Heterogenous effects of rural electrification on child labor in Nigeria

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January 2022

Abstract

In this paper we assess the impact of rural electrification on child labor in Nigeria using panel data provided by the General Household Survey. This relationship is theoretically ambiguous and the few existing empirical results do not converge. Given unreliability of the power grid and heterogenous equipment rates, electrification cannot be only captured using access to the grid. We investigate in particular how child labor varies depending on the nature of electricity supply and the electrical appliances used in the household. When controlling for a large set of individual characteristics and for selection on unobservables, we find that the employment probability of children from electrified households is lower than that of children living in non-electrified households only when the household combines grid access and a generator as sources of electricity. This combination allows households to be able to use appliances that allow them to save time and reallocate it among their members. While this channel is the preferred one to explain the decline in child labor, it is difficult to relate it statistically to time-saving appliances given their low use among rural households in Nigeria. In addition, we find that girls from households using entertainment appliances (mostly television) are more likely to work than other girls, a result which is robust to both selection on unobservables and heterogenous effects of the treatment.

Keywords: rural electrification, child labor, developing countries

JEL Classification: C33, D1, J22, O13

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[‡]Jeremy Tanguy acknowledges the support of the Chair Energy and Prosperity, under the aegis of the Risk Foundation.

1 Introduction

Recent data on electricity supply in Nigeria demonstrates the extent of progress that remains to be made. Despite a steady increase of electrification over the past two decades and the adoption of a Rural Electrification Strategy and Implementation Plan in 2016, only 55% of the population has access to grid electricity in 2019. This rate drops to 25% in rural areas (World Bank 2021).[1] Due to the severe deficit in on-grid generation capacity, the quality of electricity supply towards connected households is generally poor, with frequent and erratic power cuts and brownouts. Nigerian households and firms frequently rely on private diesel generators for their daily operation. Even when power is available, low reliability of electricity supply limits end users' potential utilization of electricity. While the electricity provided to households might be sufficient to power a light bulb, the capacity and the reliability are not sufficient to power a fan or even more a refrigerator (Blimpo and Cosgrove-Davies 2019).

The literature provides strong evidence on the effect of electrification on several dimensions of development.[2] At a micro level, the economic benefits of rural household electrification are based on the idea that households take advantage of the arrival of electricity to equip themselves in lighting and appliances that respectively extends the day and save time for a range of household chores. Moreover, rural electrification is supposed to expand new job opportunities and to increase productivity that could impact employment and incomes. Empirical literature has explored these hypotheses and provided a fine understanding of the consequences of rural electrification on adult employment and especially on women employment. However, less is known about how electrification affects child labor in rural areas.

Investigating the consequences of rural electrification on child labor is particularly suitable in Nigeria, which reports the highest rate of working children in West Africa, with about 15 million child laborers (International Labor Organization).[3] Child labor in Nigeria today is found predominately in the informal sector, and particularly in rural areas (Alfa et al. 2012), where most working children operate in agriculture, particularly in crop and livestock farming, fishing, agriculture and cattle herding (Asamu 2005). While child labor has always been prevalent in Nigeria, its incidence has increased significantly over the years (Idowu et al. 2013) despite its ban over the whole country.

1. Electrification rates vary substantially across states. The lowest electrification rates are found in the North West states, with 12% in Taraba and Jigawa, and 13% in Kebbi, Sokoto and Zamfara.

2. References can be made to historical studies in the US (Kitchens and Fishback 2015; Kline and Moretti 2014; Lewis and Severnini 2020) or studies on Nigeria (Bernard 2012) and Brazil (Lipscomb et al. 2013).

3. 53% of children eligible for primary education are working while about 81% of children eligible for secondary school are actually not schooling or are combining work with schooling (Odey and Sambe 2018).

To date, the Child's Right Act, that meets international standards for the prohibition of the worst forms of child labour and exploitation, has been adopted by only 25 out of Nigeria's 36 states.

In this paper, we assess the impact of rural electrification on child labor in Nigeria. Following existing literature, we first investigate whether the connection of the household to the electricity grid changes the probability of child labor within the household. The relationship is not unambiguous given the indirect effects involved with electrification. Electrification alone is not expected to affect household time allocation unless combined with the use of electric lighting or electrical appliances that increase available time. Therefore, we consider different forms of electrification beyond grid connection, including the use of a generator as a complementary or alternative source of electricity to the grid and the use of different electrical appliances. Some appliances allow to save homework time in the household (*e.g.* for meals), and can increase the possible working time of some household members outside the house. Conversely, other appliances can increase the time spent at home for leisure (*e.g.* TV set) at the expense of more working time of adults and/or children.

We use data from the different waves of the General Household Survey in Nigeria. We exploit the panel nature of the data to control for selection on time-invariant unobservables using individual fixed effects. We check whether and to what extent our estimates are affected by selection on time-varying unobservables using the method proposed by Oster (2019). We assess the potential bias due to heterogenous treatment effects using the approach of de Chaisemartin and D'Haultfœuille (2020) and we rely then on their difference-in-difference (DiD) estimator, which is robust to heterogenous treatment effects.

We show that children living in electrified households are potentially less likely to work than children living in non-electrified households only when both grid access and a generator are used as power sources. Access to the grid *per se* has not significant effect on child labor. The combined effect of grid and generator seems to be partly driven by the use of time-saving appliances, although their low presence among electrified households does not allow identifying a significant causal relationship with child labor. However, our analysis of end-uses reveals a positive effect of television on the employment probability of girls, which proves to be robust to selection on unobservables and heterogenous treatment effects. Our results have significant implications in terms of public policy. The role of rural electrification in reducing child labor in Nigeria supposes an improvement of the quality of electricity received in these areas, possibly through alternative solutions such as mini-grid or off-grid systems. Our results encourage promoting and raising awareness about the productive agricultural and domestic applications of electricity, as well as facilitating household purchases of appliances, through associated financing program, as the US in the twentieth century (Lee et al. 2020).

We combine and contribute to different streams of the literature. We first contribute to the literature investigating the impact of electrification on household time allocation devoted to work. Most papers devoted to the impact of electrification on households in rural areas have focused on adult labor supply. This literature points out that positive effects of rural electrification on employment, particularly on female employment, rely on the use of appliances requiring a high electricity capacity and effective effects to alleviate household chores (Dinkelman 2011; Grogan and Sadanand 2013; Kohlin et al. 2011). In her seminal paper, Dinkelman (2011) attributes the positive effect of rural electrification on female employment in South Africa to the use of electric stoves and other time-saving appliances. As these appliances do not rely on the use of biomass fuels, they lead to a reduced time spent collecting and preparing such fuels. Since then, this relationship has been the subject of many studies in various developing countries with contrasting results (*e.g.* Grogan 2018; Grogan and Sadanand 2013; Salmon and Tanguy 2016).[4] In fact, the specificity of the findings from Dinkelman (2011) comes from the specificity of her study area: rural households in South Africa commonly use electricity for cooking, while rural households in other developing countries traditionally use electricity first and foremost for lighting, followed by powering televisions and fans (Bernard 2010; IEG 2008). In these contexts, despite the electrical connection, households continue to use traditional fuels and technologies for domestic tasks (*e.g.* cooking) and so collection time is unlikely to drop significantly. Without use of time-saving appliances, access to electricity is likely to have little effect on labor supply decisions, apart from the positive influence of electric lighting on the potential working day with artificial light. Indeed, electric lighting extends the time available for activities that need good lighting, thus enabling household members to continue their enterprise work, domestic duties, homework and reading into the evening (van de Walle et al. 2017). Several studies show that the impact of connecting to electricity on lighting is generally strong (Barron and Torero 2017; Bensch et al. 2011; Dinkelman 2011; Khandker et al. 2014).

In case of a positive effect of electrification on adult employment, a negative effect can then be expected on child labor. Indeed, if parents increase their labor supply following electrification, we may expect a decrease in child labor relying on the so-called "luxury axiom" (Basu and Van 1998), that states that child labor is largely the result of extreme poverty and the lack of adults

4. In a related way, the introduction of electrical appliances played a major role in increasing women's labor force participation in the US in the 20th century (Coen-Pirani et al. 2010; Greenwood et al. 2005).

monetary resources. The substitution effects at work between parents and children, due to the use of time-saving electrical appliances, are the first force that can lead to a decrease in child labor.

A second force is the change in the returns to schooling, resulting from the introduction of electricity in an area and productivity increases. The direction in which electricity changes the returns to schooling will depend on whether electricity is a complement or a substitute to child labor. The substitution effect is likely to dominate when most child labor takes place in agriculture, because technological development is likely to substitute labor (Grimm et al. 2015). In addition, new job opportunities will affect differently child labor depending on the type of jobs offered and the skills required for those jobs. When the jobs offered mostly require (high) skills learned at school (*e.g.* literacy and numeracy), the effect on child labor of new employment opportunities due to electrification is likely to be negative because of increases in returns to schooling. Parents prefer to enroll their children in school rather than put them at work because they anticipate that their children will be able, thanks to their education, to access these more skilled and better paid jobs . This role of changing returns to schooling with regard to children's school enrollment is well documented in the literature. It allows to explain the positive effects on schooling of the opening of new outsourcing facilities in India (Jensen 2012; Oster and Steinberg 2013) and garment factories in Bangladesh (Heath and Mushfiq Mobarak 2015). [5] In contrast, if new jobs offered are mostly low skilled they are likely to reduce school enrollment and increase child labor because they increase the opportunity cost of schooling more than the returns to education. Such effect on schooling has been shown, for instance, in response to positive agricultural demand shocks in India (Shah and Steinberg 2017), India's national public works program (Shah and Steinberg 2021), expansion of natural gas fracking in US (Cascio and Narayan 2015) or expansion of export manufacturing in Mexico (Atkin 2016), especially for middle school children and older children. In the context of rural Nigeria, where most child labor takes place in agriculture and electricity provided by the grid is unreliable, little effect of electrification is expected on returns to education. New job opportunities enabled by electrification are more likely to be low-skilled jobs and therefore increase the opportunity cost of schooling.

This paper is also related to the literature investigating the consequences of exposure to media – especially television – on social and economic behavior within households. Indeed, the arrival of electricity means for many households the arrival of television at home. There is an extensive

5. Heath and Mushfiq Mobarak (2015) show that the explosion of garment jobs (which reward literacy and numeracy) in Bangladesh has induced an increase in school enrollment of young girls.

literature analyzing the effects of exposure to media on social and economic behavior (see survey of DellaVigna and La Ferrara 2015), but little is known about the consequences of television on the allocation of time within households, and in particular on the relationship to child labor. In this paper, we provide evidence on this theoretically uncertain relationship. According to the literature, exposure to media can affect individual behaviors through three main channels: by providing information, by changing individual preferences and time use (La Ferrara 2016). Media exposure can affect people's preferences for instance through the use of role models that people may take as positive or negative examples. This influence of media exposure is particularly likely to be at work for outcomes that rely on social norms and culture, such as preferences on gender roles (La Ferrara 2016). Jensen and Oster (2009) find that the introduction of cable television is associated with significant decreases in son preference, increases in women's autonomy and increases in school enrollment for younger children, perhaps through increased participation of women in household decision making. Bernard et al. (2019) explore in Ethiopia with poor rural households the effects of an intervention aimed to boost inspirations for a better future, through exposure to documentaries featuring local male and female role models, on parents' aspirations and investment in education for boys and girls. They find high educational aspirations at baseline but the latter are biased against girls.[6] In addition, as time spent in front of television or listening to the radio is not allocated to other activities, the effect on child labor will depend on whether the activities that are crowded out by the media are more or less conductive to this outcome (La Ferrara 2016). In particular, if time spent in front of the media implies less time devoted by adults to market and domestic work, exposure to media is likely to increase child labor.

The remainder of the paper is organized as follows. Data and sample selection are described in section 2. Section 3 provides a descriptive analysis of the forms of electrification among rural households in Nigeria and how they relate to child labor. The econometric strategy is detailed in section 4. Estimation results are analyzed in section 5 and section 6 concludes.

2 Data

We mainly rely on the General Household Survey (GHS) implemented by the Nigerian government and the World Bank. In Nigeria, the GHS is the analogous to the Living Standards Measurement Survey (LSMS) of the World Bank in terms of variable coverage. In its standard

6. At a six-month follow-up, there was no catching up of girls relative to boys.

form, the survey is conducted yearly, with data collected from randomly selected households all over the country during the four quarters of the year. A drawback of the standard GHS is that it covers different households every survey year. However, it was revised in 2010 to include a panel component, the GHS-Panel, which surveys the same households in subsequent editions. We use the three waves of this panel component : 2010-2011, 2012-2013, and 2015-2016.

The GHS-Panel is a nationally representative survey of 5,000 households, which are also representative of the geopolitical zones, at both the urban and rural level. The households included in the GHS-Panel are a sub-sample of the overall GHS sample households. GHS-Panel households were visited twice: first after the planting season between August and October and second after the harvest season between February and April (National Bureau of Statistics). Labor-related characteristics come from post-harvest data for the three waves, as well as other characteristics of children and households when available. Post-planting data is used instead when information is not available in post-harvest data. For instance, in the third wave, the dwelling characteristics are available only in post-planting data while these are available in post-harvest data in the other two waves. In all waves of the survey, we consider that a child is working when, over the past seven days, (*i*) she has worked for someone who is not a household member, and/or (*ii*) she has worked on a farm owned or rented by a household member, and/or (*iii*) she has worked on her own account (or in a household business enterprise in wave 3).

We restrict our analysis to households living in rural zones. We keep households with monogamous couples with at least one child (own child, step child or adopted child) aged between 5 and 14 [7]. To avoid large differences in household composition, that could affect children employment and we cannot totally control for, we exclude from the sample households that include members who are not the spouse or a child of the head of the household (*e.g.* parent, grandchild, brother/sister, niece/nephew, brother/sister in law, domestic help, other relation). Our analysis focuses on children aged between 5 and 14 from these households, which were surveyed over the three waves. Given the age condition to integrate the sample, we cannot have a balanced panel : some children were less than 5 in the first wave (2010-2011), others exceed 14 before the last wave (2015-2016).

Among individuals surveyed over two or three waves, we remove those for whom abnormal time variation is observed in characteristics such as gender, relationship with the head of the household, or age. For some of these individuals, who were surveyed over the three waves, only one observation

7. The 5 to 14-year old bracket is the usual bracket considered to measure child labor in Nigeria (*e.g.* International Labor Organization, UNICEF).

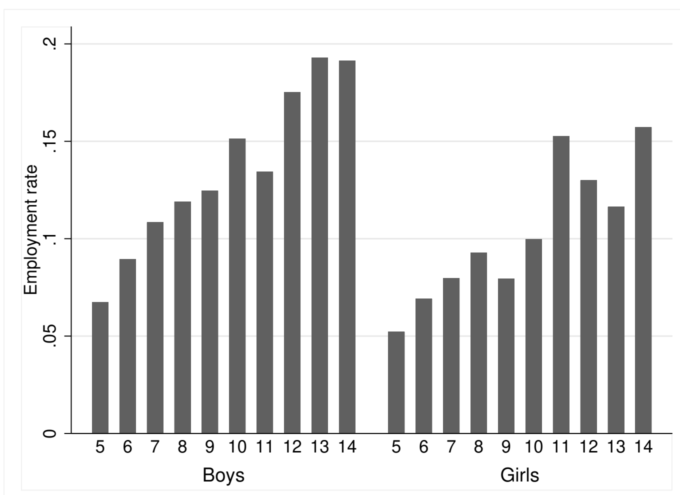
(year) is abnormal. In these rare cases (47 girls, 40 boys), only the abnormal observation was removed. Once removed the missing values for our variables of interest, we keep $3,752$ observations in the pooled cross-section sample of girls, corresponding to $1,969$ girls, and $4,081$ observations in the pooled cross-section sample of boys, corresponding to $2,132$ boys. In each of these two sub-samples, several individuals were interviewed in two or three waves of the survey. In total, $1,258$ girls and $1,348$ boys were interviewed in at least two waves (consecutive or not) of the survey. The different temporal patterns of the sample are summarized in Table A.1 in Appendix.

3 Descriptive analysis

In this section, we characterize child labor in our data and describe its variations according to household access to electricity and electricity end-uses.

3.1 Overview of child labor

Figure 1 – Child employment rate by gender and age



Let us first look at the extent of child labor in our data. We report in Figure 1 the evolution of child labor by age. The employment rate of children increases sharply and almost continuously with age for both boys and girls: it ranges from 5% for girls aged 5 to about 20% for boys aged 14. Except for age 11, the employment rate of boys is higher than the employment rate of girls on all other ages. Note that the employment rates reported in Figure 1 are average rates over the three waves, that erase variations over time.

We then present in Table 1 the activities in which working children are operating. Most children are working on a farm owned or rented by a household member ("household farm"). This activity is particularly dominant among working boys : on average over the entire period, nearly 90% of them are doing this activity. The share of working girls doing this activity is smaller, *i.e.* 82.5%, implying that a larger share of them are involved in other activities. Specifically, more than 10% of working girls are working on her own account or in a household business enterprise ("household nonfarm"). In comparison, less than 5% of working boys are involved in such activity, while this is as for girls the second most important activity after "household farm". Working for someone who is not a household member ("salaried") is very rare among children. They are more likely to combine the two previous activities, as shown in the last two rows of the table. Gender differences in the structure of jobs are important to keep in mind to understand any differences in findings by gender.

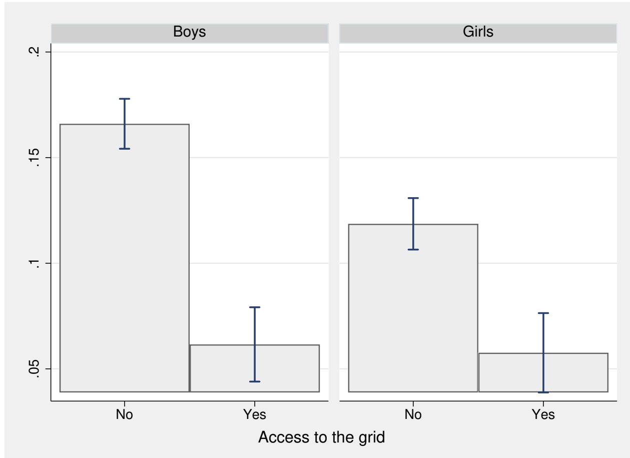
Table 1 – Distribution of working children by activity

	Boys	Girls
Household farm	0.897	0.825
Household nonfarm	0.031	0.109
Salaried	0.009	0.008
Household farm + nonfarm	0.046	0.045
Household farm + salaried	0.015	0.011

3.2 Child labor by electrification status

Then, we examine in Figure 2 child employment rates by grid connection status, *i.e.* depending on whether the household is connected to the grid or not. For both girls and boys, the employment rate is higher in connected households than in non-connected households. The rate is around 6% for both girls and boys in connected households, while the rate rises to nearly 12% among girls and 17% among boys of non-connected households. This gender gap only among non-connected households is interesting to keep in mind for the subsequent econometric analysis. These differences should not be interpreted as a causal negative relationship between electricity access and child labor, because they also reflect differences in other household and individual characteristics. We propose in the next section to control for both observables and unobservables affecting child labor in order to identify the causal relationship between electricity access and child labor. Before investigating this causal relationship, it is important to characterize the different forms of access to electricity within households, bearing in mind that the supply of electricity through the grid is generally unreliable.

Figure 2 – Child labor rates by electrification status

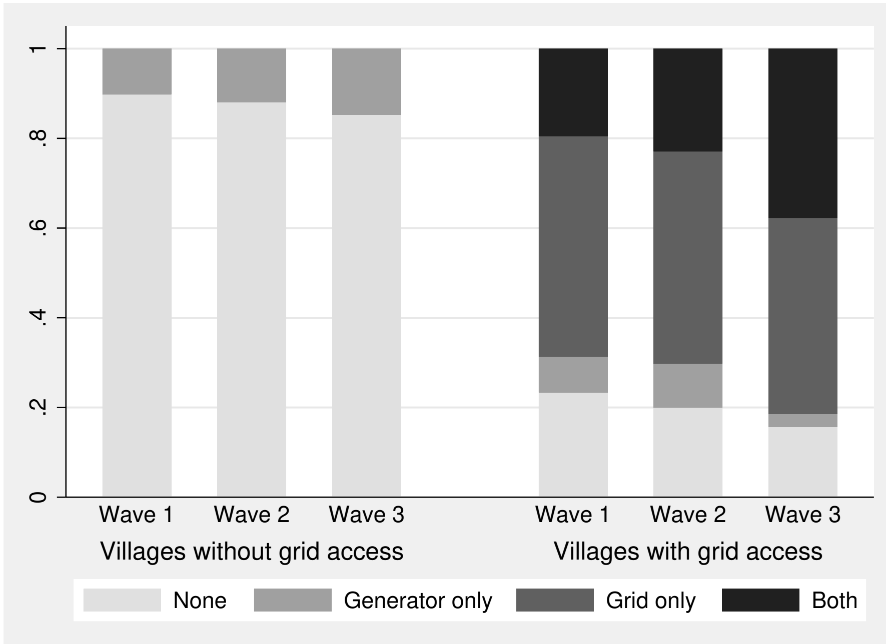


3.3 Child labor by source of electricity supply

Figure 3 provides interesting insights on the situation and the evolution of access to electricity in Nigerian rural areas. It presents for each wave the proportion of households having access to electricity depending on the source of electricity (grid only, generator only, both grid and generator) and depending on whether the village is connected to the grid or not. In villages without grid access (see left-hand side panel), a minority of households have access to electricity on each wave, *i.e.*between 10% and 20%, and this access goes exclusively via a generator. In villages having access to the grid (see right-hand side panel), around 20% of households are not connected to electricity, most connected households in these villages have electricity exclusively through the grid. A minority of households use a generator as the only source of electricity. Interestingly, a large and growing share of households in these villages use both grid and generator. This significant share reflects the poor quality of electricity supply in Nigeria, affected by frequent outages and brownouts. Given unreliability of the grid, more and more households self-produce electricity with a generator to ensure continuity of service.

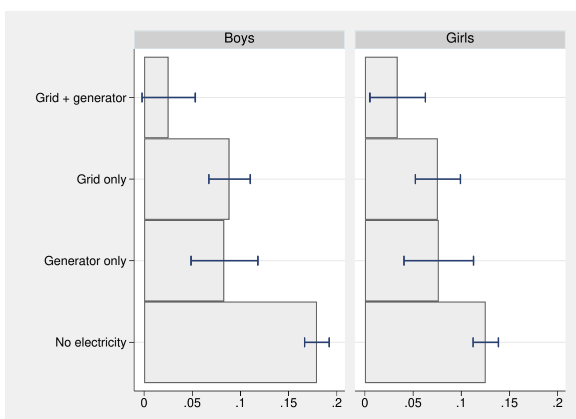
We then compare in Figure 8 the employment rates of children depending on the source of electricity used in the household. Boys' employment rates are significantly lower in electrified households than in non-electrified households (around 18%), whatever the source of electricity. The situation is somewhat different for girls, whose employment rate does not differ much between non-electrified households and households using a single source of electricity (see 95% confidence intervals in the right-hand side panel). Electrified households where the employment rate of girls

Figure 3 – Distribution of households by source of electricity supply



is much lower than in non-electrified households are those using both grid and generator. Thus, unlike non-electrified households, electrified households report similar employment rates for boys and girls.

Figure 4 – Child labor rates by type of electricity access



For both boys and girls, the employment probability does not vary significantly across households using a unique source of electricity. The employment rate of boys from households using both grid and generator is lower compared to that of boys from households using only the grid but not compared to that of boys from households using only a generator. This suggests that end-uses associated to combined use of grid and generator differ more from end-uses associated to the grid alone than from end-uses associated to the generator alone. This difference is specific to the employment of boys. Girls' employment rates do not differ among electrified households by the type of electricity access.

These particularly low child employment rates among households using both grid and generator point to an apparent role of electricity consumption, as suspected from the existing literature. In particular, we expect a lower employment rate for children living in households that consume significant electricity, due to the use of household appliances and electric lighting. Given the unreliability of grid electricity supply and the absence of mini-grid and off-grid alternatives, the use of these appliances is likely to be predominant in households that supplement their access to the grid by the use of a generator. We explore this hypothesis using data on the appliances owned by the households. [8]

3.4 Child labor by household equipment in appliances

Let us look at the equipment rates of the different appliances across the survey waves depending on whether the household has access to electricity or not (see Table 2).

Consistently with existing literature, we distinguish between two broad categories of appliances: time-saving appliances and entertainment appliances. At the bottom of the table, we also report the share of households using electricity as the main source for lighting. While equipment rates in time-saving appliances are zero or close to zero in non-electrified households, they are also rather low in electrified households. Almost no electrified household has a microwave, an electric dryer, or a washing machine. Fridge is the most possessed time-saving appliance by connected households (around 20%), followed by the freezer (around 7%) and the electric stove (between 3 and 5%). Equipment rates in entertainment appliances are higher, particularly for radios, TV sets (more than 50% of connected households) and DVD players. Interestingly, equipment rates in these three appliances have increased over time, which is not true overall for time-saving appliances (except the freezer). Unlike other entertainment appliances, radio is not exclusive to electrified households. More than 50% of non-electrified households own a radio and this proportion is increasing over time. The share of electrified households relying on electric lighting has also increased over time,

8. The fact that the household owns the appliance does not mean that it uses it. Unfortunately, we have no information on the daily use of these appliances. However, we can reasonably expect that households owning a given appliance are more likely to use it than households that do not own it.

from 43% in wave 1 to 54.5% in wave 3.

Table 2 – Equipment rates in electrical appliances and electric lighting

	Wave 1		Wave 2		Wave 3	
Electricity in the dwelling	No	Yes	No	Yes	No	Yes
Time-saving appliances						
Fridge	0.006	0.184	0.001	0.181	0.001	0.163
Freezer	0.000	0.063	0.003	0.064	0.000	0.075
Electric stove	0.000	0.032	0.000	0.041	0.000	0.026
Microwave	0.000	0.006	0.000	0.005	0.000	0.009
Washing machine	0.000	0.000	0.000	0.000	0.000	0.001
Electric dryer	0.000	0.000	0.000	0.003	0.000	0.000
Entertainment appliances						
Radio	0.511	0.665	0.602	0.706	0.654	0.706
TV set	0.037	0.559	0.035	0.584	0.036	0.582
DVD player	0.024	0.376	0.024	0.445	0.018	0.467
Computer	0.000	0.022	0.000	0.021	0.000	0.036
Electric lighting	0.011	0.430	0.019	0.495	0.012	0.545

Notes: Overall, 30 households without electricity access (neither grid nor generator) report using electricity as the main source for lighting.

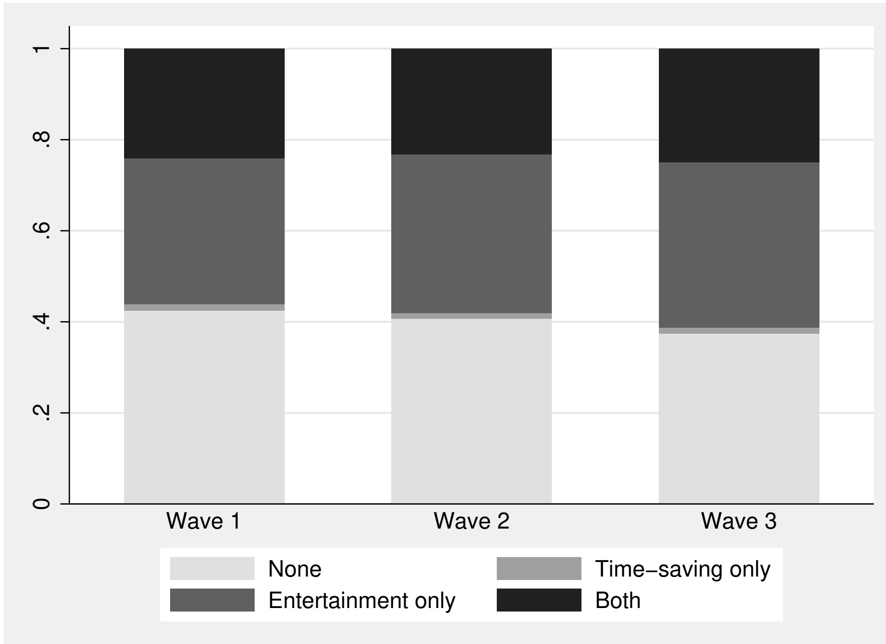
Once defined these two broad categories of appliances, we consider that households have time-saving (respectively entertainment) appliances when they own at least one time-saving (respectively entertainment) appliance.[9]

We examine in Figure 5 the share of households owning one or both categories of appliances. Proportions are fairly stable over time. About 40% of electrified households have no electrical appliances. Among electrified households equipped with electrical appliances, they are very few to own only time-saving appliances[10]. Most own only entertainment appliances and a slightly smaller share of these households own both categories of appliances. These descriptive statistics reveal that rural Nigerian households who get access to electricity equip themselves first in entertainment appliances and then in time-saving appliances. This is a stylized fact common to most (African) developing

9. Analyzing the behavior of households owning time-saving appliances is likely to come down to assessing the effect of using a fridge. Indeed, about 80% of households having time-saving appliances own a fridge, a much higher rate than that recorded for the second most owned time-saving appliance, *i.e.*the freezer. Likewise, the behavior of households owning entertainment appliances is highly likely to result from using a TV set, given that 98% of these households own a TV set (see Table B.1 in Appendix B).

10. This makes it difficult to identify the specific effect of these appliances on child labor.

Figure 5 – Proportion of electrified households equipped with electrical appliances



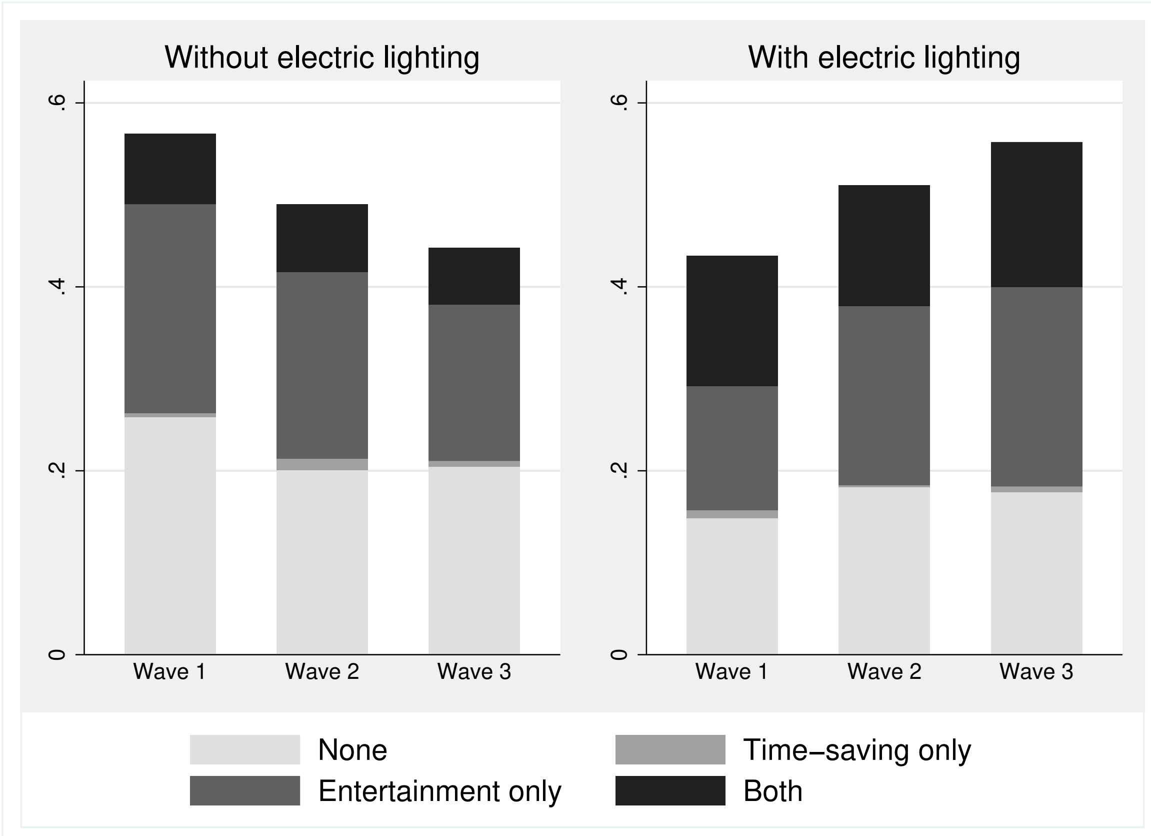
countries. According to Lenz et al. (2017), apart from electric lamps, the typical appliances bought by connected households in rural Africa are televisions, radios and mobile phones. They show specifically in Rwanda that the electrical appliances most frequently used by connected households are entertainment appliances (radio, TV, DVDs) and mobile phones. In contrast, they show, as Jacobson (2007) in Kenya [11], that the share of households that use appliances productively, *i.e.*for home production, is very low.

What use of electricity have the 40% of households that are connected but not equipped with electrical appliances? Almost half of them use it as the main source of lighting, as shown by Figure 6, at least on the two most recent waves of the survey. On the latter waves, most connected households use electricity as the main source of lighting in their dwelling, their share increasing over time. The major part of households using electric lighting also have electrical appliances. In addition, the share of households having both entertainment and time-saving appliances is significantly larger when electricity is used as the main source of lighting. Almost 70% of households having both entertainment and time-saving appliances use electric lighting, while it concerns around 60% of households that have only one type of appliances.

In Figure 7, we examine whether electricity uses vary depending on the source of electricity

11. Jacobson (2007) finds that solar electrification in Kenya leads to a substantial increase in the usage of electrical devices for communication and information, but a modest increase in their usage for productive purposes.

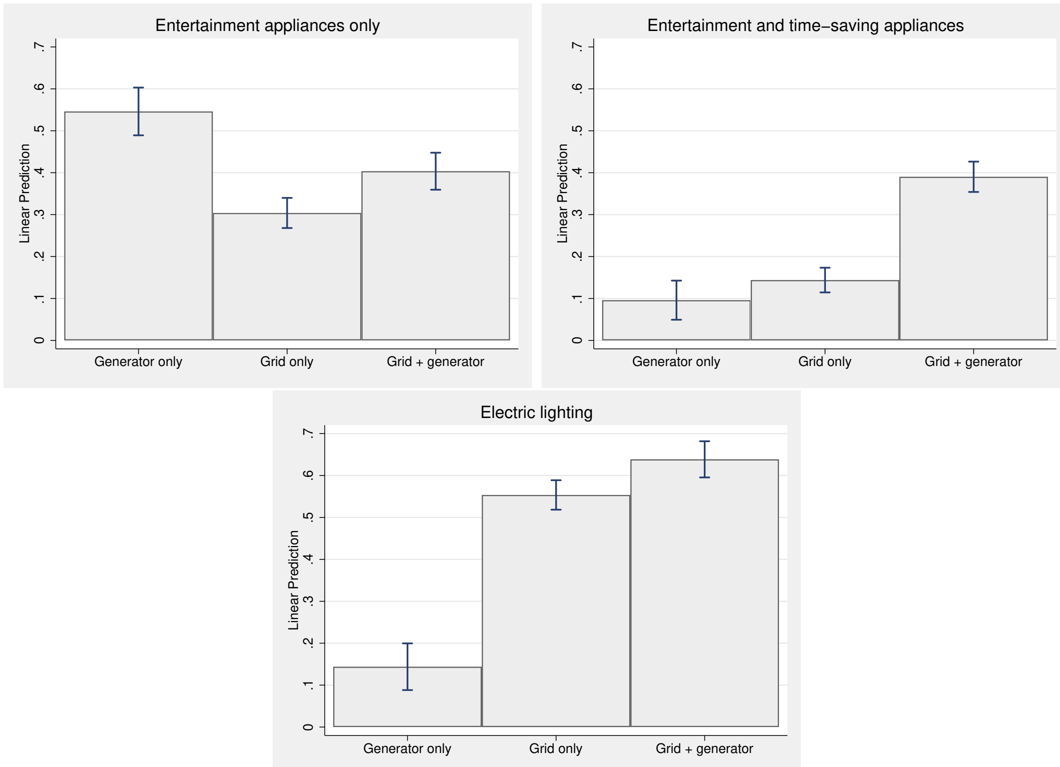
Figure 6 – Proportion of electrified households with electrical appliances by electric lighting



Note : Households are considered to have appliances if they have at least one of the time-saving and entertainment appliances listed in Table 2, except the radio which is largely owned by non-connected households.

supply (generator only, grid only, generator and grid). The upper left panel describes a surprising (unexpected) fact : households accessing electricity only via a generator are more numerous in proportion to own entertainment appliances (about 55%) than households using just electricity from the grid (about 30%) and even households combining grid access and generator (about 45%). The former may have other specific characteristics that may explain this particularly high rate of equipment. If so, this specific behavior should be attenuated or erased in the econometric analysis. Interestingly, households with only one source of electricity (generator or grid) have the same probability to own both entertainment and time-saving appliances (around 10%), which is much lower than the probability of households combining both sources of electricity (about 40%) – see the upper right panel. This echoes the poor reliability of electricity supply in Nigeria, as previously described. The electricity capacity provided through the grid is sufficient to power an electric lamp but not sufficient to power a refrigerator. Grid-connected households who want to use such appliances often

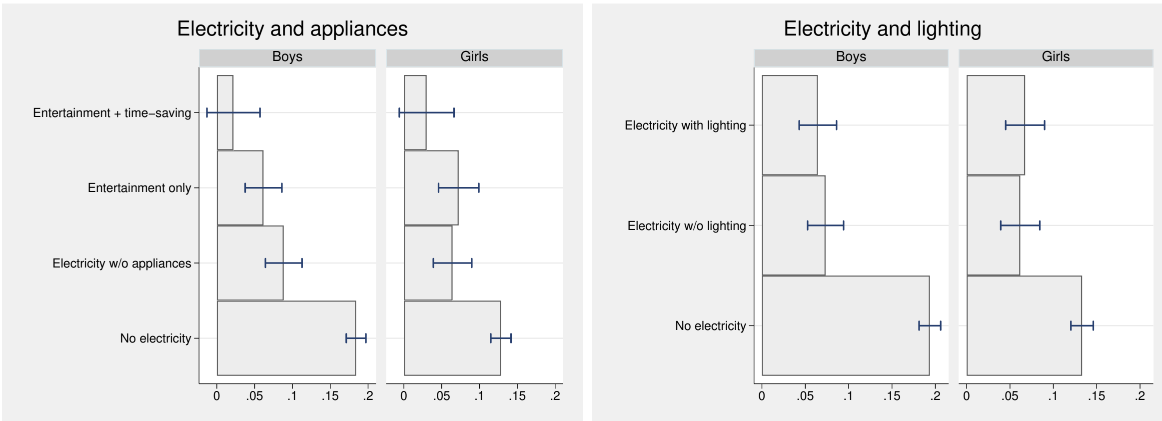
Figure 7 – Proportion of households with electrical appliances and electric lighting by source of electricity supply



use in addition a generator. Consistently, having a generator in addition to the grid access does not imply a wider use of electricity as the main source of lighting (see lower left panel). But access to the grid clearly implies a wider use of electric lighting with respect to the generator: around 60% of households having grid access alone or in conjunction with a generator use electricity as the main source for lighting while this concerns only 15% of households having only a generator. Given these facts, electric lighting appears as the main use of electricity from the grid.

Before assessing the *ceteris paribus* effect of rural electrification on child employment, we examine in Figure 8 variations in children employment rate depending on the appliances owned by the household and the use of electric lighting. The left panel provides interesting insights on the relationship between electrical appliances and child labor. First of all, appliances are not enough to explain variations in children employment probabilities with electrification. Indeed, we can observe for both boys and girls that employment probabilities are lower among electrified households without appliances than among non-electrified households. Other specific household or/and individual

Figure 8 – Children employment rates depending on the use of electrical appliances and electric lighting



characteristics may explain this difference. For girls from connected households, their employment probability does not vary with the type of appliances held (none, one or both categories). For boys from electrified households, only one significant difference exists: their employment probability is lower when their household has both entertainment and time-saving appliances than when their household has none. Interestingly, we find the same pattern of employment rates when considering the fridge and the TV set instead of the broad categories of appliances, time-saving and entertainment appliances respectively (see Figure B.1 in Appendix B). This suggests that the behaviors associated with the ownership of these broad categories of appliances might result in fact from owning these specific appliances, *i.e.*a fridge or/and a TV set. In the right panel, the central fact is that among connected households, the employment probability of children (boys and girls) does not vary depending on whether the household uses electricity as main source of lighting.

4 Method

Since rural electrification did not have an experimental design in Nigeria, any difference in the employment of children between electrified and non-electrified households would be a biased estimate of the effect of the treatment. Several confounding factors may be correlated with both electricity access (or electricity end-uses) and child employment.[12] Although we are able to include a large set of covariates, there may remain unobserved confounding factors. In particular, we cannot fully

12. Several studies document important confounding factors that are correlated with both living standards and time allocation (Basu et al. 2010; Fafchamps and Wahba 2006; Kruger 2007; Manacorda and Rosati 2010; Mueller 1984; Rosenzweig and Evenson 1977; Schady 2004).

control for household living standards, which is a major determinant of both household electricity access (and consumption) and child labor.[13] To deal with such unobserved and time-invariant confounding factors, we adopt non-experimental identification strategies that exploit the panel structure of the data. In addition, we assess the magnitude of the possible bias due to time-varying confounding factors using the method of Oster (2019).

4.1 Baseline specification

We first estimate the following linear probability model separately for boys and girls[14]:

$$Y_{it} = \alpha_i + \gamma_t + \delta\, E_{it} + \mathbf{X}'_{it}\, \beta + \varepsilon_{it} \tag{1}$$

where subscripts i and t denote individual and time, respectively. Y is a binary variable equal to one if the child is working and zero otherwise. E is an indicator variable equal to one if the household has electricity and zero otherwise, $\mathbf{X}_{ijt}$ is a set of time-varying controls at the individual and at the household level, including child's age, her parents' level of education, the sex of the household head, the household size, the household share of boys and girls under 5 and 5-14, the household share of men and women over 14[15], the value of farm assets, the value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community. α_i and γ_t are individual and time fixed effects (FE). ε_{ijt} is the error term. Time FE account for cyclical changes that are common to all individuals. The inclusion of λ_i allows us to capture unobserved individual heterogeneity. The counterpart of doing this is that we cannot include among controls

13. A substantial literature argues that the main cause of child labor is poverty (Edmonds and Schady 2012). This explanation is embodied by the "luxury" axiom and is supported by an extensive empirical evidence, showing that children are less likely to work in richer households and they work less as the household gets richer (see Basu 1999; Basu and Tzannatos 2003; Basu and Van 1998; Edmonds 2005; Edmonds and Pavcnik 2005; Ray 2000). Note that this explanation is however debated in the literature, some authors showing conversely that child labor may increase with household wealth. In particular, they show that when households become wealthier, *i.e.*they get more land, their children are likely to work more (Basu et al. 2010; Bhalotra and Heady 2003; Dumas 2007). To explain this finding, Basu et al. (2010) argue that parents usually do not have information/access to off-farm labor markets close to home and are not inclined to send their children work in distant farms or factories. Edmonds and Turk (2004) also provide evidence of such labor market imperfection, showing that households in Vietnam are more likely to have their children working when they have their own businesses.

14. Distinct effects on boys and girls can be expected among other things because there are gender inequalities in human capital investment in developing countries. The reasons of these inequalities are diverse. First, girls would have lower market returns to human capital (Rosenzweig and Schultz 1982). Second, parents probably do not benefit from the returns to education of their daughter(s), as girls leave the family upon marriage (Kambhampati and Rajan 2008). Therefore, parents have little incentive to invest in girls' schooling.

15. Edmonds (2006) observes in Nepal that older boys and girls are more likely to work and less likely to attend school than their younger siblings, and argues that this mainly results from a comparative advantage of older children in home production.Parish and Willis (1993) show that the oldest girl in Taiwanese households plays a supportive role, by caring for younger siblings and providing income through wage employment. This supportive of the oldest girl helps for the schooling outcomes of younger siblings.

time-invariant characteristics – *e.g.* the education of parents, the gender of the household head.

Using this two-way fixed-effects strategy, the identifying assumption is that unobserved confounders are time-invariant. However, access to electricity is likely to be correlated with time-varying factors that jointly determine current and expected child employment. For instance, without subsidies for electricity connections, the households that are connected to electricity are probably those with higher incomes, wealth, access to credit, or those who believe they would benefit most from an access to electricity (Lee et al. 2020). Then, some of the change in employment status for an individual from a period to another may be due to the change in access to electricity but some of it possibly would have happened anyway. Thus, ignoring the influence of these unobserved (time-varying) factors would lead us to overestimate the causal effect of electricity access on the outcome, given the non-zero correlation between E_{it} and ε_{it}.

4.2 Selection on time-varying unobservables

We choose for several reasons not to rely on the instrumental variables (IV) used in previous studies trying to identify the impact of electrification on employment or employment growth. First, the use of geological or topological features of the land, which are the more convincing sources of exogenous variation used in the literature, is questionable in the rural Nigerian context. Such identification strategy, inspired by the approach of Duflo and Pande (2007) [16], was used in several subsequent studies. In particular, Dinkelman (2011) and then Grogan and Sadanand (2013) use local land gradient as an instrument for electricity placement, based on the idea that flatter land makes it cheaper to lay cables. One concern with this instrument in a rural setting is that it may directly affect agricultural outcomes and thus employment. This direct effect of gradient on employment is limited when most people are not farming, as in Dinkelman (2011). [17] This is more a concern in rural Nigeria, where most people and especially children work on the farm. Another concern with this instrument is that people may sort non-randomly across flat and steep areas, which could result in different children employment probabilities independent of new electrification. Second, exogeneity of the alternative instruments used in the literature have almost all been questioned (van de Walle et al. 2017). [18] Third, we are also interested in the use of generator and the end-uses of electricity in

16. Duflo and Pande use local river gradient interacted with predicted district level dam construction as an IV (in their case for dam construction)

17. Less than 10 percent of employed individuals are involved in agriculture in the South-African context studied by Dinkelman (2011).

18. This is the case, for instance, for the geographic proximity to an electricity line (Khandker et al. 2009), the density of transmission lines in the district of residence (Chakravorty et al. 2014), the local geographic mean electrification (or appliance ownership) rate (Coen-Pirani et al. 2010; Khandker et al. 2014).

housing (*i.e.* electric lighting and appliances), for which there are no credible sources of exogenous variation outside of a randomized control trial. Based on real-world data, we prefer not to use such an identification strategy rather than to use a weak or/and invalid instrument, which could bias the estimators more than time-varying unobserved heterogeneity.

Instead, we assess the magnitude of the possible bias resulting from selection on unobservables using the method proposed by Oster (2019), that consists in either placing bounds on the treatment effect or calculating the degree of selection on unobservables relative to observables that would be necessary to explain away the treatment effect.[19] The method relies on assumptions about the values of two parameters: the degree of selection on unobservables relative to observables and the hypothetical R-squared from a regression of the outcome on all observables and unobservables (R^{max}).[20] We compute and report for each specification two parameters: β and δ. β corresponds to the lower or upper bound of the coefficient assuming an equal degree of selection on observables and unobservables as well as $R^2 = R^{max}$. δ represents the degree of selection on unobservables relative to observables that would be necessary to explain away the treatment effect (*i.e.* obtain an estimated coefficient equal to zero).[21] According to Oster (2019), the true coefficient should range between the coefficient estimate obtained when including all control variables – assuming zero selection on unobservables – and β. If this range of values does not include zero, we can conclude that the coefficient estimate is robust.

4.3 Heterogenous effects

In sharp designs with many groups and periods, de Chaisemartin and D'Haultfœuille (2020) show that the two-way FE estimator may be a misleading measure of the treatment effect, under the standard common trends assumption, if the treatment effect is heterogenous across groups and time periods.[22] This bias is especially of concern if treatment effects differ between periods with many versus few treated groups, or between groups treated for many versus few periods. In our

19. The ratio of selection on unobservables to selection on observables can be interpreted as the magnitude by which the significant effect of the treatment is due to selection bias.

20. Oster (2019) shows, like Altonji et al. (2005), that simply comparing coefficient changes with the addition of control variables is not enough to show that bias from unobservables is negligible. Such changes must also be scaled by changes in R-squared. But unlike Altonji et al. (2005), Oster (2019) relaxes the assumption that $R^{max} = 1$ and allows for measurement errors in the data. Oster (2019) suggests to use $R^{max} = 1.3R^2$, as she shows that this hypothetical R-squared allows to reproduce 90% of treatment parameters from randomized control studies published in top economic journals between 2008 and 2013, against only 20% when $R^{max} = 1$.

21. Note that $\delta = 1$ is the rule-of-thumb threshold suggested by Oster (2019). Any value below this threshold would suggest a possible bias due to selection on unobservables.

22. Regressions with covariates may rely on a more plausible common trends assumption than those without covariates, but still require that the treatment effect be homogenous over time and across groups.

case, we can expect different effects of electrification between the first electrified households and the more recently electrified households, due in particular to the effects of electrification on one household on other nearby households.

As pointed out in several papers on staggered adoption difference-in-differences (DiD) research designs (*e.g.* Borusyak and Jaravel 2017; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021), in which treatment of different groups starts at different times, the two-way FE estimator is a weighted average of individual treatment effects, where some of the weights may be negative. Negative weights occur in situations when the treatment effect is heterogenous over time or across individuals. Due to the negative weights, the linear regression coefficient may for instance be negative while all the treatment effects are positive. When some of the weights are negative, the two-way FE estimator may still be robust to heterogeneous treatment effects across groups and periods only if the weights are uncorrelated with the intensity of the treatment effect in the treated cells (*i.e.*individual-year cells) – but this is often implausible. In fact, the weights are likely to be correlated with covariates that are themselves associated with the intensity of the treatment effect in each cell.

According to de Chaisemartin and D'Haultfœuille (2020), the two-way FE estimator cannot be robust to heterogenous treatment effects if it significantly differs from the first-difference (FD) estimator. In that case, the parallel trends assumptions associated to these two estimators cannot jointly hold. We will prefer then the DiD estimator proposed by de Chaisemartin and D'Haultfœuille (2020), which relies on a variant of the standard common trends assumption, requiring that the mean evolution of the outcome in switching groups would have been the same in the absence of treatment, as that of control groups. [23] To assess the plausibility of this common trends assumption, we rely on the placebo estimator proposed by de Chaisemartin and D'Haultfœuille (2020), that consists here in comparing the evolution of child employment in households changing and not changing their access to electricity one period before that change. If the placebo estimator is not significantly different from 0, this means that individuals from households where access to electricity has changed between $t-1$ and t did not experience significantly different trends in child labor from $t-2$ to $t-1$ than individuals where access to electricity has not changed.

In addition, this estimator relies on the stable groups assumption. This assumption requires in our case that there are individuals whose access to the source of electricity (or the type of electric

23. The estimand of de Chaisemartin and D'Haultfœuille (2020) identifies the treatment effect on the switchers at the time they switch.

appliance) in question does not change between each pair of consecutive time periods (*i.e.*waves).[24] This assumption holds in our setting because, for each source of electricity and each type of electric appliance, the sample includes both households that did not have access on any wave and households that were connected on all three waves (see Table B.2 in Appendix B). In addition, for all sources of electricity and electrical appliances considered, and for each pair of consecutive time periods, *i*) households switching from being untreated to treated ("joiners"), *ii*) households switching from being treated to untreated ("leavers"), *iii*) households treated over the two periods, *iv*) households untreated over the two periods (see Table B.3 in Appendix B).

5 Results

This section includes our estimation results. We first report and discuss the results about the effect of grid access on child employment. We then investigate the differentiated effects of the different sources of electricity on child employment. Finally, we assess the role of electricity end-uses, through electric lighting and appliances, to explain the differences in children employment.

5.1 Child employment depending on grid access

In Table 3 we first estimate the effect of grid access on child employment. We run separate regressions for boys and girls and present estimates for different specifications. The first specification, for both boys and girls, includes year FE and state FE – not individual FE. In this specification, access to the grid affects negatively the employment probability of both girls and boys. When replacing state FE by LGA FE, the effect is no longer significantly different from 0. There is no change in the significance of the coefficient when replacing LGA FE by household FE and then by individual FE in the panel subsample.[25] Thus, controlling for all time-invariant unobserved characteristics that could induce an endogeneity bias is previous estimates does not affect the significance of the coefficient on grid access.

Across all specifications, the β parameter corresponds to the lower bound or otherwise the upper bound of the coefficient, under the assumption that selection on unobservables is equal to selection

24. The stable groups assumption requires that between each pair of consecutive time periods, if there is a "joiner" (*i.e.*a group switching from being untreated to treated), then there should be another group that is untreated at both dates. This assumption also requires that between each pair of consecutive time periods, if there is a "leaver" (*i.e.*a group switching from being treated to untreated), then there should be another group that is treated at both dates.

25. This panel-data specification is preferred over a random-effect specification, as the Hausman test leads to reject the null hypothesis that both fixed-effect and random-effect models are consistent and thus supports that only the fixed-effect model is consistent. This means that at least one regressor is correlated with time-invariant unobserved factors of child labor.

Table 3 – Effect of grid access on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grid access	-0.035**	0.028	0.007	0.007	-0.032**	-0.008	-0.011	-0.012
	(0.014)	(0.017)	(0.019)	(0.020)	(0.013)	(0.018)	(0.020)	(0.021)
β	0.009	0.277	0.825	0.978	-0.021	0.084	0.593	0.761
δ	0.823	0.239	0.041	0.040	2.107	0.187	0.160	0.168
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	Yes	No	No	No
LGA FE	No	Yes	No	No	No	Yes	No	No
Household FE	No	No	Yes	No	No	No	Yes	No
Individual FE	No	No	No	Yes	No	No	No	Yes
Observations	2828	2828	2828	2828	2627	2627	2627	2627
R-squared	0.158	0.312	0.469	0.518	0.114	0.258	0.501	0.539
Sample	Boys	Boys	Boys	Boys	Girls	Girls	Girls	Girls

Notes: Standard errors are in parentheses and are clustered at the individual level. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. β is the lower or upper bound on the coefficient under the assumption of equal degree of selection on included control variables and on unobservables ($i.e. \delta = 1$). δ is the ratio of selection on unobservables to selection on observables required to obtain a coefficient of zero. The calculation assumes $R^{max} = 1$, which is the hypothetical R-squared from a regression including all observables and unobservables. Controls include child's age, parents' level of education, sex of household head, household size, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).

on observables ($i.e.$ $\delta = 1$). The interval between the estimated coefficient and the β parameter includes the possible values of the effect of grid access going from a zero selection on unobservables to a a selection on unobservables equivalent to that on observables. Thus, if this interval includes 0, it is difficult to conclude that there is a significant effect of grid access assuming a non-zero selection on unobservables. The δ parameter is complementary with the β parameter as it represents the degree of selection on unobservables relative to selection on observables required for the effect (of grid access) to be zero. Both parameters are derived from Oster (2019). For the two significant coefficients, in columns (1) and (5), the β parameter is negative like the estimated coefficient and the relative degree of selection on unobservables is (slightly) greater than 1, meaning that a selection on unobservables larger than the selection on observables would imply a zero effect of grid access. In an environment quite well controlled, these parameters would support the significant negative effect of grid access on child labor. However, the specifications (1) and (5) only include state FE in addition to our controls and year FE. Unobserved heterogeneity within states is likely to be higher than the heterogeneity controlled by our covariates. Thus, the degree of selection on unobservables is likely to be higher than the degree of selection on observables. As a consequence, the treatment effect in columns (1) and (5) is (very) likely to be zero. We do not discuss the values of β and δ in other specifications because the estimated coefficient, while assuming zero selection on unobservables, is not significant.

As shown in section 3, households can access electricity not only through the grid but also through a generator. A significant part of households that declare having electricity in their dwelling rely on a generator either exclusively or in combination with access to the grid. Therefore, assessing the effect of electrification on child labor through grid access may not be suitable because many individuals in the control group have access to electricity through a generator. We report in Table C.1, Appendix C, the results from the same specifications as in Table 3 but considering as treatment variable a dummy variable indicating the household has access to electricity, whether by the grid or/and by a generator. The coefficient estimates reported in Table C.1 are quite similar to those reported in Table 3, suggesting that households relying exclusively on a generator do not behave very differently from other electrified households or their weight among electrified households is too low for their specific behavior to affect the average effect for these households.

5.2 Child employment depending on the source of electricity

At this stage, we conclude for both boys and girls that household electricity access has no impact on their likelihood to work. Yet, households with access to electricity are very heterogenous in their use of electricity, as suggested in section 3. In particular, electricity end-uses vary sharply depending on whether the household is only connected to the grid or whether it exclusively uses a generator or whether it combines the two sources of electricity supply.

We investigate then in Table 4 the differentiated effects on child labor of the different sources of electricity supply. We now include among regressors a dummy variable for grid access, a dummy variable for generator and the interaction term between the two previous dummy variables (Grid and generator). This allows us to capture the effects on child labor of access to electricity through the grid only, through a generator only, or by combining the two. The different econometric specifications are modeled on those reported in Table 3. Again, coefficient estimates strongly vary across specifications. Our preferred specification is that including individual FE (see columns (4) and (8)), given the result of the Hausman test for both girls and boys, indicating that other estimates are presumably biased due to time-invariant unobserved heterogeneity. It is nevertheless relevant to report these "naive" estimates, to show that we reach very different conclusions when ignoring such

Table 4 – Effect of electricity source on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grid only	-0.037**	0.047**	0.029	0.029	-0.023	0.011	0.015	0.011
	(0.017)	(0.021)	(0.024)	(0.026)	(0.016)	(0.021)	(0.022)	(0.023)
β	0.0230	0.414	1.479	1.738	0.00200	0.229	1.394	1.670
δ	0.698	0.321	0.133	0.127	0.934	0.167	0.154	0.117
Generator only	-0.050**	0.011	0.011	0.012	0.006	0.045**	0.025	0.017
	(0.020)	(0.023)	(0.031)	(0.035)	(0.020)	(0.021)	(0.029)	(0.032)
β	0.0150	0.226	1.926	2.238	0.0660	0.222	1.729	2.295
δ	0.849	0.110	0.056	0.056	0.144	0.692	0.257	0.167
Grid and generator	0.025	-0.060**	-0.062*	-0.061	-0.031	-0.067**	-0.075**	-0.067*
	(0.024)	(0.027)	(0.034)	(0.037)	(0.024)	(0.026)	(0.033)	(0.036)
β	0.205	0.226	4.852	5.818	0.0330	-0.0710	-17.47	-231.3
δ	0.234	0.525	0.312	0.295	0.661	1.294	0.851	0.713
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	Yes	No	No	No
LGA FE	No	Yes	No	No	No	Yes	No	No
Household FE	No	No	Yes	No	No	No	Yes	No
Individual FE	No	No	No	Yes	No	No	No	Yes
Observations	2828	2828	2828	2828	2627	2627	2627	2627
R-squared	0.160	0.313	0.470	0.519	0.115	0.259	0.502	0.540
Sample	Boys	Boys	Boys	Boys	Girls	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. β is the lower or upper bound on the coefficient under the assumption of equal degree of selection on included control variables and on unobservables (*i.e.*$\delta = 1$). δ is the ratio of selection on unobservables to selection on observables required to obtain a coefficient of zero. The calculation assumes $R^{max} = 1$, which is the hypothetical R-squared from a regression including all observables and unobservables. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).

unobserved factors of child labor. We find that the grid alone and the generator alone cannot change household decisions regarding the employment of their children, whether boys or girls. Indeed, for all specifications including fixed effects at a finer-than-state level, coefficients on the variables Grid and Generator are not significantly different from 0. For boys, the coefficient on the interaction term Grid $\times$ Generator is negative but also not significant in these specifications. For girls, however, this coefficient is negative and significant in these specifications. However, when controlling for time-invariant unobserved factors with the inclusion of individual FE, the significance of the coefficient drops to 10% (see column (8)). For this coefficient, the β parameter is negative as the coefficient but its magnitude is surprising, much greater than 1 in absolute value – the expected threshold for a probability. Moreover, the δ parameter suggests that the effect is zero as soon as the degree of selection on unobservables represents 71.8% of the selection on observables, which is below the threshold of 1 suggested by Oster (2019).

Table 5 – Weights of the FE estimator

	Grid only		Generator only		Grid and generator	
	Boys	Girls	Boys	Girls	Boys	Girls
β_{fe}	0.029	0.011	0.012	0.017	-0.061	-0.067
Share of negative weights	0.3225	0.3146	0.2846	0.2368	0.1735	0.1379
$\underline{\sigma}$	0.003	0.008	0.017	0.018	0.048	0.067
$\sqrt{3} \times \underline{\sigma}$	0.005	0.014	0.029	0.031	0.083	0.116
$\lvert\beta_{fe}\rvert \geqslant \sqrt{3} \times \underline{\sigma}$	Yes	No	No	No	No	No
B	0.05	0.05	0.05	0.05	0.08	0.08
$B \geqslant \sqrt{3} \times \underline{\sigma}$	Yes	Yes	Yes	Yes	No	No
Plausible treatment effect heterogeneity	Yes	Yes	Yes	Yes	No	No

Notes: β_{fe} is the coefficient obtained using the two-way FE estimator as in Table 4, columns (4) and (8). $\underline{\sigma}$ is the minimal value of the standard deviation of the treatment effect under which the coefficient and the ATT could be of opposite signs. B is the largest expected treatment effect in absolute value.

These latest estimates suggest heterogenous effects of sources of electricity supply across households. The FE estimator (β_{fe}) would be biased in that case. Following de Chaisemartin and D'Haultfœuille (2020), we compute the weights attached to the coefficients on Grid only, Generator only, and Grid and generator. As shown in Table 5, we find in each case that a significant share of these weights are negative – between 14% and 32% depending on the case. These weights are significantly correlated with some of the control variables, in particular those capturing the education of parents, the gender composition of children and the value of the dwelling. Given that the individual treatment effects are likely to depend on these dimensions, the estimation of the average treatment effect based on the FE estimator might be biased. In addition, we report in Table 5 the minimal value of the standard deviation of the treatment effect – across the treated groups and time periods – under which the coefficient and the average treatment on the treated (ATT) could be of opposite signs. This is denoted $\underline{\sigma}$ and corresponds to the ratio between the absolute value of the coefficient and the standard deviation of the weights. When this ratio is large, this means that the coefficient and the ATT can only be of opposite signs if there is a lot of treatment effect heterogeneity. When this ratio is low, this means that the coefficient and the ATT can be of opposite signs even if there is not a lot of treatment effect heterogeneity. To determine whether the value of $\underline{\sigma}$ is large or low in each case, we follow de Chaisemartin and D'Haultfœuille (2020) and assume that the treatment effects are drawn from a uniform distribution. Then, for the mean of this distribution to be 0 while its standard deviation is $\underline{\sigma}$, the treatment effects should be uniformly distributed on the interval $[-\sqrt{3} \times \underline{\sigma}, \sqrt{3} \times \underline{\sigma}]$. Under this distribution, if $\beta_{fe} \geqslant \sqrt{3} \times \underline{\sigma}$, $\underline{\sigma}$ may not be an implausibly high amount of treatment effect heterogeneity and the ATT may be equal to 0. We come to this conclusion for the effect of the grid on boys' employment probability. In contrast, if $\beta_{fe} < \sqrt{3} \times \underline{\sigma}$, $\underline{\sigma}$ may or may not be an implausibly high amount of treatment effect heterogeneity, depending on whether $B < \sqrt{3}\underline{\sigma}$ or $B \geqslant \sqrt{3}\underline{\sigma}$, where B is the largest expected treatment effect in absolute value. For the effect of the grid on girls' employment probability and the effect of the generator (for both boys and girls), we find that $\beta_{fe} < \sqrt{3} \times \underline{\sigma}$ and $B > \sqrt{3} \times \underline{\sigma}$, so $\underline{\sigma}$ may not be an implausibly high amount of treatment effect heterogeneity, so the ATT may be equal to 0. In contrast, for the effect of Grid and generator (see columns (5) and (6)), the value of $\underline{\sigma}$ may be an implausibly high amount of treatment effect heterogeneity as $B < \sqrt{3}\underline{\sigma}$, so treatment effect heterogeneity is less of a concern for the validity of the FE estimator.

Table 6 – Heterogenous effects of electricity source on child employment

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	FE	FD	DiD	FE	FD	DiD
Grid only	0.027	0.032	0.005	0.012	0.017	-0.010
	(0.033)	(0.025)	(0.024)	(0.029)	(0.021)	(0.022)
Generator only	0.012	-0.009	-0.032	0.019	0.035	-0.017
	(0.046)	(0.039)	(0.030)	(0.041)	(0.033)	(0.023)
Grid and generator	-0.062	-0.025	-0.057*	-0.068	-0.064*	-0.058*
	(0.048)	(0.038)	(0.033)	(0.047)	(0.035)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,828	1,662	1,662	2,627	1,522	1,522
Sample	Boys	Boys	Boys	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are here excluded). FE, FD and DiD stand for fixed-effects, first differences and de Chaisemartin and D'Haultfœuille (2020)'s difference-in-difference models.

We check these heterogenous effects in Table 6 by comparing estimates from the FE estimator with those of the FD estimator and the DiD estimator proposed by de Chaisemartin and D'Haultfœuille (2020). These results do not bring anything new on the influence on child labor of accessing electricity through grid alone and generator alone. Coefficient estimates on corresponding variables in FD and DiD models are not significant, as in the FE model. Differences in coefficient estimates between the FE and FD models confirm these variables have heterogenous effects, as shown above with Table 5, and support the use of the DiD model of de Chaisemartin and D'Haultfœuille (2020). The coefficient on Grid and generator in the DiD model is negative and significant at the 10% significance level for both girls and boys. Interestingly, the magnitude of the effect is not very different between the FE and DiD estimators – only the significance of the coefficient differs for boys. This is consistent with the previous analysis, where we conclude on the validity of the FE estimator with respect to treatment effect heterogeneity. FE and DiD then suggest that children from households using both sources of electricity are less likely to work than children from non-electrified households. The low level of significance of the coefficients may be explained by the small size of the sample but it can also result from heterogenous uses of electricity in these households. Indeed, as shown in descriptive statistics, not all these households are equipped with appliances that are likely to provide extra time to households. In addition, for a given level of equipment, the actual use of appliances may vary between households and induce different effects on child labor.

5.3 Child employment depending on electrical appliances

In Table 7, we investigate further on this heterogeneity between electrified households by analyzing the effect on child labor of each type of device: entertainment appliances, time-saving appliances and electric lighting. We identify with the dummy Electric Lighting households using electricity as main source of lighting. Entertainment (time-saving) identifies households equipped with at least one appliance classified as such.

The coefficient associated to entertainment appliances is positive for both boys and girls, but it is more significant for girls (1%) than for boys (10%) once including both year and individual FE (see columns (4) and (8)). In addition, the Δ parameter associated to this coefficient is much less than 1 for boys, while it exceeds 1 for girls. This suggests that, unlike boys, selection on unobservables among girls should be greater than than selection on observables to cancel out the positive effect of entertainment estimated on the employment probability of girls. Thus, girls living in households equipped with entertainment appliances are more likely to be employed than girls living in households without access to electricity *ceteris paribus*. We compare in Table 8 the coefficient estimates from this two-way FE model with those from FD and DiD models for both boys and girls. The FD

Table 7 – Effect of electrical appliances on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entertainment	-0.00300	0.047***	0.051**	0.051*	0.0210	0.052***	0.105***	0.103***
	(0.015)	(0.018)	(0.026)	(0.027)	(0.016)	(0.019)	(0.025)	(0.027)
β	0.0580	0.184	0.724	0.831	0.0620	0.149	0.728	0.810
δ	0.0510	0.524	0.314	0.304	0.687	1.067	1.068	1.039
Time-saving	-0.029*	-0.0260	-0.0300	-0.0340	-0.0260	-0.0230	-0.056**	-0.052*
	(0.016)	(0.019)	(0.026)	(0.026)	(0.018)	(0.021)	(0.028)	(0.031)
β	0.0220	0.0880	1.579	2.057	-0.00400	0.0310	6.860	7.785
δ	0.611	0.327	0.180	0.197	1.147	0.560	0.748	0.659
Electric lighting	-0.029**	0.0110	0.0250	0.0250	-0.038***	-0.0180	-0.0200	-0.0210
	(0.014)	(0.016)	(0.019)	(0.019)	(0.014)	(0.016)	(0.017)	(0.018)
β	0.00700	0.100	0.241	0.265	-0.0320	0.0100	0.0330	0.0340
δ	0.837	0.180	0.266	0.262	3.253	0.728	0.561	0.577
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	Yes	No	No	No
LGA FE	No	Yes	No	No	No	Yes	No	No
Household FE	No	No	Yes	No	No	No	Yes	No
Individual FE	No	No	No	Yes	No	No	No	Yes
Observations	2828	2828	2828	2828	2627	2627	2627	2627
R-squared	0.159	0.314	0.470	0.519	0.115	0.260	0.506	0.544
Sample	Boys	Boys	Boys	Boys	Girls	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. β is the lower or upper bound on the coefficient under the assumption of equal degree of selection on included control variables and on unobservables ($i.e. \delta = 1$). δ is the ratio of selection on unobservables to selection on observables required to obtain a coefficient of zero. The calculation assumes $R^{max} = 1$, which is the hypothetical R-squared from a regression including all observables and unobservables. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).

model also gives for girls a positive coefficient on Entertainment (see column (5)), which is close to that of the FE model, suggesting that the latter is robust to heterogenous treatment effects. This is confirmed by the coefficient estimate of the DiD model (see column (6)), which is also positive but of lower magnitude compared to the FE model. This positive effect of Entertainment appliances on the employment probability of girls seems thus robust to both selection on unobservables and heterogenous treatment effects. It should be noted that this positive effect is drawn by the TV set, which is the main entertainment appliance owned by households. Indeed, when replacing in the regression the Entertainment dummy variable by a dummy variable indicating whether the household owns a TV set, we also find a significant positive coefficient whose magnitude is even larger than for all entertainment appliances (see Table C.2 in Appendix C).

The coefficient associated to time-saving appliances is negative in all specifications for both boys and girls in Table 7 but it is only (weakly) significant for girls (see column (8)). Both the β and δ parameters tend to question the robustness of the coefficient to selection on unobservables: the sign of β is different from that of the coefficient and $\delta < 1$. In addition, the corresponding effect in the DiD model (see Table 8 is not significant, suggesting that the FE coefficient is also not robust to heterogenous treatment effects. Thus, the effect of time-saving appliances on the employment probability of girls is very likely to be not different from 0. This zero effect of time-saving appliances can be explained by the small number of households equipped with such appliances in our sample (see Table B.2 in Appendix B). Thus, we can expect that a negative effect of these appliances on child labor would emerge if they were more common among Nigerian rural households.

Electric lighting does not affect significantly the employment probability of both boys and girls once including individual fixed effects.

Table 8 – Heterogenous effects of electrical appliances on child employment

Estimator	(1) FE	(2) FD	(3) DiD	(4) FE	(5) FD	(6) DiD
Entertainment	0.051*	0.047*	0.046	0.103***	0.087***	0.074***
	(0.027)	(0.028)	(0.033)	(0.027)	(0.025)	(0.026)
Time-saving	-0.034	-0.025	-0.036	-0.052*	-0.032	-0.029
	(0.026)	(0.026)	(0.030)	(0.031)	(0.026)	(0.034)
Electric lighting	0.025	0.039**	0.051**	-0.021	-0.019	-0.026
	(0.019)	(0.017)	(0.022)	(0.018)	(0.016)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,828	1,662	1,662	2,627	1,522	1,522
Sample	Boys	Boys	Boys	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are here excluded). FE, FD and DiD stand for fixed-effects, first differences and de Chaisemartin and D'Haultfœuille (2020)'s difference-in-difference models.

6 Conclusion

This paper explores the relationship between household electrification and child labor in rural Nigeria. This relationship has been little studied to date, and Nigeria is a suitable setting given the extent of child labor and the diversity of electrification situations across the country. Controlling for several individual characteristics and for time-invariant unobservables, we show that the simple connection of the household to the electricity grid has no consequences on child labor. We find that the employment probability of children from electrified households may be lower than that of children living in non-electrified households only when the household combines grid access and a generator as sources of electricity. This combination allows households to be able to use appliances that allow them to save time and reallocate it among their members. In addition, we find that girls from households using entertainment appliances (mostly TV) are more likely to work than other girls, a result which is robust to selection on unobservables and to heterogenous effects of the treatment. These results should be studied further. They suggest that the luxury axiom may outweigh the other effects for boys but not for girls.

In Nigeria, the context of rural electrification has undergone profound changes in recent years with the gradual deployment of the Rural Electrification Strategy and Implementation Plan in 2016. Specifically, the development of mini-grids and off-grid solutions in rural areas is supposed to improve the reliability of electrification process. It therefore seems important to deepen our first results by a fieldwork capturing the effects of the arrival of these new modes of access to electricity.

References

Alfa, A., Garba, T., Abdullahi, A., and AbdulRahim, M. (2012). Impact of child labour on school attendance: evidence from Bida Local Government Area of Niger State, Nigeria. *Spanish Journal of Rural Development*, 3(3).

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(1):151–184.

Asamu, F. F. (2005). Poverty and child labour in Nigeria: Challenges for youth development in the 21st century. In *International Conference on Challenges of Human Development in 21st Century*.

Atkin, D. (2016). Endogenous skill acquisition and export manufacturing in mexico. *American Economic Review*, 106(8):2046–85.

Barron, M. and Torero, M. (2017). Household electrification and indoor air pollution. *Journal of Environmental Economics and Management*, 86:81 – 92. Special issue on environmental economics in developing countries.

Basu, K. (1999). Child Labor: Cause, Consequence, and Cure, with Remarks on International Labor Standards. *Journal of Economic Literature*, 37(3):1083–1119.

Basu, K., Das, S., and Dutta, B. (2010). Child Labor and Household Wealth: Theory and Empirical Evidence of an Inverted-U. *Journal of Development Economics*, 91(1):8 – 14.

Basu, K. and Tzannatos, Z. (2003). The Global Child Labor Problem: What Do We Know and What Can We Do? *The World Bank Economic Review*, 17(2):147–173.

Basu, K. and Van, P. H. (1998). The Economics of Child Labor. *The American Economic Review*, 88(3):412–427.

Bensch, G., Kluve, J., and Peters, J. (2011). Impacts of rural electrification in rwanda. *Journal of Development Effectiveness*, 3(4):567–588.

Bernard, T. (2010). Etudes d'impact des programmes d'électrification rurale en Afrique subsaharienne. Série Analyse d'impact N°3, Agence Française de Développement, Division Évaluation et Capitalisation.

Bernard, T. (2012). Impact Analysis of Rural Electrification Projects in Sub-Saharan Africa. *The World Bank Research Observer*, 27(1):33–51.

Bernard, T., Dercon, S., Orkin, K., and Taffesse, A. S. (2019). Parental Aspirations for Children's Education: Is There a "Girl Effect"? Experimental Evidence from Rural Ethiopia. *AEA Papers and Proceedings*, 109:127–32.

Bhalotra, S. and Heady, C. (2003). Child Farm Labor: The Wealth Paradox. *The World Bank Economic Review*, 17(2):197–227.

Blimpo, M. P. and Cosgrove-Davies, M. (2019). *Electricity Access in Sub-Saharan Africa: Uptake, Reliability, and Complementary Factors for Economic Impact*. The World Bank.

Borusyak, K. and Jaravel, X. (2017). Revisiting event study designs.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230. Themed Issue: Treatment Effect 1.

Cascio, E. U. and Narayan, A. (2015). Who Needs a Fracking Education? The Educational Response to Low-Skill Biased Technological Change. Working Paper 21359, National Bureau of Economic Research.

Chakravorty, U., Pelli, M., and Ural Marchand, B. (2014). Does the quality of electricity matter? Evidence from rural India. *Journal of Economic Behavior & Organization*, 107:228–247.

Coen-Pirani, D., León, A., and Lugauer, S. (2010). The effect of household appliances on female labor force participation: Evidence from microdata. *Labour Economics*, 17(3):503–513.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

DellaVigna, S. and La Ferrara, E. (2015). Chapter 19 - Economic and Social Impacts of the Media. In Anderson, S. P., Waldfogel, J., and Strömberg, D., editors, *Handbook of Media Economics*, volume 1 of *Handbook of Media Economics*, pages 723–768. North-Holland.

Dinkelman, T. (2011). The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review*, 101(7):3078–3108.

Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2):601–646.

Dumas, C. (2007). Why Do Parents Make Their Children Work? A Test of the Poverty Hypothesis in Rural Areas of Burkina Faso. *Oxford Economic Papers*, 59(2):301–329.

Edmonds, E. and Turk, C. (2004). Child Labor in Transition in Vietnam. In Glewwe, P., Agrawal, N., and Dollar, D., editors, *Economic Growth, Poverty and Household Welfare in Vietnam*, pages 505–550, Washington DC. World Bank.

Edmonds, E. V. (2005). Does Child Labor Decline with Improving Economic Status? *The Journal of Human Resources*, 40(1):77–99.

Edmonds, E. V. (2006). Understanding Sibling Differences in Child Labor. *Journal of Population Economics*, 19:795–821.

Edmonds, E. V. and Pavcnik, N. (2005). Child labor in the global economy. *The Journal of Economic Perspectives*, 19(1):199–220.

Edmonds, E. V. and Schady, N. (2012). Poverty Alleviation and Child Labor. *American Economic Journal: Economic Policy*, 4(4):100–124.

Fafchamps, M. and Wahba, J. (2006). Child Labor, Urban Proximity, and Household Composition. *Journal of Development Economics*, 79(2):374 – 397. Special Issue in honor of Pranab BardhanSpecial Issue in honor of Pranab BardhanConference in honor of Pranab Bardhan.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277. Themed Issue: Treatment Effect 1.

Greenwood, J., Seshadri, A., and Yorukoglu, M. (2005). Engines of Liberation. *The Review of Economic Studies*, 72(1):109–133.

Grimm, M., Sparrow, R., and Tasciotti, L. (2015). Does Electrification Spur the Fertility Transition? Evidence From Indonesia. *Demography*, 52(5):1773–1796.

Grogan, L. (2018). Time use impacts of rural electrification: Longitudinal evidence from guatemala. *Journal of Development Economics*, 135:304–317.

Grogan, L. and Sadanand, A. (2013). Rural Electrification and Employment in Poor Countries: Evidence from Nicaragua. *World Development*, 43(C):252–265.

Heath, R. and Mushfiq Mobarak, A. (2015). Manufacturing growth and the lives of bangladeshi women. *Journal of Development Economics*, 115:1–15.

Idowu, A. B., Amos, O. A., and Olabisi, A. A. (2013). Analysis of Child Labour among Rural Household of Oyo State, Nigeria. *Asian Journal of Agriculture and Rural Development*, 3(05):1–9.

IEG, I. E. G. (2008). The welfare impacts of rural electrification: A reassessment of the costs and benefits. an ieg impact evaluation. Technical report, World Bank,, Washington, DC.

Jacobson, A. (2007). Connective Power: Solar Electrification and Social Change in Kenya. *World Development*, 35(1):144–162.

Jensen, R. (2012). Do Labor Market Opportunities Affect Young Women's Work and Family Decisions? Experimental Evidence from India *. *The Quarterly Journal of Economics*, 127(2):753–792.

Jensen, R. and Oster, E. (2009). The Power of TV: Cable Television and Women's Status in India. *The Quarterly Journal of Economics*, 124(3):1057–1094.

Kambhampati, U. S. and Rajan, R. (2008). The 'Nowhere' Children: Patriarchy and the Role of Girls in India's Rural Economy. *The Journal of Development Studies*, 44(9):1309–1341.

Khandker, S. R., Barnes, D. F., and Samad, H. A. (2009). Welfare impacts of rural electrification : a case study from Bangladesh. Policy Research Working Paper Series 4859, The World Bank.

Khandker, S. R., Samad, H. A., Ali, R., and Barnes, D. F. (2014). Who Benefits Most from Rural Electrification? Evidence in India. *Energy Journal*, 35(2):75 – 96.

Kitchens, C. and Fishback, P. (2015). Flip the switch: The impact of the rural electrification administration 1935–1940. *The Journal of Economic History*, 75(4):1161–1195.

Kline, P. and Moretti, E. (2014). Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority. *The Quarterly Journal of Economics*, 129(1):275–331.

Kohlin, G., Sills, E. O., Pattanayak, S. K., and Wilfong, C. (2011). Energy, Gender and Development: What Are the Linkages ? Where is the Evidence? Policy Research Working Paper Series N°5800, The World Bank.

Kruger, D. I. (2007). Coffee production effects on child labor and schooling in rural brazil. *Journal of Development Economics*, 82(2):448–463.

La Ferrara, E. (2016). Mass Media and Social Change: Can We Use Television to Fight Poverty? *Journal of the European Economic Association*, 14(4):791–827.

Lee, K., Miguel, E., and Wolfram, C. (2020). Does household electrification supercharge economic development? *Journal of Economic Perspectives*, 34(1):122–44.

Lenz, L., Munyehirwe, A., Peters, J., and Sievert, M. (2017). Does Large-Scale Infrastructure Investment Alleviate Poverty? Impacts of Rwanda's Electricity Access Roll-Out Program. *World Development*, 89:88–110.

Lewis, J. and Severnini, E. (2020). Short- and long-run impacts of rural electrification: Evidence from the historical rollout of the u.s. power grid. *Journal of Development Economics*, 143:102412.

Lipscomb, M., Mobarak, A. M., and Barham, T. (2013). Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. *American Economic Journal: Applied Economics*, 5(2):200–231.

Manacorda, M. and Rosati, F. C. (2010). Local labor demand and child work. In Akee, R. K. Q., Edmonds, E. V., and Tatsiramos, K., editors, *Child Labor and the Transition between School and Work*, volume 31, pages 321–354, Bingley. Emerald.

Mueller, E. (1984). The Value and Allocation of Time in Rural Botswana. *Journal of Development Economics*, 15(1):329 – 360.

Odey, S. A. and Sambe, N. (2018). Analysis of child labour practices in urban and rural communities in cross river state, nigeria. *Advances in Social Sciences Research Journal*, 5(3).

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Oster, E. and Steinberg, B. M. (2013). Do IT service centers promote school enrollment? Evidence from India. *Journal of Development Economics*, 104:123–135.

Parish, W. L. and Willis, R. J. (1993). Daughters, Education, and Family Budgets: Taiwan Experiences. *The Journal of Human Resources*, 28(4):863–898.

Ray, R. (2000). Child Labor, Child Schooling, and Their Interaction with Adult Labor: Empirical Evidence for Peru and Pakistan. *The World Bank Economic Review*, 14(2):347–367.

Rosenzweig, M. R. and Evenson, R. (1977). Fertility, Schooling, and the Economic Contribution of Children of Rural India: An Econometric Analysis. *Econometrica*, 45(5):1065–1079.

Rosenzweig, M. R. and Schultz, T. P. (1982). Market opportunities, genetic endowments, and intrafamily resource distribution: Child survival in rural india. *The American Economic Review*, 72(4):803–815.

Salmon, C. and Tanguy, J. (2016). Rural electrification and household labor supply: Evidence from nigeria. *World Development*, 82:48–68.

Schady, N. R. (2004). Do macroeconomic crises always slow human capital accumulation? *The World Bank Economic Review*, 18(2):131–154.

Shah, M. and Steinberg, B. M. (2017). Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital. *Journal of Political Economy*, 125(2):527–561.

Shah, M. and Steinberg, B. M. (2021). Workfare and Human Capital Investment: Evidence from India. *Journal of Human Resources*, 56(2):380–405.

van de Walle, D., Ravallion, M., Mendiratta, V., and Koolwal, G. (2017). Long-term Gains from Electrification in Rural India. *World Bank Economic Review*, 31(2):385–411.

World Bank (2021). Chapter 1: Access to Electricity. In IEA, IRENA, UNSD World Bank WHO, editor, *Tracking SDG 7: The Energy Progress Report*, Washington DC. World Bank.

Appendices

A Sample

Table A.1 – The different temporal patterns in the sample

Waves	Boys		Girls	
	Individuals	Percent	Freq.	Percent
123	601	28.19	525	26.66
12.	344	16.14	358	18.18
.23	363	17.03	336	17.06
1.3	40	1.88	39	1.98
1..	374	17.54	338	17.17
.2.	124	5.82	95	4.82
..3	286	13.41	278	14.12
Total	2,132	100	1,969	100

B Descriptive statistics

Table B.1 – Equipment rates in appliances among equipped households

	Wave 1	Wave 2	Wave 3
% households having at least one time-saving appliance			
Fridge	0.830	0.832	0.784
Freezer	0.259	0.301	0.387
Electric stove	0.152	0.186	0.135
Microwave	0.027	0.027	0.054
Washing machine	0.000	0.000	0.009
Electric dryer	0.000	0.009	0.000
% households having at least one entertainment appliance			
TV set	0.983	0.975	0.981
DVD player	0.684	0.752	0.794
Computer	0.044	0.046	0.060

Table B.2 – Share of households with access to electricity and use of electrical appliances on none, one, two or three waves

	None	One wave	Two waves	Three waves
Grid	0.576	0.124	0.177	0.124
Generator	0.658	0.170	0.109	0.064
Grid and generator	0.784	0.144	0.050	0.022
Entertainment appliances	0.634	0.119	0.128	0.119
Time-saving appliances	0.855	0.056	0.059	0.030
Electric lighting	0.636	0.187	0.129	0.048

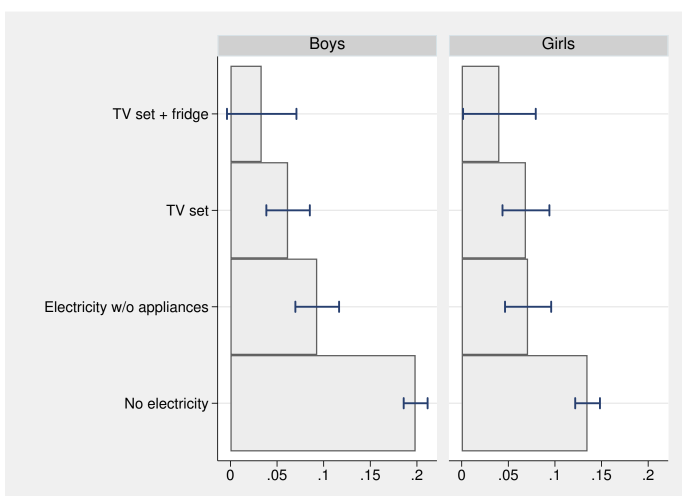
Notes: Sample of 1,080 households used for all econometric regressions.

Table B.3 – Share of joiners, leavers and non-switchers for access to electricity and use of electrical appliances between the three waves

	Wave 1 ⇒ Wave 2				Wave 2 ⇒ Wave 3			
	Joiners	Leavers	Stay in	Stay out	Joiners	Leavers	Stay in	Stay out
Grid	0.082	0.059	0.231	0.628	0.111	0.056	0.253	0.581
Generator	0.100	0.066	0.121	0.713	0.114	0.056	0.144	0.686
Grid and generator	0.062	0.046	0.039	0.853	0.109	0.039	0.057	0.794
Entertainment appliances	0.089	0.057	0.208	0.647	0.072	0.051	0.217	0.659
Time-saving appliances	0.032	0.032	0.068	0.868	0.036	0.022	0.069	0.873
Electric lighting	0.123	0.075	0.103	0.699	0.117	0.094	0.142	0.647

Notes: 1,055 households present in the sample over at least two waves of the survey. The column "Joiners" indicates the share of households that gained access to the source of electricity or type of appliance between the two waves, while the column "Leavers" reports the share of households that lost access between the two waves. "Stay in" and "Stay out" are shares of households that remained with and without access between the two waves, respectively.

Figure B.1 – Child labor depending on specific appliances owned by the household



C Additional Estimates

Table C.1 – Effect of electricity access on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grid and/or generator	-0.046***	0.023	0.016	0.016	-0.020	0.021	0.011	0.006
	(0.014)	(0.017)	(0.022)	(0.024)	(0.013)	(0.017)	(0.019)	(0.021)
β	-0.003	0.186	0.800	0.922	0	0.113	0.541	0.651
δ	1.065	-0.228	-0.0840	-0.0810	0.986	-0.415	-0.141	-0.0730
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	Yes	No	No	No
LGA FE	No	Yes	No	No	No	Yes	No	No
Household FE	No	No	Yes	No	No	No	Yes	No
Individual FE	No	No	No	Yes	No	No	No	Yes
Observations	2828	2828	2828	2828	2627	2627	2627	2627
R-squared	0.160	0.312	0.469	0.518	0.113	0.258	0.501	0.539
Sample	Boys	Boys	Boys	Boys	Girls	Girls	Girls	Girls

Notes: The dependent variable is one if an individual is working in a farm owned or rented by a household member and zero otherwise. All errors are clustered at the individual level. Standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. β is the lower or upper bound on the coefficient under the assumption of equal degree of selection on included control variables and on unobservables ($i.e. \delta = 1$). δ is the ratio of selection on unobservables to selection on observables required to obtain a coefficient of zero. The calculation assumes $R^{max} = 1$, which is the hypothetical R-squared from a regression including all observables and unobservables. Controls include child's age, parents' level of education, sex of household head, household size, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).

Table C.2 – Heterogenous effects of specific electrical appliances on child employment

	FE	FD	DiD	FE	FD	DiD
TV set	0.040	0.032	0.038	0.102***	0.087***	0.083***
	(0.035)	(0.027)	(0.032)	(0.036)	(0.025)	(0.026)
Observations	2,805	1,629	1,629	2,605	1,497	1,497
Fridge	-0.021	-0.024	-0.045	-0.010	0.007	0.011
	(0.030)	(0.025)	(0.033)	(0.042)	(0.029)	(0.057)
Observations	2,805	1,629	1,629	2,605	1,497	1,497
Electric lighting	0.026	0.039**	0.051**	-0.021	-0.019	-0.026
	(0.024)	(0.017)	(0.024)	(0.023)	(0.016)	(0.019)
Observations	2,828	1,662	1,662	2,627	1,522	1,522
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Boys	Boys	Boys	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are here excluded). FE, FD and DiD stand for fixed-effects, first differences and de Chaisemartin and D'Haultfœuille (2020)'s difference-in-difference models.

Table C.3 – Effect of electrical appliances on child employment

	(1)	(2)	(3)	(4)	(5)	(6)
Entertainment	0.051*	0.047*	0.042	0.103***	0.099***	0.098***
	(0.027)	(0.028)	(0.034)	(0.027)	(0.026)	(0.030)
β	0.822	0.909	1.763	0.805	0.939	1.706
δ	-0.307	-0.273	-0.191	-1.043	-0.976	-0.790
Time-saving	-0.034	-0.113	-0.153	-0.052*	-0.092	-0.161
	(0.026)	(0.085)	(0.117)	(0.031)	(0.106)	(0.153)
β	2.095	547.1	-280.3	7.459	-122.0	-54.23
δ	0.195	0.106	0.103	0.667	0.193	0.234
Electric lighting	0.025	0.024	0.018	-0.021	-0.021	-0.043
	(0.019)	(0.019)	(0.030)	(0.018)	(0.018)	(0.027)
β	0.261	0.261	1.843	0.0330	0.0320	15.87
δ	-0.264	-0.251	-0.103	0.579	0.588	0.568
Entertainment × Time-saving		0.088	0.141		0.044	0.069
		(0.085)	(0.121)		(0.110)	(0.167)
β		27.91	37.73		31.50	46.13
δ		-0.0820	-0.0830		-0.0890	-0.0840
Entertainment × Lighting			0.014			0.013
			(0.041)			(0.040)
β			5.665			8.235
δ			-0.0490			-0.0930
Time-saving × Lighting			0.141			0.183
			(0.128)			(0.145)
β			112.4			52.01
δ			-0.0390			-0.181
Entertainment × Time-saving × Lighting			-0.159			-0.113
			(0.131)			(0.158)
β			-921.1			-237.3
δ			0.0430			0.119
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
LGA FE	No	No	No	No	No	No
Household FE	No	No	No	No	No	No
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2817	2817	2817	2620	2620	2620
R-squared	0.518	0.518	0.518	0.544	0.544	0.545
Sample	Boys	Boys	Boys	Girls	Girls	Girls

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. δ is the ratio of selection on unobservables to selection on observables required to obtain a coefficient of zero. The calculation assumes $R^{max} = 1$, which is the hypothetical R-squared from a regression including all observables and unobservables. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).

Table C.4 – Effect of electrical appliances on child employment

	(1) Boys	(2) Boys	(3) Boys	(4) Girls	(5) Girls	(6) Girls
TV set	0.039	0.034	0.027	0.110***	0.109***	0.111***
	(0.027)	(0.027)	(0.034)	(0.027)	(0.027)	(0.031)
β	0.849	0.924	2.014	0.790	0.908	1.584
δ	-0.240	-0.203	-0.122	-1.068	-1.017	-0.849
Fridge	-0.032	-0.155*	-0.205*	-0.044	-0.058	-0.089
	(0.024)	(0.094)	(0.122)	(0.034)	(0.116)	(0.130)
β	0.842	-175.1	-103.2	0.190	-641.8	-125.1
δ	0.229	0.164	0.164	0.842	0.166	0.224
Electric lighting	0.027	0.025	0.017	-0.024	-0.024	-0.036
	(0.019)	(0.019)	(0.030)	(0.018)	(0.018)	(0.026)
β	0.269	0.268	1.719	0.0280	0.0280	6.781
δ	-0.275	-0.259	-0.100	0.645	0.649	0.468
TV set × Fridge		0.138	0.204		0.016	-0.017
		(0.096)	(0.125)		(0.116)	(0.137)
β		27.25	33.43		54.93	139.7
δ		-0.137	-0.139		-0.0440	0.0380
TV set × Lighting			0.019			-0.002
			(0.040)			(0.038)
β			4.987			9.580
δ			-0.0710			0.0150
Fridge × Lighting			0.205			0.133
			(0.135)			(0.141)
β			120.8			199.1
δ			-0.0570			-0.0840
TV set × Fridge × Lighting			-0.228*			-0.043
			(0.136)			(0.148)
β			-377.9			-29181
δ			0.0640			0.0290
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
LGA FE	No	No	No	No	No	No
Household FE	No	No	No	No	No	No
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2794	2794	2794	2598	2598	2598
R-squared	0.523	0.524	0.524	0.549	0.549	0.550

Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable indicating the existence of a school (primary or/and secondary) in the community (time-constant variables are excluded when including individual fixed effects).