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Master's Thesis in Economics

Electrification and Children's Education: A Cross-Country Analysis

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Abstract

Access to electricity is undoubtedly an essential part of economic and social development in the developing world. For children, electrification can improve education as it enables studies after nightfall and it can help alleviate the burden of household chores. This study adds to the existing literature by using a cross-country approach as well as including test scores to examine the relationship between electrification and educational outcomes, in order to help clarify whether the results found in previous studies are local phenomenon or if they hold at a larger scale. Using OLS fixed-effects regressions based on panel data from the Young Lives survey between 2002 and 2013, focusing on Ethiopia and Peru, we find positive relationships between access to electricity and test scores, school enrollment and time spent in school, while we could not find any statistically significant differences between girls' and boys' outcomes. However, our results suggest that mere access to electricity is not enough to raise children's educational attainment, but that electrification must be combined with other efforts that aim to increase the quality of the education the children receive in school.

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Key words*: electrification, electricity, children's education, cross-country analysis*

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1. Introduction

According to The Sustainable Development Goals Report (United Nations 2017), more than 1 billion people lack access to electricity. The lack of basic energy access is often argued to be one of the major impediments to economic development (IEA 2017, Asian Development Bank 2010) and the issue has received increased attention over the last decade. Many organizations devote substantial resources to help spur economic development through this manner, one of the more recent initiatives is the Sustainable Energy for All, which aims to provide universal access to clean and modern energy by 2030.

Without access to electricity, necessities that are common in the developed world such as having a fridge, a washing machine and mere lighting after sunset, can require solutions that may have negative effects on individual development in terms of education, health and income. For example, to be able to study after sunset, children in most developing countries rely on light from kerosene lamps or candles, which due to its harmful emissions pollute the indoor air of the household. Many children, especially girls, are also expected to stay home from school to help their parents with household chores which, without access to electrified technology, often require manual labor and are time consuming. As a consequence, the prospects of getting a good education become small. The amount of time that must be devoted to household chores also means that there is not much time available for work that could earn the household an extra income.

Although it is true that a lot of the economic activity we observe throughout the developed countries depends on electricity in one way or another, does it necessarily mean that we can expect the mere access to electricity to promote human development? Previous studies on this topic seem to suggest that this is the case. Several papers that have studied the impact of electrification have shown that it can improve the household members' education, health and income through different channels. Improved education can for example be channeled through the access to light after sunset (Gustavsson 2007) as well as through easing the burden of household chores which allows children to go to school instead of staying home to help their parents (Daka & Ballet 2011).

Previous studies have mostly focused on the effect of electrification in local villages or provinces of a specific developing country. There has generally been a tendency to study the relationship in an experimental setting to ensure the validity of the obtained results. However, to our knowledge there exists no cross-country analysis approach to the relationship between electrification and children's education. We intend to fill this gap by studying the relationship between electrification and children's educational attainment in developing countries. A cross-country analysis can help clarify whether the results found in previous studies are local phenomenon or if they hold at a larger scale. As girls tend to suffer more from household chores, we also explore whether the relationship is the same for boys and girls to see if electrification has an alleviating effect on gender inequalities with respect to education. In order to examine the relationship between access to electricity and educational attainment, we use OLS fixed-effects regressions as well as the binary response models Linear Probability Model (LPM), Logit and Probit. Our study finds that electricity access has a positive correlation with test scores and school enrollment. Regarding the gender perspective of this study, we do not find any significant differences in girls' and boys' school outcomes when households have access to electricity.

The rest of this paper is structured as follows; the second section examines the current literature dealing with electrification in developing countries; the third section discusses the conceptual framework and theory; the fourth section describes the data; the fifth section describes the empirical method used in our analysis; the sixth section presents our results and analysis, followed by a discussion in the seventh section, and finally conclusions in the eighth section.

2. Literature review

The literature dealing with rural electrification has shown that basic energy access has the potential to generate substantial welfare gains in terms of increased household incomes, improved health and greater educational attainment (Jimenez 2017, Khandker et al. 2012, 2013, 2014, Lenz et al. 2017). Increased household incomes and educational attainment can be achieved in the short run through improved lighting which enables and facilitates business activities and studying after sunset. Households have also been shown to invest in radios, TVs and other electronics in the short term, and these devices provide access to information which can further improve the educational attainment and health of the household members (Fujii et al. 2018, Khandker et al. 2014, Lenz et al. 2017). Although electricity has been shown to reduce the need for kerosene lamps and biomass for indoor heating or cooking purposes, it has not always proved to be a perfect substitute for the traditional energy sources (Aklin et al. 2017, van de Walle et al. 2017). A reason to this is that many households rely on old cooking and heating technology, which can be too costly to upgrade in the short term. The government's subsidization of kerosene has been argued to be another reason behind why many household still rely on kerosene even after they receive access to electricity in many parts of rural India (Aklin et al. 2017).

Although there seems to be a consensus in the literature that basic energy access can be a catalyst to development, many studies have made clear that the access itself is seldom enough. Several studies underline the fact that the access to electricity comes at a time that is often accompanied with other government programs or development projects, and it is not always obvious to distinguish one's impact from the other. Hence, the question of what the actual causal impact of basic energy access has been addressed in several studies that exploit various experimental research approaches, for example instrumental variable and differences-in-differences designs and randomized control trials. A common instrument used in literature is the proximity to larger electricity infrastructure, where the cost of connecting a community is inversely correlated with distance. Studies using this approach have shown positive effect on study time for both girls and boys in Peru (Aguirre 2017) and on girls in Bangladesh (Samad & Zhang 2017), as well as increasing households' income and children's schooling years and study time in Bangladesh (Khandker et al. 2012). Opposite results can be found in a study from Honduras showing a drop in school attendance, especially in the early school years, due to the increased job opportunities for children that access to electricity brings (Squires 2015). Using the differences-in-differences method, studies have found that household members are awake longer and children's study time after nightfall increase without substantial changes in total study time in Rwanda (Lenz et al. 2017).

The majority of the households without electricity live in remote areas without connectivity to the national electricity grid (United Nations 2017). Connecting these household by expanding the grid requires enormous investments in the countries' infrastructure. Such undertakings are not only costly, but often also very lengthy. Considering the fact that national grids in developing countries struggle to supply the increasing amount of power demanded by the already connected households and enterprises, with power outages and power rationing as a result, many studies and development programs have explored the potential of off-grid (decentralized) solutions to rural electrification. Technological advancements in renewable energy solutions have made off-grid power systems increasingly attractive and affordable to communities, households and small-scale businesses. Although most off-grid solutions are capable of only providing minimal energy access for lighting and charging purposes, studies have found that it is in many cases enough to meet the rural households' low levels of electricity demand (Ahlborg & Hammar 2014, Peters & Sievert 2016). Hence, off-grid energy solutions can be a cost-effective way to achieve immediate electricity access and to improve the quality of life for the energy-poor in the short run. However, Aklin et al. (2016, 2017) points out that small-scale off-grid technologies, such as solar powered systems, may not supply enough energy for productive uses that lead to socioeconomic benefits. The findings underscore the advantages and pitfalls of providing minimal electricity access through off-grid technologies, such as solar powered home systems. It can be a cost-efficient and fairly simple alternative to grid electricity in the short term, however it may not be enough to generate the socioeconomic benefits traditionally associated with grid electricity (Aklin et al. 2016, 2017).

There are several aspects of the impact of electrification on educational attainment. Access to light can spur educational outcomes by increasing number of schooling years and increasing study time (Aguirre 2017, Samad & Zhang 2017, Khandker et al. 2012, Gustavsson 2007). While some studies show increasing study time, there is empirical evidence showing only a reallocation of study time from day to after nightfall without an increase in total study time (Lenz et al. 2017, Peters & Sievert 2016). There is also a gender aspect to electrification. Since girls tend to account for more household work than boys, access to electricity helps to ease the burden of household work for girls and enables them to study after sunset (Daka & Ballet 2011). The study by Gustavsson (2007), which shows increased study time, lacks data on school marks making it challenging to draw any further conclusions about the actual effect on school outcomes. The lack of studies on the impact of electrification on test results is an important note since a change in study time does not disclose the quality of studies, while it also does not necessarily imply better test scores. A discussion paper by Dasso et al. (2015) shows decreasing test scores at school level in Peru in the short-run, but positive effects on test scores as treatment exposure increases. Furthermore, it finds no impact on boys' educational outcomes, but an increase in girls' school enrollment and investment in education. The different results found in previous studies and the lack in number of studies examining test scores calls for more empirical evidence in the area of electrification and education, which is the aim of this study.

3. Conceptual framework

In this section we explore the linkages between electrification and the welfare of household members in terms of health, income and education. Although the focus of our study is the relationship between electrification and children's education, it is important to establish a general understanding of how electrification can generate socioeconomic benefits through various channels and how some of them might be connected, in order to isolate and distinguish the effect on children's education.

Benefits of electrification regarding health include the transition from kerosene lamps to electric light which greatly improves the household's indoor air quality (Lenz et al. 2017, Khandker et al. 2014). The transition from traditional lighting sources, such as kerosene, to electric powered alternatives have in some cases also been shown to lead to increased disposable income for the households thanks to decreasing costs per lighting hour (Peters & Sievert 2016). Other income generating effects include extended hours for productive activities (Khandker et al. 2012). With increased income, the household can afford to invest in appliances such as a refrigerator, television and radio, greatly improving the household members' quality of life.

Access to electric light is also one of the main channels behind the benefits related to children's educational attainment. Other factors of importance that have been identified in the literature regarding children's educational attainment include the children's family background, such as parental education, income, social class, family size and composition, and individual-child characteristics such as their sex and engagement in the labor market (Kulkarni & Barnes 2017). Electric lighting is expected to increase the time spent studying by extending and facilitating the possibility to study after nightfall, since traditional lighting sources such as kerosene lamps or candles provide only very little and low-quality light (Khandker et al. 2014). Access to electric light also means that the children can alter their time between productive activities (paid labor, studying) and leisure in a way that might result in longer study hours. Another possible result to expect is higher school attendance since with greater flexibility on how to organize their activities, children can choose to pursue activities which previously made them skip school in the evening instead (Peters & Sievert 2016). An indirect benefit of electrification regarding children's education is channeled through the introduction of household amenities such as televisions and radios. Through television and radio programs, household members get increased exposure to information, awareness of current events and education of various sorts.

Some studies have pointed out that this can lead to increased educational outcomes (Lenz et al. 2017, Khandker et al. 2012, Hirmer & Guthrie 2017), while other studies have argued that with the introduction of televisions and radios in the household, the time children spend studying might decrease as a consequence. Moreover, computers and mobile phones can improve digital literacy and technological knowledge, facilitate social interaction and narrow down social and educational gaps between rural and urban communities (Hirmer & Guthrie 2017). Another important aspect is how electrification affects the marginal return of activities, and thus the opportunity cost. When electricity is introduced to the household, so is also new possibilities to earn an income, making leisure time less appealing. However, as households acquire appliances like televisions, the marginal value of leisure time increases. Therefore, since the impact might be positive on both the opportunity cost of productive time and leisure time simultaneously, the net effect is uncertain.

To put what has been discussed above in a more formal setting, one can consider Gary Becker's "A Theory of the Allocation of Time" (1965). The paper studies the allocation of time within a household with respect to four different activities; 1) market production, 2) home production, 3) recreational activities and 4) human capital formation (Becker 1965, Heckman 2015). The first category includes time devoted to paid labor while the second category covers household labor such as child care, cooking, washing and other unpaid activities. The third category involves recreational activities such as entertainment, playing sports and sleeping. The final category covers time spent in school and the time spent studying at home. The household's objective is to maximize its utility by managing its disposable time and devote it to each of these categories. With the introduction of electricity, productive market or home activities can become more effective thanks to improved lighting and the help of electric appliances, hence the time and effort required to produce the same amount of work which was produced before electrification is likely to decrease. As a result, the household will have more time at its disposal which can be used to further increase the household's utility level. Depending on the family's situation (income, education) and how the economy rewards the different activities (market work or investments in human capital formation), the family can choose to devote its increased disposable time to paid labor or to invest it in human capital formation. Thus, if the economy favors investments in human capital, households might be more inclined to prioritize children's schooling, leading to increased educational attainment. Furthermore, another important result of electrification is that the households will no longer be constrained by daylight or low-quality light sources to the same extent. This means that the total amount of time that the households have at their disposal to maximize their utility will increase, and the households will have greater freedom to choose between activities from all four categories. Following the previous argument, the household can choose to devote its increased disposable time differently depending on its own situation and how the economy rewards investments in the different categories, but overall, we should expect an upward shift in the households' utility level resulting from the increased amount of time households have at their disposal.

3.1. Hypothesis

With reference to our theoretical exposition, we expect electrification to improve children's education by allowing reallocation of time and extended study hours, especially after sunset. Thus, our hypothesis is that electrification has a positive correlation with children's educational attainment, and that this positive correlation might be larger for girls since they tend to do more housework and are likely to benefit more from the increased flexibility that follows with having access to light even after sunset.

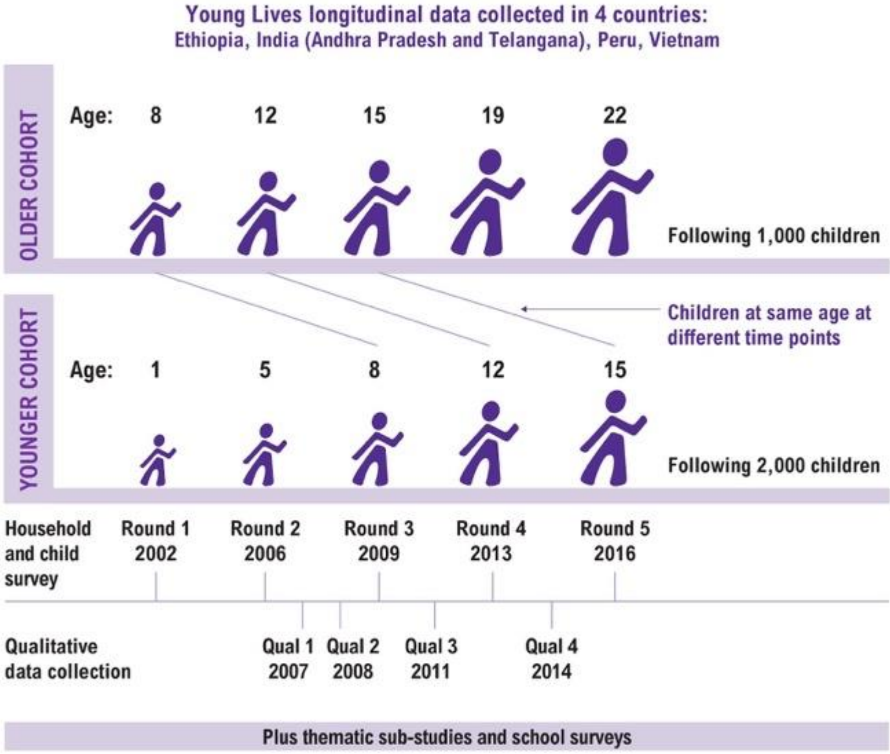
4. Data

4.1. Data source

For our study, we need information about children's education as well as other important characteristics, such as access to electricity and the location of the households in order to separate the rural households from the urban, and we need data from developing countries since that is the scope of our study. To be able to treat unobservable heterogeneity we need panel data for our analysis. This kind of data is available from the Young Lives at the University of Oxford, a study that specializes in childhood poverty in developing countries. The aim of the project is to present what factors cause and affect childhood poverty and to bring forth evidence for policymakers in order to design programs that can help poor children and their families (Young Lives n.d. 1). It follows the lives of around 12 000 children over a period of 15 years in Ethiopia, India, Peru and Vietnam, and has country teams in each of the nations. The children consist of two groups, an older cohort born in 1994-1995 and a younger cohort born in 2001-2002. This, combined with the time perspective, can further deepen our analysis of the effects of electrification.

The data is collected by field workers in 20 sites in each country and contains extensive information about households' socioeconomic characteristics such as income, education, health, livestock ownership and shocks, as well as information about the local community such as schools and infrastructure.

Figure 1: The cohorts and observation points of the Young Lives study



Source: Young Lives (n.d. 2)

Figure 1 describes the dataset. The longitudinal panel data of the cohort in the four countries has been collected in four different periods, carried out in 2002 (Round 1), 2006 (Round 2), 2009 (Round 3), and 2013 (Round 4), using a household and child survey when the young cohort was 1, 5, 8 and 12 years old and the older cohort was 8, 12, 15 and 19 years old. The Young Lives unit has published a harmonized dataset (Boyden 2016) which has been constructed using the four rounds for the countries and includes over 200 selected key variables available for all nations. This main dataset is consequent over countries and over time periods, where most of the variables are comparable, making it suitable for cross-country analysis. Additionally, there is round specific raw data available for each country.

4.2. Variables of interest

For our research topic, the dependent variables we use in the dataset are educational variables. We use children's enrolment in school, mathematics test scores (corrected for item misfits, gender and language bias) and the PPVT raw test score (Peabody Picture Vocabulary Test, a measurement for an individual's receptive vocabulary) as proxies for children's educational outcomes. Thus, we use two test score variables, focusing mainly on cognitive ability, and one variable on formal school attendance to examine the relationship between electrification and education. By using test scores, we can display changes in educational attainment over time compared to when only using school enrollment. School enrollment is still common in impact evaluation studies in developing countries since it is often available, making it suitable for over-time analysis (Kulkarni & Barners 2017). The variable for school enrollment is only available for the older cohort in the first round but includes the younger cohort at pre-school level from the second round onwards. Dasso et al. (2015) argue that due to the low quality of schools in developing countries, only using school enrollment as a proxy for educational attainment might be misleading, and therefore suggest that test scores can be a better measurement of schooling outcomes. In our dataset, the PPVT raw test scores and the math corrected test scores are available for the second and third round, and the math test scores is available only for the older cohort during these two periods (see Appendix 3). Therefore, examining the relationship between electrification and PPVT and math outcomes is only possible between two adjacent time periods. Conclusively, using these variables enables us to observe potential effects of electrification between households with access to electricity compared to those without.

The dataset also contains detailed information about the children's time allocation for different daily activities, like household chores, study time and time spent in school, amongst other. With reference to the literature review, there are several potential channels through which electrification can affect the daily lives of household members in developing countries, and therefore it is of interest to study time distribution. Examining the time allocation allows us to analyze whether access to electricity is associated with increased study time at home, or change in time spent on other activities.

As for the independent variables, we include access to electricity as our main variable of interest. It contains information about whether the household at the specific time period has electricity access, without stating how the electricity is being used. The data on electricity access is available at household level for all time periods and all countries, except Vietnam in the fourth round. As can be seen Appendix 1, the access to electricity in India and Vietnam is relatively high all through the four rounds. Because of this we limit our single- and cross-country analyses to only include Ethiopia and Peru since these two countries have larger shares of non-electrified households from the first time period with a gradual development onwards, and these two countries are highly relevant for the efforts to increase electricity access in the developing world in both Africa and in South America. Furthermore, we also include a variable indicating whether the child is a girl or a boy to check whether the effect of electrification differs between the two, based on observations in previous literature, in order to test our hypothesis.

Our control variables include several child-individual and household characteristics as well as country variables. The individual-child variables include gender, as mentioned earlier, and if the child is stunted in order to control for the correlation between health and education (a child's poor health might affect its education, and long-term poor health can result in restricted growth). Finally, we include literacy of mothers and fathers to control for parents' education. Regarding the household, we include a location dummy (urban or rural household), a wealth index (based on indexes for housing quality, access to services and consumer durables), household size, and shocks indicator for the birth of a new household member (as this might increase the burden of chores on already existing household members). Furthermore, we include a set of dummy variables to control for country-specific characteristics as well as yearly fixed effects.

To conclude, in order to answer our research question where we aim to examine the relationship between electrification and children's education and control for the difference of the effect between girls and boys, we will focus our analysis on Ethiopia and Peru.

4.3. Descriptive statistics

Table 1 present summary statistics for the two countries included for the single-country analysis, and Appendix 2 presents the descriptive statistics for all four countries for reference. Regarding the two countries, the highest possible test score for PPVT is 125 in Peru while 203 in Ethiopia, which results from the different versions of the PPVT tests containing a different number of items (the test in Peru is a version of the so called PPVT-R test while the one conducted in Ethiopia is the PPVT-III test). The math test consists of fewer observations in comparison because of its focus on the older cohort, and the possible test score ranges between 0 and 30. Approximately 71 % are enrolled in school at the time of the survey. The sample consists of 48.3 % girls and 70.3 % belong to the younger cohort. The child health proxy indicating if the child is stunted shows that approximately 28 % of the children experience stunted growth. Approximately 63.7 % have access to electricity and 44.8 % live in rural areas. The wealth index indicates household wealth below the average of the index. The average household consists of almost 6 members while the smallest household size consists of one member (89 observations), implying the child lives by itself, and the largest consist of 18 members (3 observations), but sizes larger than 12 or more members have less than 100 observations each. Around 11 % of the households have experienced the birth of a new member during the survey period, and 48.5 % of mothers and 62.1 % of fathers are literate.

Table 1: Descriptive statistics – Ethiopia & Peru

Variable	Observations	Mean	Standard Deviation	Min	Max
Schooling characteristics					
PPVT raw test score[A]	10 196	59.391	41.118	0	203
Math test	3 270	6.850	5.126	0	29.0
School enrollment	18 071	0.710	0.454	0	1
Child characteristics					
Girl	22 308	0.483	0.50	0	1
Age	22 039	8.515	5.117	0.416	22.667
Stunted	21 259	0.283	0.450	0	1
Younger cohort	23 060	0.703	0.457	0	1
Household characteristics					
Electricity access	22 073	0.637	0.481	0	1
Rural	22 105	0.448	0.497	0	1
Wealth index	22 017	0.403	0.231	0.000	0.953
Household size[B]	22 091	5.751	2.098	1	18
Birth of hh member	20 817	0.110	0.313	0	1
Mother is literate	20 531	0.485	0.50	0	1
Dad is literate	17 295	0.621	0.485	0	1

Note: A) The highest PPVT test score possible in Ethiopia is 203 and 125 in Peru. B) Although the mean household size is closer to 6 members, 20 % have 5 members while 17 % have 4 or 6 members.

Our variables on cognitive capacity, the PPVT and math test score, have a considerable share of missing values (see Appendix 3). However, the valid observations in the second and third rounds still allow us to run regressions with both test score variables over two time periods, with the difference that the math test score considers the older cohort. For the purpose of this study, the data can be used in order to examine our hypotheses.

5. Methodology

5.1. Motivation

In this study we want to assess whether access to electricity comes with benefits in the form of improved education for the children living in the affected households, and also whether this improvement is greater for girls. The relationship between electrification and children's educational attainment is estimated with the use of several OLS fixed-effects regressions on different outcomes related to children's education. The advantage of conducting the analysis within the framework of a fixed-effects regression is that we can remove unobservable and time-invariant heterogeneity, and hence decrease the bias of our estimates. However, the results of the OLS fixed-effects regressions will not be enough evidence for a causal relationship. To isolate causal relationships with observational data, it is common to make use of different econometric techniques such as the Instrumental Variable approach or the Difference-in-Differences (DiD) approach. Unfortunately, we have been unable to find a convincing instrument in the dataset. Furthermore, there are many conditions that need to be met in order to successfully go through with a DiD approach, for example one must isolate treatment- and control groups with parallel trends in the outcome variables. Given the nature of the data, we find it unlikely that we will be able to isolate groups that share this characteristic. Although simple in its nature, OLS fixed effects regressions can still provide a lot of information about a potential relationship on a more descriptive level, i.e. in terms of correlation. Thus, we will focus on studying our research question with the help of OLS fixed effects regression and then, drawing on the theoretical framework we laid out in an earlier section, we intend to see if a potential relationship can be supported by children's time allocation to daily activities.

5.2. LPM, Logit & Probit

Due to the binary nature of the dependent variable school enrollment, the model of analysis needs to consider discrete values. A binary, or dummy, variable requires that the output value equals either 0 or 1, which in the case of school enrollment characterizes being enrolled in school if the variable equals 1, and otherwise 0. The methods used to for this binary dependent variable is Linear Probability Model (LPM), Logit model and Probit model.

The first model, LPM, is called linear because the response probability is linear - when there is a change in an independent variable, holding all other factors fixed, the probability of the outcome being equal to 1 will increase linearly. The main advantage of the LPM is the interpretability, but there are some limits to it. Firstly, certain combinations of the independent variables can result in nonsensical predictions as the outcome variable can take on values smaller than 0 and larger than 1. Secondly, there is a problem of constant marginal effects, since a unit change in the independent variable is associated with a constant change in the dependent variable, regardless of the value of the independent variable. These issues can be tackled by using the non-linear Logit or Probit models (Wooldridge 2014). The former is based on logistic function and the latter on standard normal cumulative distribution function, and the difference of the two can be observed in the distribution of the tails. The main advantage of these rather similar models is that the probability stays between 0 and 1 and the estimates obtained are likely to be alike unless large samples. The main disadvantage is that the estimated coefficients by themselves cannot be interpreted directly (except their signs) since the coefficients depend on the starting point, implying that the impact of a change in a certain variable has to be evaluated at some fixed level of the other included independent variables in order to receive an interpretable result (Wooldridge 2014, Burney & Irfan 1991).

By using all three methods, a similar output value in all three models could indicate relatively similar results, thus the results from the LPM can be used in the analysis for easy interpretation. If acquiring a similar result from the Logit and Probit, this could indicate that the results are not driven by the choice of method.

5.3. Model specification

The model we intend to estimate is specified as follows:

$$y_{it} = \varphi_{it}'\beta + \delta_{it}'\beta + \theta_i + \gamma_t + \alpha_c + (\mu_{it}\omega_i)\beta + \varepsilon_{it}$$

y_{it} is the outcome variable of interest; the children's educational attainment, measured by either enrollment, the score on a math test or PPVT test, and time allocation to daily activities, for child *i* in round *t*. φ_{it}' is a vector of individual child characteristics such as the health status of child *i* in round *t*. δ_{it}' is a vector of household characteristics such as household size, wealth and access to electricity for child i in round *t*. θ_i controls for observable time invariant characteristics such as the sex of child i. γ_t controls for unobservable time variant characteristics for all children in round *t* (yearly time fixed effects). α_c controls for unobservable time invariant characteristics for all children in country c (country fixed effects). μ_{it} is a dummy variable indicating whether or not child *i* had access to electricity in round *t*. ω_i is a dummy variable indicating whether child *i* is a girl or not. The interaction term, $\mu_{it}\omega_i$, captures if and how the impact of having access to electricity on educational attainment differs between girls and boys. ε_{it} is the unobserved error term for child *i* in round *t*.

6. Results & analysis

6.1. Test scores and school enrollment

Table 2: Children's PPVT raw test scores

Explanatory variables	(1) Cross-country OLS	(2) Ethiopia OLS	(3) Peru OLS
Access to electricity	5.431***	3.778*	1.529
	(0.937)	(1.774)	(0.940)
Stunted	-3.014***	-3.930***	-3.268***
	(0.545)	(0.884)	(0.558)
Rural residence	-8.841***	-13.684***	-4.094***
	(0.768)	(1.552)	(0.640)
Wealth index	26.904***	23.989***	35.851***
	(1.882)	(4.425)	(1.516)
Household size	-0.436**	-0.361	-0.676***
	(0.138)	(0.233)	(0.126)
Birth of household member	0.246	-0.038	2.439***
	(0.665)	(0.980)	(0.716)
Girl	-0.697	-1.684	0.528
	(0.793)	(0.977)	(1.057)
Mother is literate	6.466***	9.595***	4.147***
	(0.803)	(1.459)	(0.673)
Father is literate	4.140***	4.129***	1.240
	(0.754)	(1.002)	(0.841)
Girl x Electricity	-0.790	0.411	-2.145
	(1.015)	(1.829)	(1.161)
Younger cohort	-60.905***	-60.663***	-39.121***
	(0.958)	(0.968)	(0.514)
Constant	76.812***	80.731***	52.931***
	(1.677)	(2.644)	(1.530)
Country FE	Yes	No	No
Time FE	Yes	Yes	Yes
Observations	7727	3948	3779
R^2	0.701	0.681	0.773

Note: PPVT only for round two and three. The dependent variable called *PPVT raw test score* is a continuous variable indicating test score. Access to electricity is a binary variable taking the value 1 if the household has access, otherwise 0. For explanation of other variables, see Data section. All estimates are obtained using the Young Lives dataset.
Standard errors in parenthesis.
* p<0.05, ** p<0.01, *** p<0.001

Table 2 illustrates the results for the cross- and single-country regressions on children's PPVT scores. The sample includes observations from round two and three. Our main variable of interest, access to electricity, is estimated to increase the PPVT score by 5.4 points in the cross-country regression. The estimate is highly significant and the corresponding estimates reported from the single-country regressions indicate a positive relationship as well, although only significant in the case of Ethiopia. Our proxy for children's health, *stunted*, is estimated to decrease the children's test score by 3 points in the cross-country model, holding all other variables constant. Although highly significant in all three regressions, it does not have a major impact on the children's test score. In contrast, household characteristics captured by the wealth index are found to be of much greater importance for the children's PPVT test scores. We also note that our second variable of interest, the interaction term *Girl x Electricity,* which captures whether the effect of having access to electricity differs between boys and girls with respect to their educational attainment, is found insignificant with relatively negligible and inconsistent estimates. The same goes for the dummy variable *girl*, which captures the systematic difference between boys and girls. Considering that the age only varies between the two cohorts, i.e. there is no variation within the cohorts with respect to age, we have only included a dummy variable, *Younger cohort,* to control for the inter-cohort variation with respect to age. The variable shows that the younger cohort scores systematically lower points than their older peers, which is reasonable considering that the older cohort has had more time to accumulate knowledge. Regarding the variables controlling for household characteristics (parental education proxied by literacy, income level proxied by wealth index, household size), the reported estimates are generally consistent and in line with previous findings in the literature dealing with children's educational attainment.

Table 3: Children's math test scores

Explanatory variables	(1) Cross-country OLS	(2) Ethiopia OLS	(3) Peru OLS
Access to electricity	-0.414 (0.306)	-0.348 (0.362)	0.077 (0.538)
Stunted	-1.064*** (0.192)	-0.898*** (0.217)	-0.939** (0.318)
Rural residence	-0.785** (0.268)	-1.050** (0.333)	-0.791* (0.372)
Wealth index	4.989*** (0.681)	3.382*** (0.973)	5.004*** (0.821)
Household size	-0.125** (0.048)	-0.079 (0.056)	-0.158* (0.069)
Birth of household member	0.522* (0.253)	0.024 (0.258)	0.256 (0.439)
Girl	-0.475 (0.255)	-0.702** (0.255)	0.717 (0.582)
Mother is literate	0.837*** (0.243)	0.523 (0.329)	1.454*** (0.344)
Father is literate	0.548* (0.219)	0.802*** (0.234)	-0.182 (0.462)
Girl x Electricity	0.077 (0.343)	0.325 (0.408)	-1.191 (0.648)
Constant	3.582*** (0.524)	5.391*** (0.596)	3.704*** (0.869)
Country FE	Yes	No	No
Time FE	Yes	Yes	Yes
Observations	2214	1300	914
R^2	0.374	0.145	0.549

Note: Math test only for round 2 and 3 and for older cohort. The dependent variable *Math test score* is a continuous variable indicating test score, where the maximum attainable test score is 30. Access to electricity is a binary variable taking the value 1 if the household has access, otherwise 0. For explanation of other variables, see Data section. All estimates are obtained using the Young Lives dataset.
Standard errors in parenthesis.
* p<0.05, ** p<0.01, *** p<0.001

Table 3 displays the results for the cross- and single-country regressions on children's math test scores. This sample includes observations from round two and three and are limited to the children belonging to the older cohort. Although most variables are similar with the output found in Table 2, many of them are now reported with insignificant estimates and some have switched signs. Access to electricity is now estimated to decrease the children's score on their math tests by 0.41 points in the cross-country regression, however the estimate is statistically insignificant and negligible considering it is very close to zero. The corresponding estimates reported in the single-country regressions are all insignificant and close to zero as well. We note that the data on children's math test scores was gathered from the country specific data sets and not from the harmonized data set constructed by the Young Lives researchers. Hence, we believe it is possible that there are issues with the quality of the data concerning the math test scores and that this might be the cause of the inconsistent results found in Table 3.

Table 4: Children's school enrollment

Explanatory variables	(1) Cross-country LPM	(2) Cross-country Logit	(3) Cross-country Probit
Access to electricity	0.100*** (0.012)	0.069*** (0.013)	0.086*** (0.016)
Stunted	-0.049*** (0.008)	-0.056*** (0.007)	-0.060*** (0.010)
Rural residence	-0.029** (0.009)	-0.037** (0.011)	-0.040** (0.014)
Wealth index	-0.010 (0.022)	0.075** (0.028)	0.072* (0.035)
Household size	0.002 (0.002)	-0.002 (0.002)	0.000 (0.002)
Birth of household member	-0.044*** (0.010)	-0.027** (0.009)	-0.045*** (0.012)
Girl	0.024* (0.011)	0.018 (0.009)	0.023 (0.012)
Mother is literate	0.034*** (0.009)	0.060*** (0.011)	0.060*** (0.014)
Father is literate	0.061*** (0.009)	0.054*** (0.009)	0.063*** (0.011)
Girl x Electricity	-0.012 (0.013)	0.006 (0.013)	0.006 (0.017)
Younger cohort	-0.262*** (0.013)	-0.268*** (0.016)	-0.256*** (0.017)
Constant	0.604*** (0.023)	0.533*** (0.152)	0.271** (0.091)
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	12 691	12 691	12 691
R^2	0.448		

Note: The Logit and Probit models estimate the marginal effect at the mean values of the explanatory variables. The dependent variable *School enrollment* is a binary variable taking value 1 if the child is currently enrolled in formal school at the time of the survey, otherwise 0. Access to electricity is a binary variable taking the value 1 if the household has access, otherwise 0. For explanation of other variables, see Data section. All estimates are obtained using the Young Lives dataset.
Standard errors in parenthesis.
* p<0.05, ** p<0.01, *** p<0.001

Table 4 displays the results for the cross-country regressions on children's school enrollment. The sample includes observations from round two and three. The reported estimates are consistent in all three models. From the linear probability model, we find that access to electricity is associated with a 0.1 unit increase in the probability of being enrolled in school.

The estimate is highly significant and the corresponding estimates from the Logit and Probit models are, although somewhat smaller, highly significant as well. Household characteristics such as parental education (literacy) and wealth are also associated with a positive increase in the probability of being enrolled in school. A striking difference in these models, compared to the previous OLS models, is that the positive effect of the household's income level is much smaller and more on par with the impact of electricity access. We further note that the estimates regarding our interaction term, *Girl x Electricity*, are found insignificant and close to zero in these models as well.

6.2. Children's time allocation of daily activities

The graphs in Appendix 4 display the mean number of hours spent in different categories of the children's daily activities. The categories are defined as follows: *Sleep* hours/day spent sleeping, *Care* hours/day spent caring for household members, *Household chores* hours/day spent doing household chores, *Household tasks* hours/day spent doing domestic tasks (farming, family business), *Work* hours/day spent in paid activity, *School* hours/day spent in school, *Study* hours/day spent studying outside school and *Play* hours/day spent in leisure activities.

Although the time devoted to sleep and leisure activities is similar for both groups the children with access to electricity and those without, there are more noticeable differences between several of the remaining categories. Regarding time spent on studying outside of school, the difference is around a half hour per day in both countries. Also, those with access to electricity tend to spend more time in school each day. Generally, household chores and tasks take up more time of the children's daily activities in households without electricity. The observed differences are consistent with what we would expect based on the conceptual framework, including Gary Becker's "A Theory of the Allocation of Time" (1965), discussed in an earlier section.

To ensure that the observed differences are statistically significant we analyze time allocation with our empirical model, and the results are found in Table 5. From this, we find a positive and significant increase in time spent in school. We also find, surprisingly, that the time children spend on chores increase when the household has access to electricity. Looking in the interaction term *Girl x Electricity* we find that access results in girls spending less time on household chores. We cannot find any significant differences in the time spent studying outside of school. So, even though there seems to be a difference between the group having access to electricity and the group without, from out graphical analysis, our regression cannot find any statistically significant differences in our sample.

Table 5: Children's time allocation

Explanatory variables	(1) Sleep OLS	(2) School OLS	(3) Study OLS	(4) Chore OLS	(5) Care OLS	(6) Task OLS	(7) Play OLS
Access to electricity	0.136***	0.606***	-0.026	0.288***	0.008	-1.083***	0.137
	(0.038)	(0.069)	(0.031)	(0.040)	(0.34)	(0.065)	(0.074)
Stunted	0.092***	-0.262***	-0.117***	0.007	0.031	-0.028	0.233***
	(0.024)	(0.045)	(0.020)	(0.025)	(0.025)	(0.036)	(0.050)
Age	-0.170***	1.261***	0.345***	0.227***	0.053	0.179***	-1.176***
	(0.036)	(0.064)	(0.031)	(0.035)	(0.035)	(0.048)	(0.066)
Age^2	0.004***	-0.054***	-0.013***	-0.009***	-0.001	-0.006***	0.053***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Rural residence	0.085**	-0.264***	-0.165***	0.100**	-0.066*	0.846***	-0.409***
	(0.030)	(0.054)	(0.025)	(0.032)	(0.031)	(0.042)	(0.066)
Wealth index	-0.402***	0.611***	0.754***	-0.498***	-0.639***	0.174	-0.286
	(0.077)	(0.132)	(0.068)	(0.074)	(0.072)	(0.095)	(0.147)
Household size	-0.020***	-0.027**	-0.025***	-0.025***	0.037***	0.020**	0.017
	(0.006)	(0.010)	(0.005)	(0.006)	(0.006)	(0.008)	(0.011)
Birth of household member	0.078*	-0.183**	0.032	-0.050	0.422***	0.029	-0.314***
	(0.033)	(0.056)	(0.025)	(0.032)	(0.037)	(0.047)	(0.066)
Girl	0.020	0.161*	0.022	0.860***	0.459***	-1.529***	0.051
	(0.037)	(0.066)	(0.027)	(0.041)	(0.041)	(0.062)	(0.077)
Mother is literate	-0.066*	0.401***	0.102***	-0.144***	-0.042	-0.169***	-0.005
	(0.031)	(0.056)	(0.026)	(0.030)	(0.030)	(0.040)	(0.060)
Father is literate	0.001	0.429***	0.111***	-0.188***	-0.049	-0.089*	-0.123*
	(0.029)	(0.053)	(0.024)	(0.032)	(0.029)	(0.045)	(0.058)
Girl x Electricity	-0.044	-0.132	0.067	-0.454***	-0.248***	1.237***	-0.301***
	(0.044)	(0.078)	(0.035)	(0.047)	(0.046)	(0.068)	(0.089)
Younger cohort	0.697**	-1.067**	-0.653***	-0.781***	0.254	0.016	2.901**
	(0.217)	(0.362)	(0.181)	(0.214)	(0.207)	(0.293)	(0.406)
Constant	10.698***	-2.432***	-0.565	0.511	-0.202	0.239	10.612***
	(0.395)	(0.663)	(0.330)	(0.382)	(0.375)	(0.521)	(0.731)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11182	11182	11182	11182	11181	11180	11182
R^2	0.231	0.387	0.319	0.291	0.096	0.304	0.374

Note: Time allocation regressions cover round two to four. The dependent variables are continuous variables indicating the child's time allocation for different daily activities, measured in hours per day. All estimates are obtained using the Young Lives dataset. Standard errors in parenthesis.
* p<0.05, ** p<0.01, *** p<0.001

7. Discussion

From our study, it is possible to see that there exists a positive relationship between access to electricity and school enrollment, the time allocated for studying in school and a small but positive relationship on school test scores. However, there are a few aspects of the model and variables that need to be discussed in order to clarify limitations in this analysis.

To start with, the main variable of interest, access to electricity, has a few restrictions. It does not disclose what the electricity is used for or the quality of the supply. Therefore, there could be a problem with omitted variable which could bias out results, namely the quality, use and reliability of the electricity which the specific households have access to. If the quality is poor, the supply level is low, and the household cannot rely on the electric light to work at home, the child might not study as much at home as one would expect, or still rely on traditional lighting sources like candles and kerosene lamps. Even though there is information available on electricity reliability in the raw data (which the constructed, harmonized dataset is based on) it is only at a community level. A local community might have better or worse reliability for different reason and this could serve as a pointer in how it might affect the children, but since this study focuses on the individual level this is not enough for our analysis. Furthermore, even if a community has a steady flow of electricity in general, this might not be the case for individual households due to, for example, poor quality of the cables connecting the house or other defects. Furthermore, we lack data on how electricity is used and to what extent the it can help spur children's educational attainment. Since previous studies emphasize that electric light normally is the first investment after getting access, one could expect this to be of use for the child. If the household acquires new technology such as a television or radio which could increase the child's cognitive abilities and understanding of surroundings, we cannot analyze if these items benefit the child thoroughly. Thus, there is a problem with omitted variable bias since we do not have data on electric light availability and can therefore only speculate that electric light is one of the first services a household gets when electricity is installed, taking the previous studies into consideration.

The variable for wealth index includes indexes for services and consumer durables, which in turn includes ownership of some goods such as radio and television. A higher wealth index could indicate that the household has access to certain facilities, and therefore absorb some of the magnitude of our main variable of interest, namely electricity access. However, it does not disclose the quality of these goods or services, how often they are being used and by which family member, although the information on the child’s time allocation for play/leisure activities could give a hint. Also, television viewing could be seen as a leisure activity at the same time as it can be informative and increase the child’s educational attainment, but the dataset does not disclose time use more specifically. A more thorough analysis of ownership of some goods, how these are being used, and more specific time allocation data could be of interest for further studies but is not within the scope of this study.

Our analysis showed some small, positive effect of electricity on PPVT test scores but could not find significant results in the case of math scores. This might be due to the fact that the sample is smaller, that it only covers a part of the children (the older cohort) and only two time periods. There is also the problem of comparing the reliability of the math test score with the PPVT test score, since the first was constructed using the raw data and the latter variable was available directly in the harmonized dataset constructed by the Young Lives unit. Their method of handling the data could differ from ours and be more reliable. Additionally, this study could have benefited from having access to better data coverage regarding time and the amount of observations.

Lastly, although our results suggest that there exists a positive relationship between access to electricity and children’s educational attainment, the relationship is quite modest. We would argue that providing mere access to electricity is not enough to raise children’s educational attainment in developing countries, but such electrification programs should be combined with efforts that focus on raising the quality of the education children receive.

8. Conclusion

This study has examined the relationship between electrification and children's educational attainment in Ethiopia and Peru, and if there might be any differences in how girls and boys are affected. We were able to find some positive relationships on school enrollment, time spent in school and small but positive relationship on test scores, meaning that electrification programs with the focus on lifting households out of poverty and creating opportunities for children to get a good education might be efficient. However, more studies are needed on how children make use of electricity and what specific factors could help increase adaption, whether it is at a local level or at a country level. Therefore, providing more access to electricity will probably not be enough to raise educational attainment but it must be combined with policies and efforts that focus on raising the schools' quality.

Finally, regarding the gender focus of this study, we were not able to show any significant differences in girls' and boys' school outcomes when households have access to electricity, and therefore we cannot confirm or reject previous research on this topic. Since existing literature points out that there tend to be gender differences where girls end up not acquiring the same level of schooling, further studies are needed in this field, especially in context of the role of electricity in households in order to reduce the burden of household chores that girls face nowadays.

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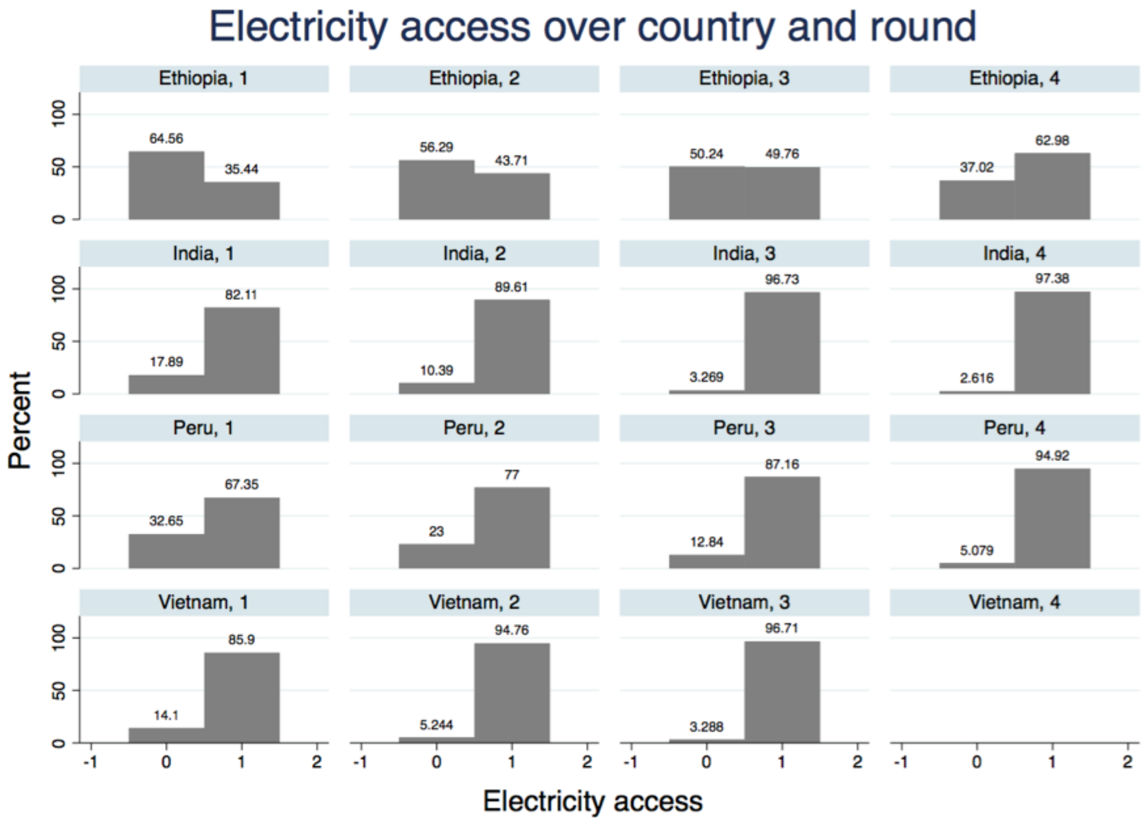
Appendix

Appendix 1 – Electricity access over country and round

Figure 2: Access to electricity over country and round



The figure shows how the access of electricity has changed over time (round) and how it differs between countries. Most notably is that the is a lack of data from the fourth round in Vietnam, and that a relatively high share of sample households in Vietnam and India have had access already from the first round.

Appendix 2 – Descriptive statistics

Table 6: Descriptive statistics – All countries

Variable	Observations	Mean	Standard Deviation	Min	Max
Schooling characteristics					
PPVT raw test score	21 343	70.437	48.413	0	203
Math test	7 180	8.493	6.390	0	30.0
School enrollment	37 461	0.792	0.406	0	1
Child characteristics					
Girl	45 710	0.485	0.50	0	1
Age	45 410	8.686	5.155	0.044	22.667
Stunted	43 492	0.280	0.449	0	1
Younger cohort	47 136	0.684	0.465	0	1
Household characteristics					
Electricity access	42 685	0.773	0.419	0	1
Rural	45 454	0.612	0.487	0	1
Wealth index	45 360	0.461	0.222	0	1
Household size	45 570	5.345	2.020	1	30
Birth of hh member	44 297	0.087	0.282	0	1
Mother is literate	43 396	0.517	0.50	0	1
Dad is literate	39 604	0.642	0.479	0	1

Note: The highest PPVT test score possible is 125 in Peru, 199 in India, 200 in Vietnam and 203 in Ethiopia. Although the mean household size is closer to 5 members, 26 % have 4 members while 22 % have 5 members.

Appendix 3 – Missing values

Figure 3: Math test score availability over country and round

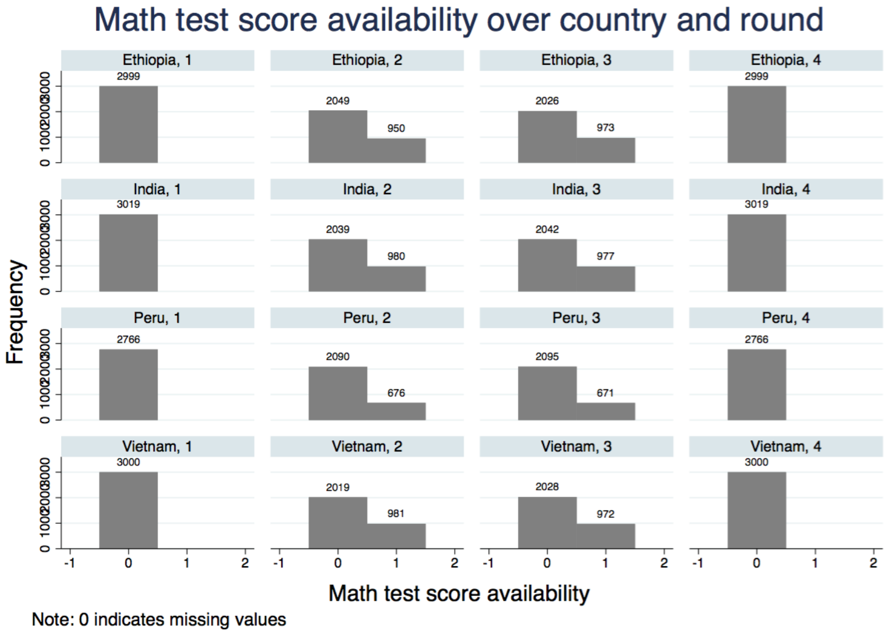
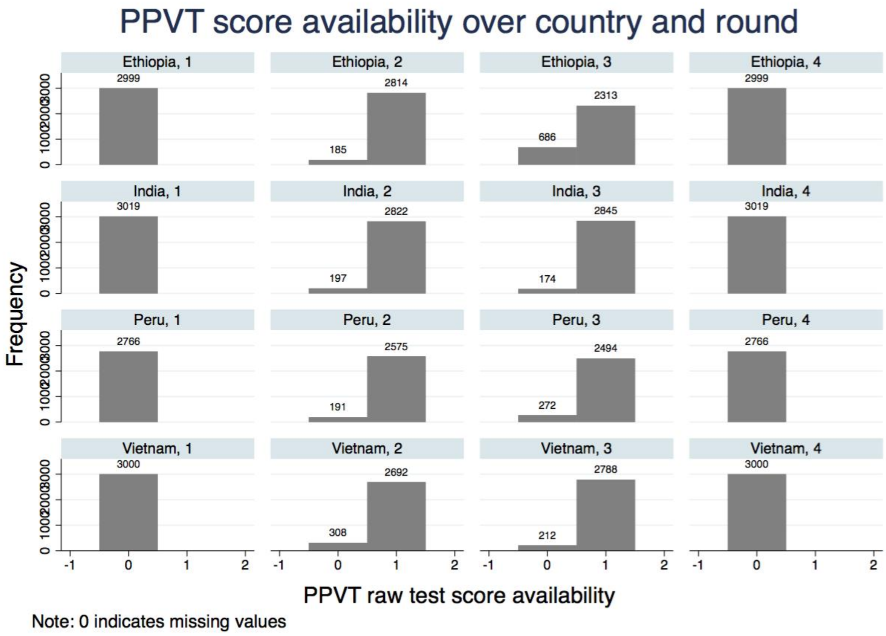


Figure 4: PPVT raw test score availability over country and round



Both figures show the availability of test scores in the dataset. The value 0 indicates that there are missing values for the observations, and 1 indicates that there are valid observations available. For both the PPVT test and the math test there are no observation available in the first and the fourth round. The PPVT test score has a relatively small amount of missing values in comparison to the math test score, but the missing values of the math test score mainly comes from the fact that it only covers the older cohort.

Appendix 4 – Country specific time allocation

Figure 5: Time allocation for children with access to electricity in Ethiopia

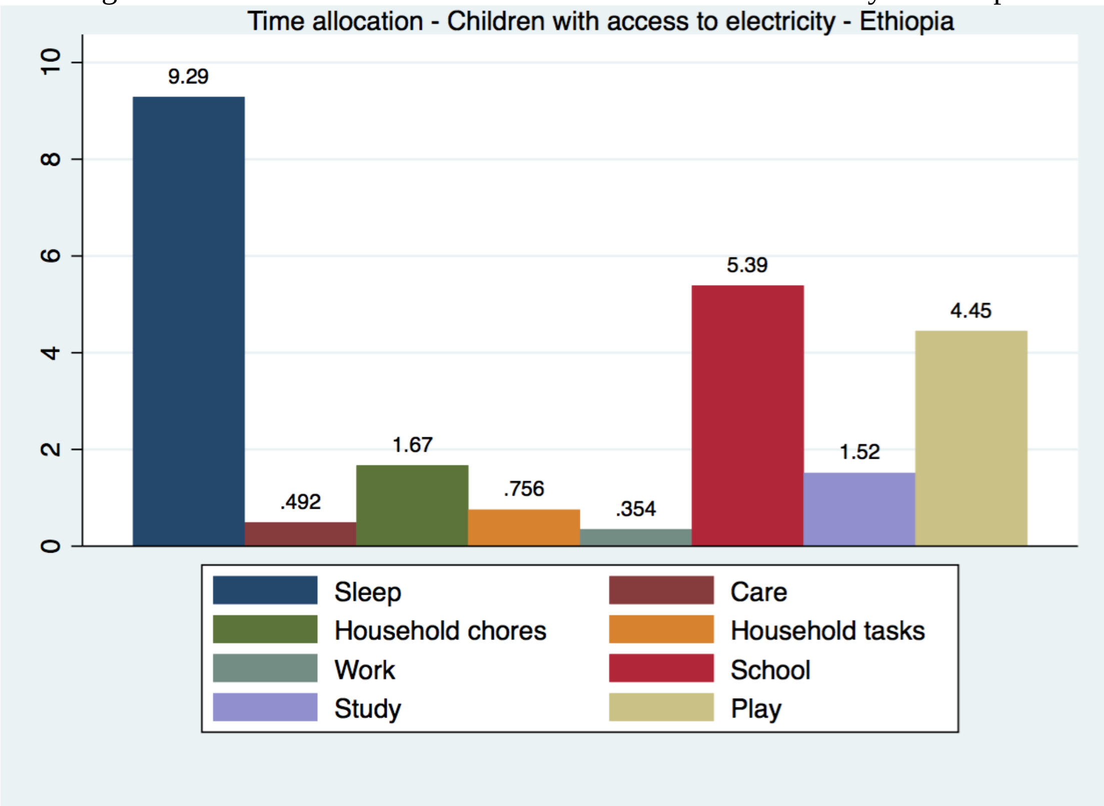


Figure 6: Time allocation for children without access to electricity in Ethiopia

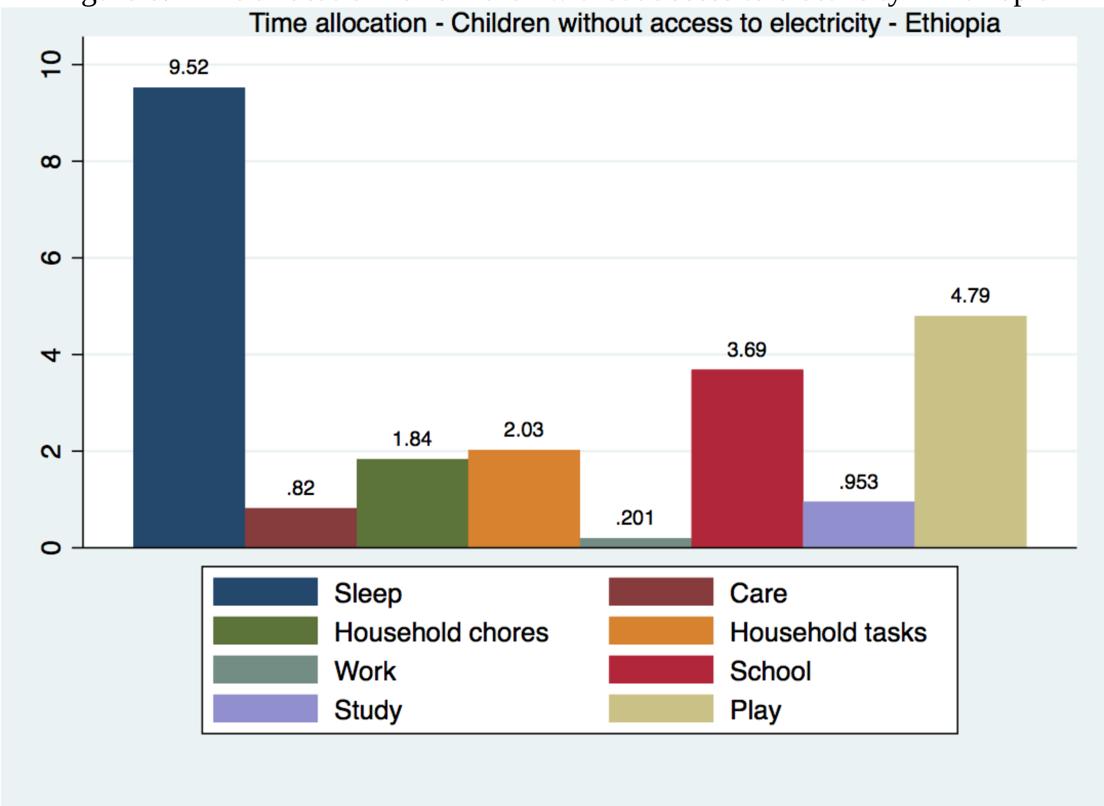


Figure 7: Time allocation for children with access to electricity in Peru

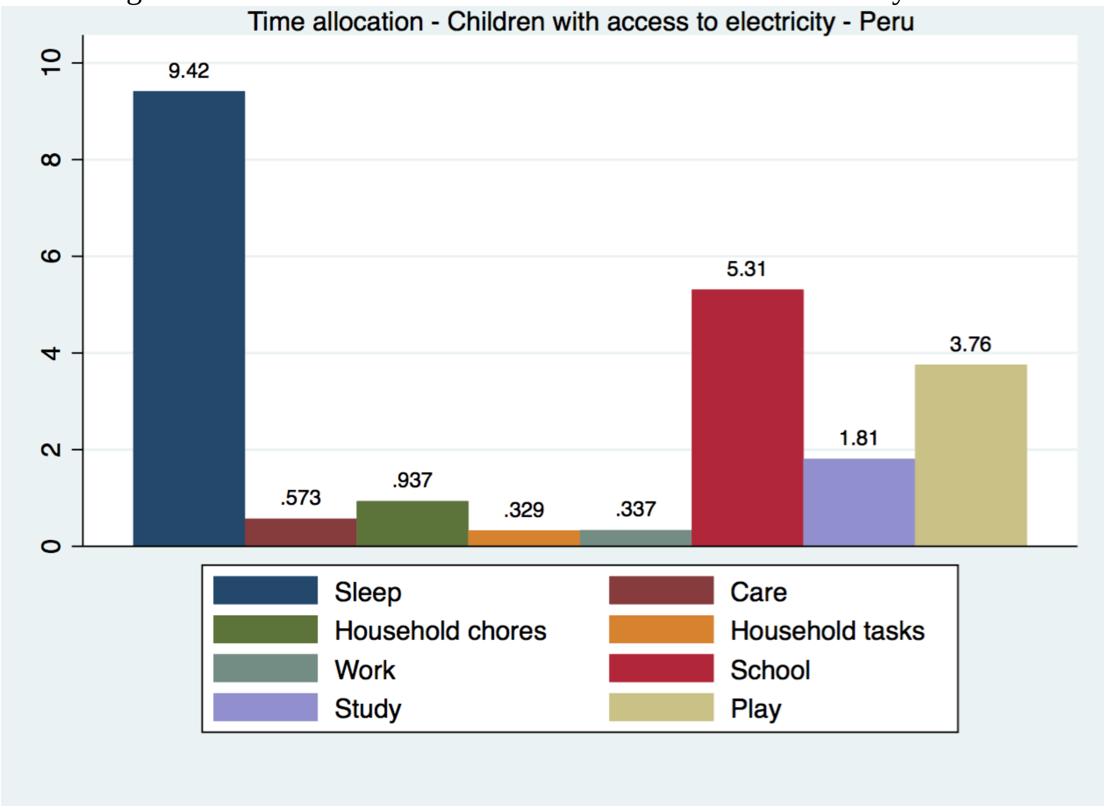


Figure 8: Time allocation for children without access to electricity in Peru