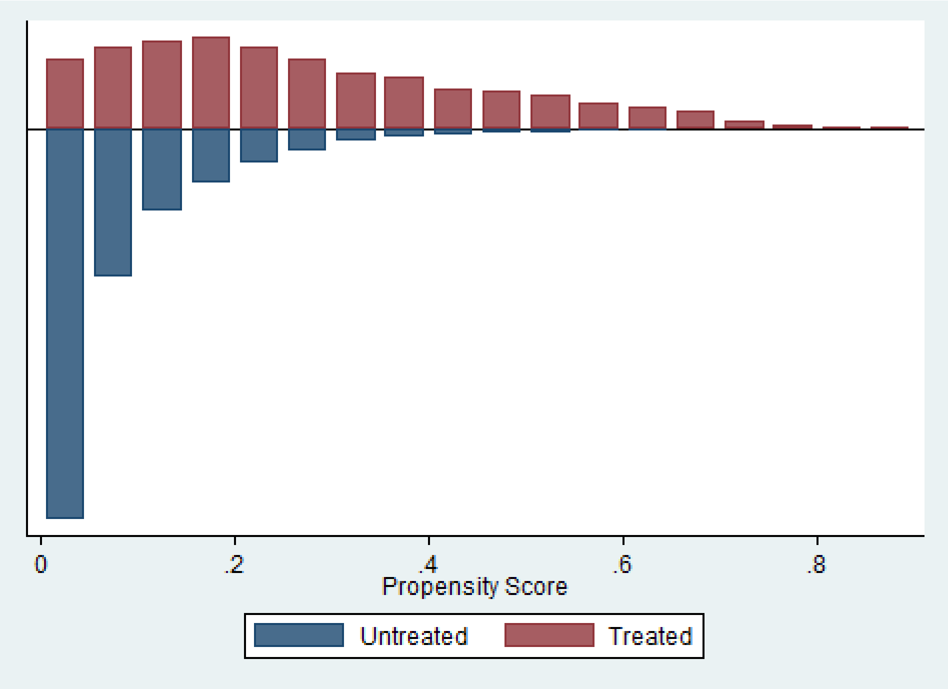
# Appendix C: Appendix for Chapter 4

Table C4.1: Probit Results for Calibrating Propensity Score

| | Coefficient | Standard Error |
|---|---|---|
| **Student Characteristics** | | |
| Age | -0.16*** | (0.04) |
| Age squared | 0.01** | (0.00) |
| Is female | -0.01 | (0.02) |
| Has some disability | -0.11 | (0.07) |
| Goes for paid tuition | 0.74*** | (0.02) |
| Current grade | -0.06*** | (0.02) |
| **Household Characteristics** | | |
| Mother's age | -0.03*** | (0.01) |
| Mother's age squared | 0.00** | (0.00) |
| Mother's Education level(ref: None) | | |
| Has primary education level | -0.05 | (0.04) |
| Has secondary education level | 0.12*** | (0.05) |
| Has post secondary education level | 0.33*** | (0.10) |
| Father's Education level(ref: None) | | |
| Has primary education level | -0.05 | (0.05) |
| Has secondary education level | 0.11** | (0.05) |
| Has post secondary education level | 0.24*** | (0.07) |
| Household has less than 10 members | -0.02*** | (0.00) |
| Household has source of water at home | 0.13*** | (0.03) |
| Household has toilet/latrine at home | 0.04 | (0.04) |
| Distance to school is less than 30 minutes | 0.08*** | (0.02) |
| Household assets | | |
| Household has a TV | 0.21*** | (0.03) |
| Household has a radio | 0.03 | (0.03) |
| Household has a computer | 0.31*** | (0.07) |
| Household has a phone | 0.13*** | (0.03) |
| Household has a car | 0.29*** | (0.05) |
| Household has a cattle | 0.09*** | (0.02) |
| Household has a donkey | 0.05 | (0.04) |
| Household has a camel | -0.04 | (0.08) |
| Household has a goat | -0.09*** | (0.02) |
| Household has a bicycle | -0.07*** | (0.02) |
| Household has a motorbike | 0.09** | (0.04) |
| Household has a cart | 0.01 | (0.06) |
| Number of Meals taken per day(ref: Three) | | |
| One meals | 0.07 | (0.07) |
| Two meals | -0.13*** | (0.03) |
| Wall material for dwelling place (ref: Bricks_stone ) | | |
| Polythene and iron | 0.01 | (0.04) |
| Timber | -0.08** | (0.04) |
| Mud | -0.14*** | (0.03) |
| Regular source of lighting (ref: Other) | | |
| Electricity | 0.40*** | (0.07) |
| Paraffin | 0.07 | (0.06) |
| **Village Characteristics** | | |
| Village has chief's office | -0.00 | (0.02) |
| Village has shopping center | 0.15*** | (0.03) |
| Village has electricity | 0.03 | (0.03) |
| Village has tarmac road | 0.08*** | (0.03) |
| Village has all-weather road | -0.04 | (0.03) |
| Village has an education committee | -0.11*** | (0.02) |
| Village has all protected water point | -0.01 | (0.02) |
| Village is rural | -0.14*** | (0.03) |
| Constant | 0.16 | (0.25) |
| Observations | 30,299 | |

Notes: (1) Standard errors in parenthesis clustered at the household level and; (2) ***1% significance level, **5% significance level and *10% significance level.

Figure C4.1: Propensity Score of Observations in and off Common Support Region



## Table C4.2: Testing of Balance between Private and Public Students after PSM Estimation

| | Unmatched | | | | | Matched | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| | Treated | Control | %bias | t-test | p>\|t\| | Treated | Control | %bias | t-test | p>\|t\| | %reduct |
| **Student Characteristics** | | | | | | | | | | | |
| Student's Age | 8.54 | 9.41 | -45.2 | -23.72 | 0.00 | 8.74 | 8.74 | 0.7 | 0.30 | 0.76 | 98.3 |
| Student's Age squared | 76.12 | 92.78 | -44.5 | -22.9 | 0.00 | 93.41 | 79.40 | 0.9 | 0.36 | 0.72 | 98.0 |
| Student is female | 0.49 | 0.47 | 3.8 | 2.10 | 0.04 | 0.49 | 0.48 | 1.3 | 0.49 | 0.63 | 65.4 |
| Student has some disability | 0.02 | 0.03 | -5.8 | -3.03 | 0.00 | 0.02 | 0.02 | 1.8 | 0.73 | 0.47 | 68.9 |
| Students goes for paid tuition | 0.72 | 0.34 | 83.6 | 45.28 | 0.00 | 0.68 | 0.68 | 0.1 | 0.05 | 0.96 | 99.8 |
| Student grade | 2.90 | 2.99 | -11.5 | -6.32 | 0.00 | 2.93 | 2.93 | -0.9 | -0.33 | 0.74 | 92.2 |
| Mother age | 33.11 | 35.61 | -18.6 | -9.91 | 0.00 | 34.29 | 34.34 | -0.8 | -0.31 | 0.76 | 95.5 |
| **Family Characteristics** | | | | | | | | | | | |
| Mother's Education level | | | | | | | | | | | |
| Has no education | 0.10 | 0.25 | -38.9 | -19.12 | 0.00 | 0.12 | 0.12 | -1.0 | -0.41 | 0.68 | 97.5 |
| Has primary education | 0.50 | 0.59 | -18.4 | -10.26 | 0.00 | 0.54 | 0.53 | 2.5 | 0.92 | 0.36 | 86.4 |
| Has secondary education | 0.36 | 0.16 | 47.5 | 29.40 | 0.00 | 0.32 | 0.33 | -1.4 | -0.47 | 0.64 | 97.1 |
| Has post secondary education | 0.04 | 0.01 | 22.9 | 19.40 | 0.00 | 0.01 | 0.02 | -2.0 | -0.88 | 0.38 | 91.3 |
| Father's Education level | | | | | | | | | | | |
| Has no education | 0.08 | 0.20 | -36.7 | -17.80 | 0.00 | 0.09 | 0.09 | -0.9 | -0.39 | 0.70 | 97.5 |
| Has primary education level | 0.39 | 0.52 | -26.9 | -14.75 | 0.00 | 0.44 | 0.43 | 0.4 | 0.15 | 0.88 | 98.5 |
| Has secondary education level | 0.46 | 0.26 | 42.4 | 24.72 | 0.00 | 0.43 | 0.42 | 2.0 | 0.69 | 0.49 | 95.4 |
| Has post secondary education level | 0.08 | 0.02 | 28.0 | 21.02 | 0.00 | 0.04 | 0.05 | -3.8 | -1.42 | 0.15 | 86.3 |
| Household size | 6.2 | 6.9 | -27.1 | -14.8 | 0.00 | 6.36 | 6.4 | -0.5 | -0.02 | 0.84 | 98.1 |
| Household has source of water at home | 0.32 | 0.15 | 41.4 | 25.7 | 0.00 | 0.26 | 0.26 | 0.2 | 0.06 | 0.96 | 99.6 |
| Household has toilet/latrine at home | 0.90 | 0.75 | 40.8 | 19.98 | 0.00 | 0.89 | 0.88 | 0.2 | 0.09 | 0.93 | 99.5 |
| Distance to school is less than 30 min. | 0.47 | 0.56 | -12.2 | -6.44 | 0.00 | 0.50 | 0.51 | -0.5 | -0.19 | 0.85 | 96.0 |
| Household Assets | | | | | | | | | | | |
| Household has a TV | 0.44 | 0.15 | 66.8 | 42.40 | 0.00 | 0.34 | 0.34 | 0.4 | 0.12 | 0.90 | 99.5 |
| Household has a radio | 0.83 | 0.71 | 28.4 | 14.69 | 0.00 | 0.80 | 0.81 | -1.2 | -0.47 | 0.64 | 95.8 |
| Household has a computer | 0.06 | 0.01 | 28.1 | 22.79 | 0.00 | 0.03 | 0.02 | 2.1 | 0.90 | 0.37 | 92.5 |
| Household has a phone | 0.82 | 0.64 | 42.2 | 21.56 | 0.00 | 0.79 | 0.80 | -1.5 | -0.61 | 0.55 | 96.4 |
| Household has a car | 0.10 | 0.02 | 31.8 | 24.07 | 0.04 | 0.05 | 0.05 | 1.8 | 0.69 | 0.49 | 94.4 |
| Household has a cattle | 0.54 | 0.56 | -3.7 | -2.06 | 0.00 | 0.56 | 0.58 | -2.8 | -1.03 | 0.30 | 25.7 |
| Household has a donkey | 0.10 | 0.16 | -18.8 | -9.65 | 0.00 | 0.11 | 0.11 | -0.4 | -0.14 | 0.89 | 98.1 |
| Household has a camel | 0.01 | 0.04 | -16.7 | -7.86 | 0.00 | 0.02 | 0.02 | 0.5 | 0.23 | 0.82 | 97.2 |
| Household has a goat | 0.38 | 0.49 | -23.4 | -12.77 | 0.00 | 0.40 | 0.40 | -0.1 | -0.03 | 0.97 | 99.6 |
| Household has a bicycle | 0.32 | 0.31 | 3.1 | 1.71 | 0.00 | 0.33 | 0.31 | 1.8 | 0.65 | 0.52 | 42.1 |
| Household has a motorbike | 0.11 | 0.05 | 22.2 | 14.25 | 0.00 | 0.09 | 0.09 | 0.9 | 0.32 | 0.75 | 95.8 |
| Household has a cart | 0.04 | 0.04 | -1.9 | -1.03 | 0.00 | 0.04 | 0.03 | 0.6 | 0.24 | 0.81 | 69.0 |
| Number of Meals taken per day | | | | | | | | | | | |
| One meal | 0.02 | 0.04 | -8.6 | -4.35 | 0.00 | 0.02 | 0.03 | -0.5 | -0.20 | 0.84 | 94.3 |
| Two meals | 0.12 | 0.23 | -29.2 | -14.74 | 0.00 | 0.13 | 0.13 | -0.3 | -0.14 | 0.89 | 98.8 |
| Three meals | 0.86 | 0.74 | 31.2 | 15.84 | 0.00 | 0.84 | 0.84 | 0.5 | 0.21 | 0.83 | 98.3 |
| Wall material for dwelling place | | | | | | | | | | | |
| Mud | 0.40 | 0.66 | -55.4 | -31.06 | 0.00 | 0.47 | 0.47 | -0.7 | -0.25 | 0.80 | 98.7 |
| Polythene and iron | 0.08 | 0.07 | 5.5 | 3.21 | 0.00 | 0.08 | 0.08 | 0.5 | 0.18 | 0.85 | 90.5 |
| Timber | 0.12 | 0.09 | 12.1 | 7.10 | 0.00 | 0.13 | 0.13 | -1.7 | -0.59 | 0.56 | 85.6 |
| Bricks_stone | 0.39 | 0.17 | 49.0 | 29.97 | 0.00 | 0.32 | 0.31 | 1.7 | 0.58 | 0.56 | 96.6 |
| Regular source of lighting | | | | | | | | | | | |
| Electricity | 0.37 | 0.10 | 66.4 | 45.16 | 0.00 | 0.26 | 0.26 | 0.1 | 0.02 | 0.98 | 99.9 |
| Paraffin | 0.61 | 0.82 | -50.0 | -30.71 | 0.00 | 0.71 | 0.71 | -1.2 | -0.41 | 0.68 | 97.7 |
| Other | 0.02 | 0.07 | -22.5 | -10.66 | 0.00 | 0.03 | 0.02 | 2.2 | 1.10 | 0.27 | 90.1 |
| **Village Characteristics** | | | | | | | | | | | |
| Village has chief's office | 0.70 | 0.62 | 18.2 | 9.83 | 0.00 | 0.68 | 0.69 | -1.0 | -039 | 0.69 | 94.3 |
| Village has shopping center | 0.35 | 0.24 | 24.0 | 13.88 | 0.00 | 0.32 | 0.31 | 0.6 | 0.20 | 0.84 | 97.6 |
| Village has police post | 0.35 | 0.24 | 24.0 | 13.88 | 0.00 | 0.31 | 0.31 | 0.6 | 0.20 | 0.84 | 97.6 |
| Village has electricity | 0.59 | 0.38 | 42.5 | 23.61 | 0.00 | 0.54 | 0.53 | 2.1 | 0.75 | 0.46 | 95.2 |
| Village has tarmac road | 0.29 | 0.15 | 33.9 | 20.68 | 0.00 | 0.25 | 0.25 | 0.3 | 0.09 | 0.93 | 99.2 |
| Village has all-weather road | 0.81 | 0.78 | 6.4 | 3.46 | 0.00 | 0.80 | 0.80 | -1.5 | -0.57 | 0.57 | 76.2 |
| Village has an education committee | 0.27 | 0.32 | -11.4 | -6.91 | 0.00 | 0.27 | 0.28 | -1.9 | -0.73 | 0.47 | 83.1 |
| Village has all protected water point | 0.42 | 0.40 | 2.1 | 1.19 | 0.23 | 0.41 | 0.40 | 3.4 | 1.26 | 0.21 | -57.6 |
| Village is rural | 0.69 | 0.83 | -36.4 | -22.12 | 0.00 | 0.74 | 0.74 | -0.6 | -0.23 | 0.82 | 98.2 |
| Village is urban | 0.32 | 0.17 | 36.4 | 22.12 | 0.00 | 0.26 | 0.26 | 0.6 | 0.23 | 0.82 | 98.2 |

Figure C4.2: Visual Inspection of Standardized Differences

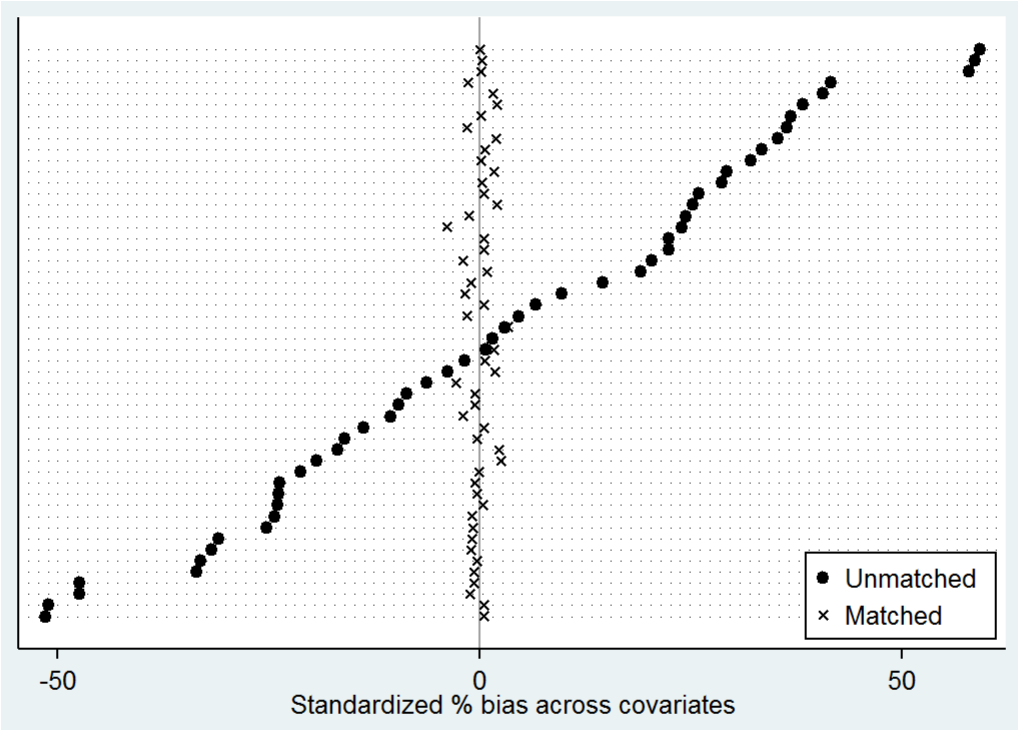
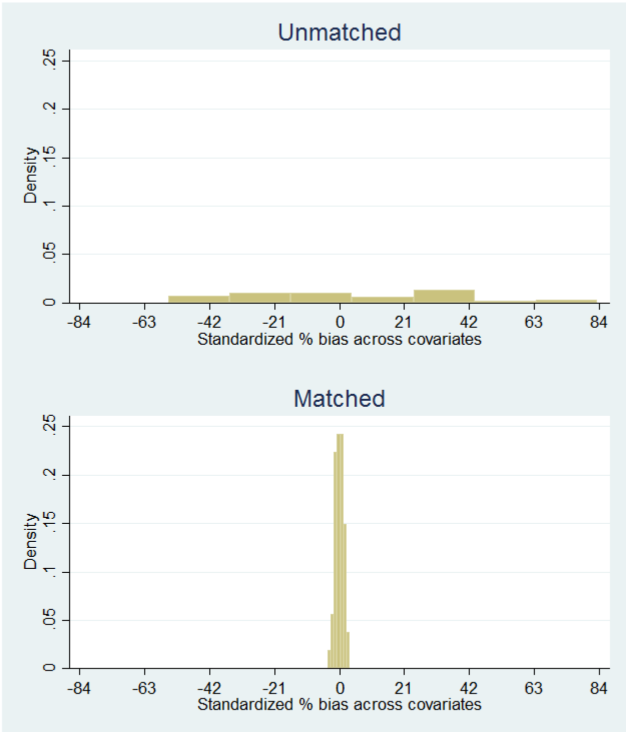



Figure C4.3: Visual Inspection of Standardized Differences



# Appendix D: Appendix for Chapter 5

Table D 5.1: Probit Results for Children Enrolment

| | Coefficient | Standard Error |
|---|---|---|
| **Student Characteristics** | | |
| Birth order (ref: First child) | | |
| Second child | -0.066** | (0.026) |
| Third child | -0.203*** | (0.031) |
| Fourth child | -0.285*** | (0.038) |
| Fifth child | -0.408*** | (0.054) |
| Age | 1.182*** | (0.020) |
| Age squared | -0.050*** | (0.001) |
| Child is female | 0.008 | (0.016) |
| Child has some disability | -0.491*** | (0.041) |
| Child goes for paid tuition | | |
| **Household Characteristics** | | |
| Mother's age | 0.029*** | (0.006) |
| Mother's age squared | -0.000*** | (0.000) |
| Mother's Education level(ref: None) | | |
| Has primary education level | 0.196*** | (0.026) |
| Has secondary education level | 0.246*** | (0.037) |
| Has post secondary education level | 0.264* | (0.135) |
| Father's Education level(ref: None) | | |
| Has primary education level | 0.246*** | (0.027) |
| Has secondary education level | 0.375*** | (0.034) |
| Has post secondary education level | 0.381*** | (0.084) |
| Household size | 0.005 | (0.004) |
| Household has source of water at home | 0.077*** | (0.028) |
| Household has toilet/latrine at home | 0.332*** | (0.021) |
| Distance to school | -0.191*** | (0.033) |
| Index of household Assets | 0.055*** | (0.008) |
| Meals taken per day(ref: Less than three meals) | | |
| Three meals | 0.102*** | (0.018) |
| Wall material for dwelling place (ref: Mud) | | |
| Polythene and iron | 0.220*** | (0.035) |
| Timber | 0.240*** | (0.037) |
| Bricks_stone | 0.150*** | (0.027) |
| Regular source of lighting (ref: Paraffin) | | |
| Electricity/solar/gas | 0.033 | (0.034) |
| Other | -0.324*** | (0.026) |
| **Village Characteristics** | | |
| Village has chief's office | 0.066*** | (0.018) |
| Village has shopping center | 0.030 | (0.021) |
| Village has electricity | -0.010 | (0.021) |
| Village has tarmac road | -0.014 | (0.026) |
| Village has all-weather road | 0.031 | (0.019) |
| Village has an education committee | 0.033* | (0.018) |
| Village has all protected water point | -0.002 | (0.017) |
| Village is rural | -0.018 | (0.024) |
| Constant | -6.311*** | (0.158) |
| Observations | 57,631 | |

Notes: (1) We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durable assets (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock assets (cattle, donkey, camel, sheep/goat); (2) Standard errors are in parenthesis; (3) ***1% significance level, **5% significance level and *10% significance level.

Table D 5.2: Effects of Gender and Birth Order: Fully Interacted with Family Wealth, as a Continuous Variable

| | (1) | (2) | (3) |
|---|---|---|---|
| | Private School enrolment | Completed Years of Education | Relative Grade Progression |
| Female | -0.007 | 0.076** | 0.016* |
| | (0.007) | (0.033) | (0.008) |
| Second born | 0.015 | -0.388*** | -0.095*** |
| | (0.011) | (0.056) | (0.014) |
| Third born | 0.032 | -0.854*** | -0.187*** |
| | (0.020) | (0.099) | (0.024) |
| Fourth child | 0.024 | -1.265*** | -0.270*** |
| | (0.029) | (0.142) | (0.037) |
| Fifth born | 0.080* | -1.685*** | -0.361*** |
| | (0.044) | (0.200) | (0.072) |
| Female*Family wealth | 0.018 | 0.142* | 0.024 |
| | (0.018) | (0.074) | (0.018) |
| Second born*Family wealth | -0.057* | 0.425*** | 0.084*** |
| | (0.029) | (0.123) | (0.031) |
| Third born*Family wealth | -0.099* | 0.989*** | 0.153*** |
| | (0.050) | (0.219) | (0.053) |
| Forth child*Family wealth | -0.078 | 1.530*** | 0.212** |
| | (0.075) | (0.316) | (0.082) |
| Fifth born*Family wealth | -0.246** | 2.329*** | 0.216 |
| | (0.110) | (0.455) | (0.169) |
| Constant | 0.308*** | -3.741*** | -0.022 |
| | (0.022) | (0.110) | (0.036) |
| Observations | 83,652 | 84,622 | 80,389 |
| | 0.792 | 0.911 | 0.677 |
| | 36,329 | 36,501 | 36,272 |

*Notes*: (1) All regressions are based on the household fixed effects model and include the following control variables: age of the child (in years), whether the child has some form of disability or not and whether the child goes for paid up tuition or not; (2) We only show estimates for gender and birth order dummies (our variables of interest); (3) Private school enrolment is defined as a dummy which equals 1 if the child was enrolled in a private school or 0 if a child was enrolled in a public school and this is estimated using LPM; (4) Completed years of education is number of years of education completed as at the time of the survey; (4) Relative grade progression equals $\frac{Completed\,years\,of\,education}{(Age-6)}$ where 6 is the school starting age in Kenya; (5) We clustered the standard errors (in parenthesis) at the household level; and (6) ***significant at 1%, **significant at 5%, *significant at 10%.

Table D 5.3: Probit Results for Children Private School Enrolment

| | Coefficient | Standard Error |
|---|---|---|
| Rural | -0.099*** | (0.029) |
| Poor | -0.042 | (0.042) |
| Rural*poor | -0.075* | (0.038) |
| **Student Characteristics** | | |
| Birth order (ref: First child) | | |
| Second child | -0.087*** | (0.021) |
| Third child | -0.177*** | (0.028) |
| Fourth child | -0.218*** | (0.040) |
| Fifth child | -0.351*** | (0.078) |
| Age | -0.105*** | (0.022) |
| Age squared | 0.001 | (0.001) |
| Child is female | 0.017 | (0.016) |
| Child has some disability | -0.087* | (0.052) |
| Child attends paid tuition | -0..433*** | (0.018) |
| **Household Characteristics** | | |
| Mother's age | 0.006 | (0.007) |
| Mother's age squared | -0.000** | (0.000) |
| Mother's Education level(ref: None) | | |
| Has primary education level | -0.252*** | (0.028) |
| Has secondary education level | -0.035 | (0.033) |
| Has post secondary education level | 0.136* | (0.074) |
| Father's Education level(ref: None) | | |
| Has primary education level | -0.259*** | (0.030) |
| Has secondary education level | -0.098*** | (0.033) |
| Has post secondary education level | -0.028 | (0.055) |
| Household size | 0.005 | (0.004) |
| Household has source of water at home | 0.118*** | (0.021) |
| Household has toilet/latrine at home | -0.032 | (0.024) |
| Distance to school | -0.040 | (0.037) |
| Index of household Assets | 0.053*** | (0.008) |
| Meals taken per day(ref: Less than three meals) | | |
| Three meals | 0.152*** | (0.021) |
| Wall material for dwelling place (ref: Mud) | | |
| Polythene and iron | 0.105*** | (0.030) |
| Timber | -0.043 | (0.031) |
| Bricks_stone | 0.040 | (0.025) |
| Regular source of lighting (ref: Paraffin) | | |
| Electricity/solar/gas | 0.374*** | (0.025) |
| Other | -0.026 | (0.037) |
| **Village Characteristics** | | |
| Village has chief's office | 0.003 | (0.018) |
| Village has shopping center | 0.160*** | (0.019) |
| Village has electricity | 0.001 | (0.019) |
| Village has tarmac road | 0.088*** | (0.021) |
| Village has all-weather road | -0.092*** | (0.019) |
| Village has an education committee | -0.059*** | (0.017) |
| Village has all protected water point | 0.027* | (0.016) |
| Constant | 0.063 | (0.178) |
| Observations | 50,558 | |

Notes: (1) We use the ordinary principal component analysis (PCA) to construct the index of household assets. The index is based on household ownership of the following assets: durable assets (TV, radio, car, computer, mobile phone, bicycle, motorbike and cart) and livestock assets (cattle, donkey, camel, sheep/goat); (2) Standard errors are in parenthesis; (3) ***1% significance level, **5% significance level and *10% significance level.