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Heterogeneous effects of rural electrification on child labour in Nigeria

Claire Salmon* Jeremy Tanguy†‡

Abstract

In this paper we assess the impact of rural electrification on child labour 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 heterogeneous equipment rates, electrification cannot be only captured using access to the grid. We investigate in particular how child labour 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. In a country with poor quality electricity, this combination allows households to be able to use appliances that allow them to save time and reallocate it among their members.

Keywords: rural electrification, child labour, developing countries

JEL Classification: C33, D1, J1, J22, O13

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1 Introduction

Recent data on electricity supply in Nigeria demonstrates the extent of progress that remains to be made. Nigeria hosts the second largest population without access to electricity in the world after India (Olaniyan et al. 2024; Tagliapietra et al. 2020). 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 60.5% of the population has access to grid electricity in 2022. This rate drops to 27% in rural areas (World Bank 2023).[1] Even when power is available, the quality of electricity supply towards connected households is generally poor, with frequent and erratic power cuts and brownouts, limiting end users' potential utilization of electricity.[2] As a consequence of these failures, Nigerian households and firms frequently rely on private diesel generators for their daily operations.

The literature provides extensive evidence on the effect of electrification on several dimensions of development.[3] 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 labour in rural areas. Investigating the consequences of rural electrification on child labour is particularly suitable in Nigeria, which reports the highest rate of working children in West Africa. In 2022, the ILO counts nearly 25 million children aged 5 to 17 in child labour situation, *i.e.* 39% of the population of the same age (ILO 2024).[4] While child labour has always been prevalent in Nigeria, its incidence has increased significantly over the years (Idowu et al. 2013).

In this paper, we explore to what extent child labour is linked to the electrification process and its failures in rural Nigeria. Following existing literature, we first investigate whether the connection of the household to the electricity grid changes the probability of child labour within

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. 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; Cicowiez et al. 2022).

3. 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).

4. Child labour in Nigeria today is found predominately in the informal sector, and particularly in rural areas (Alfa et al. 2012).

the household. Given the possible limitations in the use of grid-supplied electricity due to its low quality, we also examine the role of generator use, whether or not combined with access to the grid, in the resort to child labour within households. We also examine differences in electricity end uses across households depending on the mode of access to electricity, focusing on uses of electric lighting, time-saving appliances and entertainment appliances. We exploit these differences in electricity end uses to explain estimated differences in the probability of child labour depending on household mode of access to electricity.

We use individual 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 heterogeneous treatment effects using the approach of de Chaisemartin and D'Haultfœuille (2020) and rely then on their difference-in-difference (DID) estimator, which is robust to heterogeneous 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 labour. 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 labour. Our results have significant implications in terms of public policy. The role of rural electrification in reducing child labour 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.

This paper contributes to the literature analyzing the effects of electrification on household time allocation to work. Most papers devoted to the impact of electrification on households in rural areas have focused on adult labour 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).[5] 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 such contexts, despite the grid connection, households continue to use traditional fuels and technologies for domestic tasks (*e.g.* cooking) and so collection time is unlikely to drop significantly. In rural Nigeria, given the failures of the grid, most connected households find themselves in this situation. We show in this paper that households combining access to the grid with a private generator stand out from other connected households by their much higher likelihood of using time-saving appliances. Supplementing grid electricity with generator power thus seems necessary to be able to use time-saving appliances. We contribute then to this literature by examining the consequences of this particular access to electricity on the allocation of time to work within households. The studies closest to ours, in the literature considering the quality of electricity supplied, have focused on the effects of power cuts (*e.g.* Andres et al. 2014; Khandker et al. 2013) and the use of generators (*e.g.* Bensch et al. 2011; Deichmann et al. 2011) on household educational and productive activities.

Without use of time-saving appliances, access to electricity is likely to have little effect on labour 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). Our descriptive analysis reveals that electric lighting is also widespread among connected households in rural Nigeria. It is almost as widespread among grid-only households than among households combining grid access with a generator, suggesting that the electric capacity provided through the grid is sufficient to power an electric lamp.

In case of a positive effect of electrification on adult employment, a negative effect can then be expected on child labour. Indeed, if parents increase their labour supply following electrification, a

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

decrease in child labour may be expected in reference to the so-called 'luxury axiom' (Basu and Van 1998), that states that child labour is largely the result of extreme poverty and the lack of adults monetary resources. The substitution effects at work between parents and children are one of the forces that can lead to a decrease in child labour and the main force we focus on in this paper.[6] Our results suggest that this substitution is possible in rural Nigeria only in households combining access to the grid with a private generator, since they are the only ones among connected households to report a lower probability of child employment with respect to non-connected households. We contribute to the literature devoted to the effect of electrification on child labour (*e.g.* Ribeiro et al. 2021; Squires 2015; van de Walle et al. 2017), by showing that a reduction in child labour is possible when the electricity supplied is of sufficient quality.

This paper is also related to the literature investigating the consequences of exposure to media – especially television – on social and economic behavior within households. There is an extensive 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 labour. Exposure to media can affect individual behaviors through three main mechanisms: by providing information, by changing individual preferences and time use (La Ferrara 2016). These mechanisms can be observed including for entertainment programs, which are by far the most popular media content in households (DellaVigna and La Ferrara 2015). These programs may 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), given the importance of conformity with the norm in individual behaviors (Bursztyn et al. 2017; Bursztyn and Jensen 2015).[7] In India, for instance, the introduction of cable television was associated with significant decreases in son preference, increases in women's autonomy and increases in school enrollment for younger children (Jensen and Oster 2009). In rural Ethiopia Bernard et al. (2019) find higher educational

6. Another force is the increased returns to schooling, resulting from the introduction of electricity in an area and productivity increases. Such an increase is particularly plausible when new job opportunities associated with electricity mostly require skills learned at school (*e.g.* literacy and numeracy). In that case, parents may 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). Unfortunately, the data used in this paper does not allow us to measure such a long-term effect, moreover at a more aggregated level than the household.

7. The influence of these programs on behaviors has led to the design of entertainment programs intended to change behaviors, *i.e.* edutainment programs, particularly in Nigeria (Banerjee et al. 2019a,b; Coville et al. 2019).

aspirations of parents in poor households, particularly with regard to their sons, following exposure to documentaries intended to this purpose featuring local male and female role models. Our findings suggest that television does not contribute to changing norms towards child labour in the context of rural Nigeria. Households with a television are not less likely to use child labour than other households. Girls' work even appears more prevalent within these households. This result may be related to the time adults spend in front of media (television) that is not devoted to other activities (La Ferrara 2016), in particular market and domestic work, and/or to an increase in the desired level of consumption, that leads households to make their children and especially their daughters work more.

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 labour. 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.[8] In its standard 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). labour-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

8. In Nigeria, the GHS is the analogous to the Living Standards Measurement Survey (LSMS) of the World Bank in terms of variable coverage.

in post-harvest data.[9] 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 and having at least one child aged between 5 and 14.[10]. We keep monogamous households, whose members only include spouses and their children. We thus rule out polygamous households, which generally have lower quality internal interactions than monogamous households (Barr et al. 2019; Bove and Valeggia 2009)[11], differential bargaining power between wives (Matz 2016)[12] and more strategic behaviors (Rossi 2019)[13]. Such complexity of interpersonal relationships within polygamous households would make the identification of mechanisms more complicated. We also rule out households that take in adopted or foster children, given the special status of these children compared to natural children[14], which makes them more vulnerable to unequal treatment within the household. Although this selection may seem restrictive, it makes it possible to consider households that are fairly homogeneous in their composition and thus prevent the estimated effects of electrification from capturing differences in composition that are difficult to control for.

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

9. 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.

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

11. In experimental games in Nigeria, Barr et al. (2019) show that cooperation and altruism are lower between members of polygamous households than between members of monogamous households. Bove and Valeggia (2009) find across Sub-Saharan Africa that there is less marital communication and weaker emotional ties in polygamous households than in monogamous ones.

12. Older wives generally have higher bargaining power, which manifests itself in better education and health outcomes for their children (*e.g.* Matz 2016).

13. Members of polygamous households, especially co-wives, have a more self-interested strategic behavior than spouses of monogamous households. Rossi (2019) shows, for example, that wives in polygamous households strategically increase their fertility in response to an increase in the fertility of their co-wives so as to maintain bargaining power over the resources controlled by the husband.

14. Adopted or foster children may be orphans but they are generally children of relatives close to the household (Penglase 2021), who entrust them for specific reasons such as work, education opportunities and risk sharing between households (Ainsworth 1996; Akresh 2009; Beck et al. 2015; Serra 2009).

waves, only one observation (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 6 (see Appendix A).

3 Descriptive analysis

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

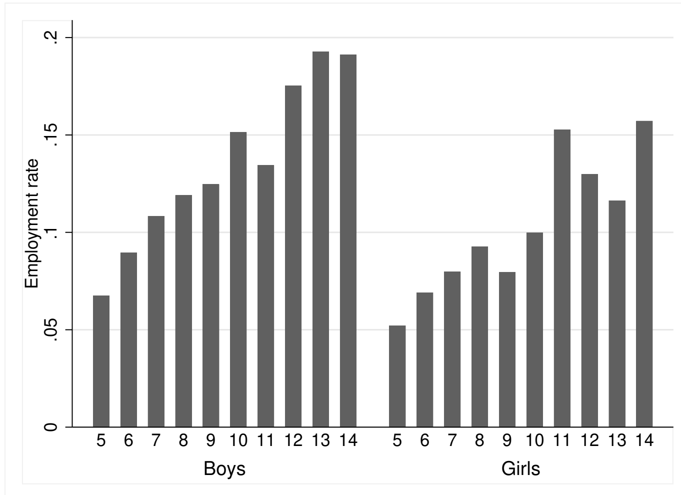
On average over the three waves, we observe that the employment rate of children increases sharply and almost continuously with age until it reaches almost 20% for boys and 15% for girls at age 14 (see Figure 1). Most children are working on a farm owned or rented by a household member ('household farm'). This activity is more widespread among working boys (nearly 90%) than working girls (82.5%), who are more 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'), against less than 5% of working boys. 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 Table 1.

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

The employment rate of both girls and boys is much lower in connected households than in non-connected households: around 6% in connected households, against nearly 12% for girls and 17% for boys in non-connected households. Connected households represent more than 70% of households in

Figure 1 – Child employment rate by gender and age



villages which have access to the grid (see Figure 2). While the share of households using only grid electricity is rather constant over time, the share of households combining access to the grid and a generator is clearly increasing over time. This fact 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. However, the share of households using a generator as the only source of electricity is relatively low both in connected and non-connected villages. Child employment rate varies significantly depending on whether the household uses one or two sources of electricity. Unlike non-electrified households, electrified households report similar employment rates for girls and boys. Interestingly, the child employment rate is almost the same in all households that use only one source of electricity, whether the grid or a generator, namely around 7-8%. This rate is lower than that observed in households without electricity but higher than that observed in households combining access to the grid and a generator (see Figure 3).

These particularly low child employment rates among households using both grid access and a generator point to an apparent role of electricity consumption. 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. Appliances that are likely to help reduce child labour are those that save time. In our sample, the most owned time-saving appliances are the fridge, the freezer and the electric stove (see Table 7). Ownership rates of these appliances are much lower than for entertainment appliances such as radio, TV set and DVD player. Unlike the

Figure 2 – Distribution of households by source of electricity supply

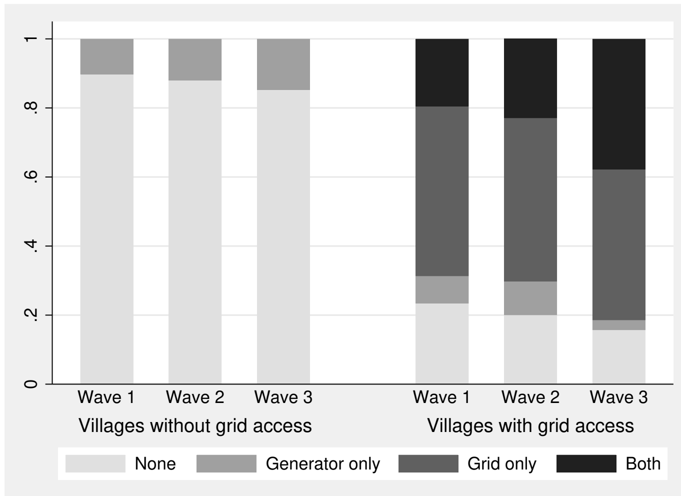


Figure 3 – Child labour rates by type of electricity access

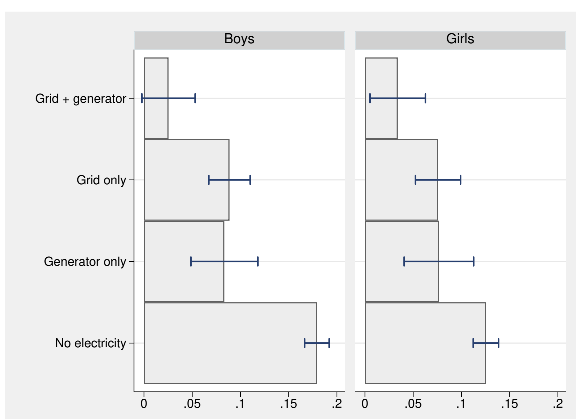
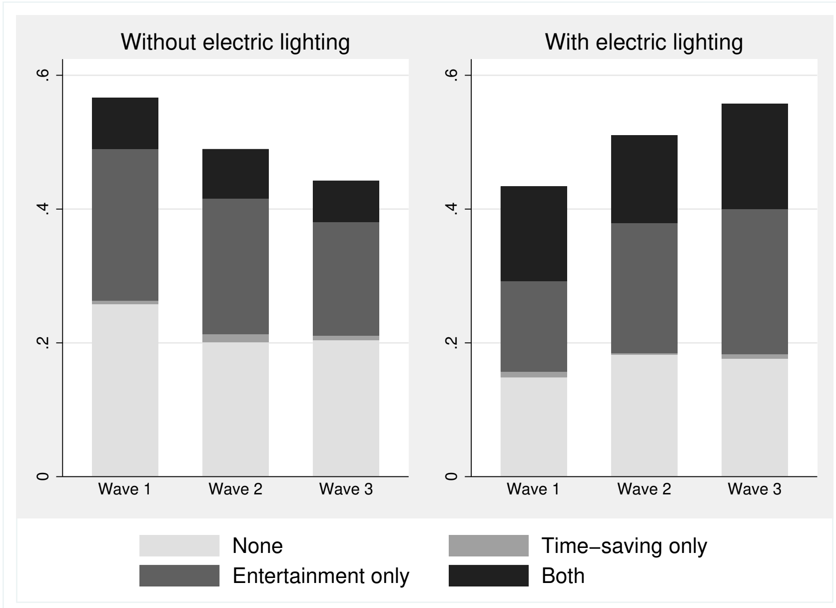


Figure 4 – Proportion of electrified households with electrical appliances by electric lighting

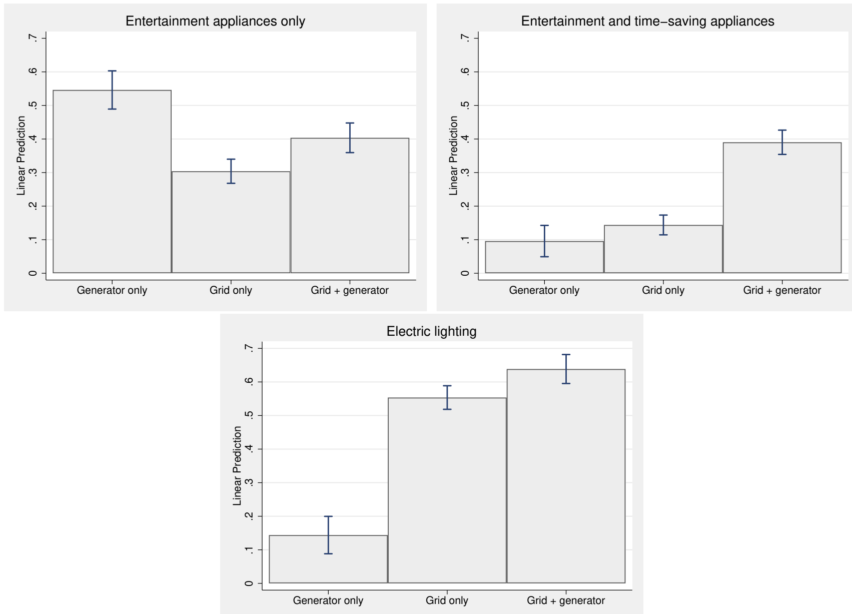


Note : Households are considered to have time-saving appliances if they have at least one of the following appliances: fridge, freezer, electric stove, microwave, washing machine, electric dryer. They are considered to have entertainment appliances if they have at least one of the following appliances: TV set, DVD player, computer. Radio is excluded here because it is largely owned by non-connected households.

former, entertainment appliances do not save time and are therefore not likely to affect child labour in this way. A significant portion of households that own entertainment appliances also own time-saving appliances, particularly among households that use electricity as main source of lighting (see Figure 4).[15] In contrast, there are almost no households that only have time-saving appliances, without any entertainment appliances. This suggests 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 found in most sub-Saharan African countries (see, *e.g.*, Jacobson 2007; Lenz et al. 2017). Note that about 40% of electrified households have no electrical appliances. Among these households without appliances, about half uses electricity as the main source of lighting, this share increasing over time (see Figure 4). But the major part of households using mainly electric lighting also have electrical appliances.

15. We consider that households have time-saving (respectively entertainment) appliances when they own at least one time-saving (respectively entertainment) appliance. 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 8).

Figure 5 – Proportion of households with electrical appliances and electric lighting by source of electricity supply



The combination of grid access with a generator appears to be a prerequisite to use time-saving appliances, given the much larger share of owners among households having both sources of electricity with respect to single-source households (see Figure 5, right panel). This seems to be less the case for entertainment appliances (upper left panel) and electric lighting (bottom panel). For entertainment appliances, it is even among generator-only households that the share of owners is the largest. Electric lighting is almost as widespread among grid-only households than among households combining grid access with a generator. But a very small share of generator-only households, in comparison, use electricity as main source of lighting. 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 fridge. Grid-connected households who want to use such appliances often have a generator in addition.

These differences in child employment according to household electrification status provide interesting insights but cannot be interpreted as causal relationships, given other sources of heterogeneity between households. In the next section, we present the empirical strategy we will adopt to control as much as possible these other sources of heterogeneity.

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.[16] Although we are able to include a large set of covariates, there may remain unobserved confounding factors. In particular, we cannot fully control for household living standards, which is a major determinant of both household electricity access (and consumption) and child labour.[17] 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[18]:

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

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, $\mathbf{X}_{it}$ 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

16. 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).

17. A substantial literature argues that the main cause of child labour 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 labour 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 labour 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 labour market imperfection, showing that households in Vietnam are more likely to have their children working when they have their own businesses.

18. 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.

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[19], 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_{it} is the error term. Time FE account for cyclical changes that are common to all individuals. The inclusion of α_i allows us to capture unobserved individual heterogeneity. The counterpart of doing this is that we cannot include among controls time-invariant characteristics – *e.g.* the education of parents, the gender of the household head.

Using this two-way fixed-effects (TWFE) 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)[20], 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

19. 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.

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

limited when most people are not farming, as in Dinkelman (2011). 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).[21] Third, we are also interested in the use of generator and the end-uses of electricity in 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.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}).[22] 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.[23] 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 Heterogeneous effects

In sharp designs with many groups and periods, de Chaisemartin and D'Haultfœuille (2020) show that the TWFE estimator may be a misleading measure of the treatment effect, under the

21. 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).

22. 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 $R^{max} = 1$ (as assumed by Altonji et al. (2005)).

23. 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.

standard common trends assumption, if the treatment effect is heterogeneous across groups and time periods.[24] 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 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 of 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 TWFE 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 heterogeneous over time or across individuals. Due to the negative weights, the coefficient may for instance be negative while all the treatment effects are positive. When some of the weights are negative, the TWFE 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 TWFE estimator cannot be robust to heterogeneous 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.[25] This estimator also relies on the stable groups assumption, which requires in our case that there are individuals whose access to the source of electricity in question does not change between each pair of consecutive time periods. 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

24. 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.

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

on all three waves (see Table 9). In addition, for all sources of electricity and electrical appliances considered, and for each pair of consecutive time periods, there are: *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 10).

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. We explore the mechanisms that support these relationships by examining the role of electricity end-uses, in particular the use of electric lighting and appliances.

5.1 Child employment depending on grid access

Starting from the stylized fact that grid-connected households have a lower probability of child employment, we first estimate the effect of grid access on child employment. In Table 2 we run separate regressions for boys and girls and present estimates for different specifications. The first specification, for both girls and boys, 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 finer FE at the level of Local Government Areas (LGA), 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.[26] Thus, controlling for all time-invariant unobserved characteristics that could induce an endogeneity bias in 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 on observables. Then, 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 selection on unobservables equivalent to that on observables. If this interval includes 0, it

26. 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 labour.

Table 2 – 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	2,828	2,828	2,828	2,828	2,627	2,627	2,627	2,627
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).

is difficult to conclude that there is a significant effect of grid access assuming 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 a fairly well-controlled environment, these parameters would support a significant negative effect of grid access on child labour. However, the specifications (1) and (5) only include state FE and year FE in addition to controls. Unobserved heterogeneity within states in a given year is likely to be higher than the heterogeneity controlled by 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 portion of households reporting having electricity in their dwelling rely on a generator either exclusively or in combination with grid access. Therefore, assessing the effect of electrification on child labour through grid access may not be relevant because many individuals in the control group have access to electricity through a generator. We report in Table 11 (see Appendix C) the results using the same specifications as in Table 2 but considering as a treatment variable a dummy variable indicating the household has access to electricity, whether by the grid or/and by a generator. These coefficient estimates are quite similar to those reported in Table 2, suggesting that households relying exclusively on a generator do not behave very differently from other electrified households or that 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 girls and boys that household electricity access has no impact on their likelihood to work. Yet, households with access to electricity are very heterogeneous in their use of electricity, as suggested in Section 3. In particular, the end uses of electricity vary greatly 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 then investigate in Table 3 the differentiated effects on child labour 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 access $\times$ Generator). This allows us to capture the effects on child labour of access to electricity through grid access only, through a generator alone, or through a combination of both. The different econometric specifications are modeled on those reported in Table 2. 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 unobserved factors of child labour.

We find that grid access and generator alone cannot change household decisions regarding the employment of their child, whether it is a boy or a girl. Indeed, for all specifications including

Table 3 – Effect of electricity source on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grid access	-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	-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 access × 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	2,828	2,828	2,828	2,828	2,627	2,627	2,627	2,627
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).

fixed effects at a finer level than LGA, coefficients on the variables Grid access and Generator are not significantly different from 0. For boys, the coefficient on the interaction term Grid access × 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).

5.3 Robustness check

These latest estimates suggest heterogeneous effects of the sources of electricity supply across households. The TWFE 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 access, Generator, and Grid access $\times$ Generator. We find in each case that a significant share of these weights are negative (see Table 12 for details). 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 TWFE estimator might be biased. Specifically, the coefficient and the average treatment on the treated (ATT) might be of opposite signs.

The question here is about the extent of treatment effect heterogeneity so that the coefficient and the ATT are of opposite signs. The bias in the TWFE estimator is significant if the coefficient and the ATT can be of opposite signs even if there is not a lot of treatment effect heterogeneity. The extent of this required treatment effect heterogeneity is provided by the ratio between the coefficient in absolute value and the standard deviation of the weights ($\underline{\sigma}$). A large value of $\underline{\sigma}$ implies that the coefficient and the ATT can be of opposite signs only if there is a lot of treatment effect heterogeneity. The value of the ratio is large when the treatment effect[27] lies within the confidence interval around 0 for a given distribution taking $\underline{\sigma}$ as the standard deviation.[28] This is what we observe for the effect of Grid access $\times$ Generator, for both girls and boys (see Table 12). Then, we can conclude that treatment effect heterogeneity is not a concern for the validity of the TWFE estimator of this effect. In contrast, bias is more likely for the separate effects of grid and generator, which are outside the confidence interval limits for both girls and boys (see Table 12). Then, in these latter cases, the coefficient and the ATT can be of opposite signs with not a lot of treatment effect heterogeneity. Thus, the separate effects of grid and generator on the employment probability of children may be equal to 0.

We check these heterogeneous effects in Table 4 by comparing estimates from the TWFE estimator with those of the FD estimator and the DID estimator proposed by de Chaisemartin and

27. The treatment effect may be either the coefficient estimated with the TWFE estimator (β_{fe}) or the largest expected treatment effect (denoted B in absolute value), defined using the largest estimate of the coefficient among the different specifications reported in Table 3.

28. We construct this confidence interval assuming that the treatment effects follow either a uniform distribution, as in de Chaisemartin and D'Haultfœuille (2020), or a normal distribution. We reach the same conclusions with both distributions (see Table 12).

Table 4 – Heterogeneous effects of electricity source on child employment

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	FE	FD	DID	FE	FD	DID
Grid access	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	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 access × 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

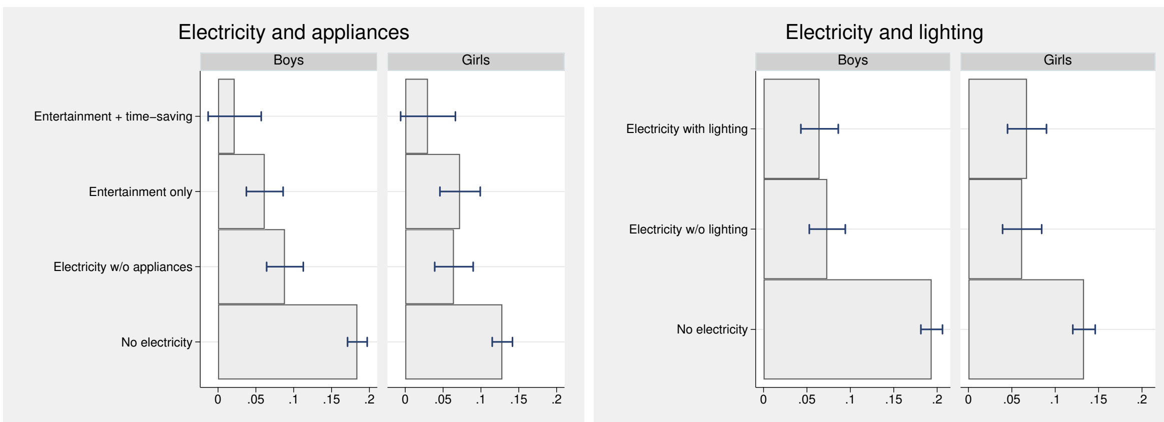
Notes: Robust standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include child's age, household share of boys and girls under 5 and 5-14, household share of men and women over 14, value of farm assets, value of the dwelling, a dummy variable 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.

D'Haultfœuille (2020). These results do not provide anything new on the influence on child labour of access to electricity via grid access alone or via a generator alone. Coefficient estimates on corresponding variables in FD and DID models are not significant, as in the TWFE model. Differences in coefficient estimates between the FE and FD models confirm these variables have heterogeneous effects, as shown above, and support the use of the DID model of de Chaisemartin and D'Haultfœuille (2020). The coefficient on Grid access × 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 supporting the robustness of the TWFE 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 heterogeneous uses of electricity in these households. Indeed, as shown in Section 3, 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 labour.

5.4 Mechanisms

We now explore the mechanisms that could explain why child labour is less prevalent in households that supplement their access to the grid with a generator. We focus on a specific characteristic of these households, as observed in Section 3: they are much more likely to own time-saving appliances than other households.

Figure 6 – Children employment rates depending on the use of electrical appliances and electric lighting



We can first of all observe in Figure 6 that the probability of child employment is lower in households that own time-saving appliances than in other electrified households.[29] For both girls and boys, the difference with respect to households that only own entertainment appliances is not significant. However, the employment of boys – not that of girls – is significantly less prevalent in households using time-saving appliances than in electrified households without appliances. The use of time-saving appliances thus seems to have more impact on household behavior regarding child labour than electric lighting, which is used in a large proportion among electrified households without appliances (see Section 3). The right panel of Figure 6 even suggests that, in the event that electric lighting provides extra time, the latter is not used to reduce child labour. Indeed, electrified households with and without electric lighting have virtually the same probability of child employment. Electric lighting therefore does not explain the large difference in child employment observed between non-connected households and connected households without appliances (left panel of Figure 6). The latter is rather explained by other differences in individual- and household-level characteristics, which are important to take into account in order to be able to conclude on a

29. As a reminder, we examine time-saving appliances in combination with entertainment appliances because almost no household owns only time-saving appliances without any entertainment appliances (see Section 3).

possible role of time-saving appliances.

Table 5 – Effect of electrical appliances on child employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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
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
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	2,828	2,828	2,828	2,828	2,627	2,627	2,627	2,627
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).

We try to control for all these differences in Table 5, where we analyse how child labour is related with each type of device: entertainment appliances, time-saving appliances and electric lighting. The dummy variable Electric Lighting identifies households using electricity as main source of lighting. Entertainment (Time-saving) identifies households equipped with at least one appliance classified as such. Note that electric lighting is not correlated with the employment probability of both girls and boys once including individual fixed effects. These estimates thus support the idea that the extra time provided by electric lighting is not used to reduce child labour in rural households.

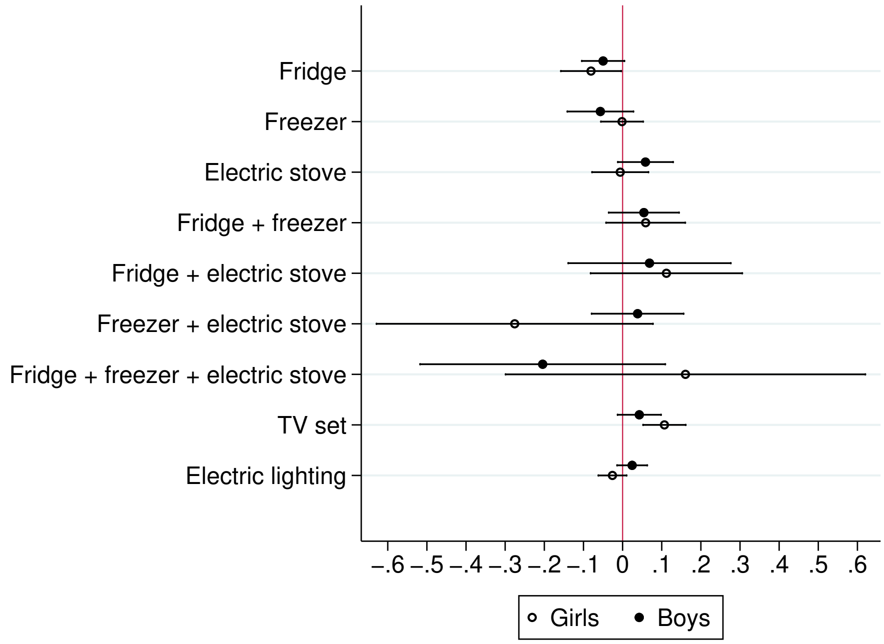
We pay particular attention to the coefficient associated with time-saving appliances, because it is a greater possession of these appliances that distinguishes households combining grid access and a generator from other electrified households. This coefficient is negative in all specifications for both girls and boys, but it is only (weakly) significant for girls (see column (8)). However, both the β and δ parameters tend to question the robustness of the coefficient to selection on unobservables: β does not have the same sign as the coefficient and $\delta < 1$. Thus, the effect of time-saving appliances on the employment probability of girls is likely to be zero. This result can be explained by the small number of households equipped with such appliances in our sample (see Table 9). Then, these appliances could possibly have a significant (and negative) influence if they were more widespread among households. This can also result from heterogeneous effects of these appliances between households, as suggested by the non-significant effect in the DID model (see Table 13). Such heterogeneity may be related to heterogeneous behaviors among households equipped with the same appliances but also to differences in time-saving appliances owned by households in this broad category.

We explore this heterogeneity by examining how child labour is related to each combination of time-saving appliances, using the same econometric strategy as in Table 5. To make these results easier to read, we plot in Figure 7 point estimates and corresponding 95%-confidence intervals from linear combinations of coefficient estimates, when including dummy variables for individual appliances and their interactions. We find that there are indeed heterogeneous effects between the different combinations of time-saving appliances. Interestingly, only the fridge alone, *i.e.* not combined with another time-saving appliance, is associated with a lower probability of employment for girls. As soon as the fridge is combined with another time-saving appliance, the correlation with child employment is no longer significant. This may be due to the low number of households with multiple time-saving appliances or other consequences associated to the use of these appliances.

Surprisingly, entertainment appliances are positively correlated to the employment probability of both girls and boys, but the coefficient is more significant for girls (1%) than for boys (10%) once including both year and individual FE (see Table 5, 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 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 work than girls living in households without access to electricity *ceteris paribus.*[30] Note that this positive correlation is driven by the TV set. When replacing in the regression

30. This positive correlation between Entertainment appliances and the employment probability of girls seems robust to heterogeneous treatment effects, as both FD and DID models also give a significant and positive coefficient (see Table 13).

Figure 7 – Effect of appliances on child employment



Notes: Estimated coefficients and 95%-confidence intervals from TWFE models. Robust standard errors. 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.

the Entertainment dummy variable by a dummy variable indicating whether the household owns a TV set, we also find a significant positive coefficient and of similar magnitude (see Figure 7). Following La Ferrara (2016), this positive correlation may result from a decrease in the time spent by other household members to market and domestic work due to television. Furthermore, television exposure is likely to lead to a shift in the desired level of consumption, leading households to make their children and especially their daughters work more to earn more. Finally, our results suggest that the effects of television on parents' aspirations for the education of their children, as shown in India (Jensen and Oster 2009) or in Ethiopia (Bernard et al. 2019), are not at work in rural Nigeria.

6 Conclusion

This paper explores the relationship between household electrification and child labour in rural Nigeria. This relationship has been little studied to date, and Nigeria is a suitable setting given the extent of child labour and the diversity of electrification situations across the country. Nigeria remains, after India, one of the largest countries in the world to offer very poor electricity coverage to a large part of its population, particularly in rural areas. Controlling for several individual characteristics and for time-invariant unobservables, we show that the simple connection of the household to the electricity grid has on average no consequences on child labour. We contribute to the literature by investigating the heterogeneous effects of access to the grid depending on whether or not it is associated with the use of a generator and depending on the different electrical appliances used in the household. 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 Nigeria, the use of generators is symptomatic of the difficulties of electricity supply. They are expensive stop-gap solutions that are unaffordable for the poorest households. Dependence on these generators can also limit investment in more sustainable solutions and affect the overall energy efficiency of rural communities. 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.

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Appendices

A Sample

Table 6 – 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

Figure 8 – Child labour depending on specific appliances owned by the household

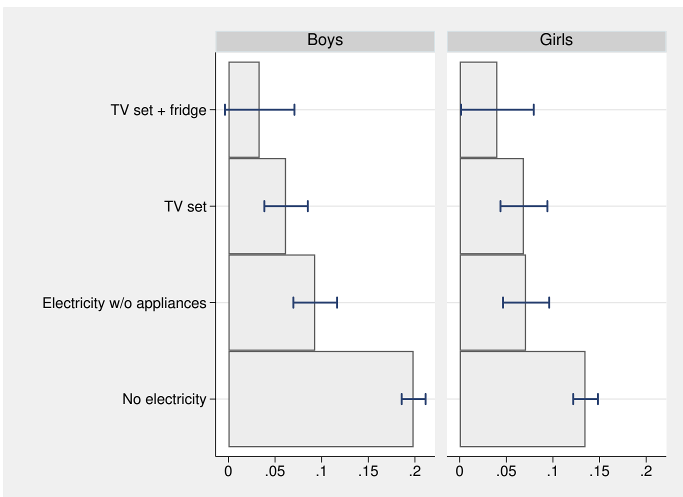

Table 7 – Equipment rates in electrical appliances and electric lighting

	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.

Table 8 – 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 9 – 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 10 – 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.

C Additional Estimates

Table 11 – 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 12 – Weights of the TWFE 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
B	0.05	0.05	0.05	0.05	0.08	0.08
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
Limit of the treatment effect interval						
- uniform distribution: $\sqrt{3} \times \underline{\sigma}$	0.005	0.014	0.029	0.031	0.083	0.116
- normal distribution: $1.96 \times \underline{\sigma}$	0.006	0.016	0.033	0.035	0.094	0.131

Notes: β_{fe} is the coefficient obtained using the TWFE estimator as in Table 3, 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, defined using the largest estimate of the coefficient among the different specifications reported in Table 3.

Table 13 – Heterogeneous effects of electrical appliances on child employment

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	FE	FD	DID	FE	FD	DID
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)
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)
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.