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Electrifying Nigeria: the Impact of Rural Access to Electricity on Kids' Schooling

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Abstract

As of 2020, 770 million people still lack access to electricity worldwide and 10% of this population is in Nigeria. Nevertheless, the country has received so far little attention in this respect from the academic community. The economic literature also does not generally agree on the impact of access to electricity on education outcomes, despite being the object of several programmes and policies, and one of the key SDGs of the 2030 Agenda. This paper aims at filling these gaps in the literature by providing a medium-term analysis of the effect of village-level electricity access on kids' schooling in rural Nigeria. It also contributes to the methodological debate using a novel instrument in this context, namely the frequency of lightning strikes in the area surrounding households. The results show that electricity access leads to an increase in school enrolment and a decrease in the grade-for-age (GFA) gap, a measure of educational performance. The paper also discusses some of the mechanisms that can lead to the observed findings, their robustness and heterogeneity, as well as the role of the quality of electricity received.

JEL classification: O12, O13, I25, Q48

Keywords: Energy Access, Rural Electrification, Education, School Enrolment, Nigeria

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1 Introduction

Access to electricity is a cornerstone of the development process. All advanced economies have secured the availability and reliability of electricity supply to underpin productivity increases, competitiveness boosts and ultimately economic growth (Ferguson et al., 2000). In developing countries, the need for affordable and reliable electricity is even more binding, since it is essential for the provision of lighting, cooking, heating, mechanical power, clean water, sanitation, healthcare, transport and telecommunication services. The international community has only recently started to recognize the role of energy for poverty alleviation and sustainable development. After excluding it from the 2000 Millennium Development Goals, the United Nations (UN) launched the Sustainable Energy for All initiative in 2011. Then, ensuring “access to affordable, reliable, sustainable and modern energy for all" became one of the 17 UN Sustainable Development Goals (SDGs) in the 2030 Agenda framework.

Several efforts at both national and international levels have followed, but the goal to reach universal access to electricity by 2030 is still very far away. There have been large improvements since 2015, when 1.1 billion people did not have an electricity source (International Energy Agency, 2016a). However, the COVID-19 pandemic delivered a setback to this positive trajectory and, as of 2020, 770 million people still live without access, 75% of which are in sub-Saharan Africa and especially in rural areas (International Energy Agency, 2016b). Despite optimistic projections thanks to the planned policies, this share is likely to further increase because of population growth, explaining the rising attention paid to Africa’s rural electrification. Children are a category that particularly carries the burden of the lack of electricity access in sub-Saharan Africa, because of the illnesses related to indoor air pollution, the lack of access to information and the time spent collecting traditional fuels such as biomass and coal, among other things (Barron and

Torero, 2017; World Health Organization, 2016). These factors, together with the impossibility of studying during dark hours, have a direct impact on kids' school performance and enrolment rates, which in turn affects their human capital.

The literature on the causal relationship between access to (and quality of) electricity and development outcomes at the micro-level is a relatively recent one. Impact evaluation studies started to emerge in the early 2010s, mostly with a focus on labor market and welfare outcomes (Bernard, 2012). The evidence related to education outcomes is more limited and, as explained in section 2, it still did not reach clear conclusions about not just the extent but also the very existence of an impact of electricity access on kids' schooling. Much of the debate revolves around the soundness of the identification strategies employed and, in the specific case of instrumental variables (IV) studies, on the choice of the instrument (see section 3.2). In general, the variety of the estimated effects depends on a combination of the methodology employed, the timeframe and unit of measurement, as well as the context analysed. Another gap in the literature is in fact related to the country under study, since Nigeria has not been the object of careful empirical evaluations of the impact of electrification, despite being the second country in the world for number of people without access. The only exception is Salmon and Salmon and Tanguy (2016), who study the effect on husband-wife labor supply decisions and with cross-sectional data.

This paper seeks to fill these gaps in the literature by studying the impact of village access to electricity on household-level outcomes related to kids' schooling, namely the enrolment rate and the grade-for-age gap, a proxy for school outcomes, in rural Nigeria. Besides contributing to an active debate for which the body of rigorous evidence is still limited and focusing on an under-studied country, this paper also provides a methodological innovation. I introduce a novel instrument in this context, the lightning strikes density in the 30-kilometers area around households' geolocation. Through their negative effect on the quality and reliability of electricity supply, lightnings can influence both grid expansion, investments in mini-/off-grid systems and households' decision to connect, thus being a promising candidate to tackle the endogeneity issue of access to electricity. The relevance and validity of this instrumental variable is discussed in sections 3.2 and 5.2. I use three waves of Nigeria's General Household Survey (GHS) between 2010 and 2016 and, by employing panel methods, I also eliminate potential bias concerns related to the presence of unobserved time-invariant heterogeneity.

I find that village-level access to electricity increases the household proportion of kids enrolled at school (extensive margin of education) by about 55% and decreases the average grade-for-age gap (intensive margin) by 1.2 years, within the span of three years. These results are robust to varying the IV radius, adding a second instrument and running overidentifying restriction tests, permuting lightning counts across sample households, controlling for migration and using bootstrapped or jackknifed standard errors (see section 5.2). I also find that the impact for households with direct access to electricity is larger than the average effect for households in connected villages, and that, after accounting for sample selection, electricity reliability (measured by the frequency of blackouts) has a positive impact on education's intensive margin. Conversely, only the results for the extensive margin are heterogenous along the wealth and gender axes, with poorer households and households with a higher proportion of boys enjoying greater enrolment benefits from electrification. This effect seems to be driven by a larger time endowment, in particular the lower need to collect firewood, rather than by a reduction in child labor.

The remainder of the paper is organised as follows: section 2 provides a review of the related literature and of the electricity context in Nigeria, together with the conceptual framework underlying the analysis; section 3 illustrates the identification strategy; section 4 describes the data and provides some descriptive statistics; section 5 presents the results and their robustness; section 6 discusses the heterogeneity of the main results and potential mechanisms; section 7 concludes and offers some policy recommendations.

2 Background and context

The literature on the development impacts of access to electricity is a relatively recent one. The last decade has witnessed a surge in the attention towards the role of energy access and reliability, but the number of rigorous impact evaluations on the subject is still low (Bayer et al., 2020). Moreover, most of the available studies focus on the impact of rural electrification programs on income or consumption, health and labor market outcomes (Tagliapietra et al., 2020). Despite its relevance for countries' human capital accumulation, productivity increases and long-term development, evidence on the education effects is instead quite limited and inconclusive so far (Bonan et al., 2017).

Most studies find positive impacts of rural electrification on both the extensive margin (enrolment, attendance rates and completed years of education) and the intensive margin (test scores, literacy rates and other schooling outcomes) of education. These findings span several regions across the globe, from Latin America (Lipscomb et al., 2013; Barron and Torero, 2014; Arraiz and Calero, 2015; Grogan, 2016, respectively in Brasil, El Salvador, Peru and Colombia) to South Asia (Khandker et al., 2014; Van de Walle et al., 2017; Khandker et al., 2013; Bridge et al., 2016, respectively in India, Vietnam and Nepal) and sub-Saharan Africa (Daka and Ballet, 2011; Bensch et al., 2011, in Madagascar and, with mixed evidence, in Rwanda), although the latter is relatively less represented.

A few recent studies, however, report statistically insignificant educational outcomes, in particular Burlig and Preonas (2016) for India, Kudo et al. (2019) for Bangladesh and Lee et al. (2020b) for Kenya. The former employs a regression discontinuity design and the other two rely upon a randomized controlled trial (RCT). Bayer et al. (2020) notice in fact that, in general, experimental evidence in the context of household electrification tends to produce fewer positive findings than quasi-experimental or observational studies, such as those using difference-in-differences and instrumental variable designs. Their systematic review highlights how, among a selection of 19 education-related impact evaluations of electrification, all observational studies generated positive results against 33% of experimental studies, with the remaining presenting neutral results.

RCTs are commonly considered the "gold standard" of research and tend to have high internal validity, especially because randomization, if well implemented, solves the issue of self-selection into treatment. Nevertheless, they are not exempt of issues, particularly when it comes to external validity (Basu, 2014; Deaton and Cartwright, 2018). In particular, there are at least four types of potential threats to RCTs' external validity, namely Hawthorne effects, general equilibrium effects, special care in treatment provision and specific sample problems (Peters et al., 2018). While RCTs are a precious source of evidence, particularly in the context of access to electricity which is difficult to randomize, they suffer from their own specific issues and their evidence should be read within the context of the larger body of literature.

Importantly, experimental studies do not all point in the same direction, which shows the limits of their external validity, even assuming a perfect internal one. For instance, a very similar experiment in El Salvador (Barron and Torero, 2014) and Kenya (Lee et al., 2020b), where economic incentives for households to connect to the grid were randomized to elicit exogenous variation, led to different conclusions with respect to educational outcomes. Another point on which the literature does not agree on is the differential effect of access to electricity by gender. With respect to schooling outcomes, several papers find a larger impact on girls than on boys (Khandker et al., 2013; Lipscomb et al., 2013; Van de Walle et al., 2017), while others do not find significant differences by gender (Khandker et al., 2012; Burlig and Preonas, 2016; Lee et al., 2020b), which could be due to the different cultures in the countries under study.

The variety of reported results can be thus attributed to a mix of the context analysed, the methodology employed, the timeframe and unit of measurement, and the type of intervention under study (Lee et al., 2020a). A lot more evidence from rigorous impact evaluations using different identification strategies is thus needed to better quantify the impact of access to electricity on different development outcomes. This paper aims at contributing to this debate within the context of children's education.

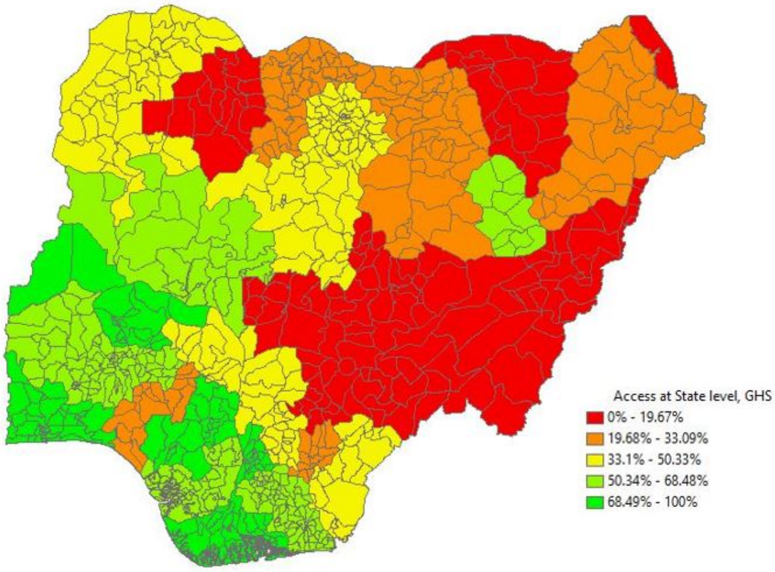
2.1 The electricity context in Nigeria

As of 2016, the last year in the survey data, 45% of the Nigerian population had access to electricity, with the access rate standing at 55% and 36% in urban and rural areas respectively. That is, 98 million people still lacked access to electricity in Nigeria (International Energy Agency, 2016a). This figure has been improving importantly over the last two decades, with average access to electricity increasing from 40% in 2000 to 55% in 2019, but very far away from the goal of attaining an overall access rate of 75% by 2020 and of 90% by 2030, as stated in "Nigeria Vision 2020".[1] Out of the 770 million people without electricity access worldwide in 2020, about one in ten lives in the largest African economy (International Energy Agency, 2016b).

As shown in Figure 1, the national average access rate hides large geographic heterogeneity. The northern and eastern states have much lower shares of households electrified than states in the western and southern parts of the country, where the major cities are located. This paper focuses on rural areas, where the access to electricity gap is generally much larger and filling it would have a more important impact on development outcomes. Moreover, as explained in section 3, the

[1] "Nigeria Vision 2020" is an economic plan prepared by the Nigerian National Planning Commission in 2009 to articulate the Federal Government development strategy for the period 2009-2020.

Figure 1: Average electricity access by state in Nigeria



Source: Nigeria's General Household Survey 2016.

employment of lightning strikes as an instrument for access to electricity works better in rural areas, where households are more dispersed and the extension of transmission lines to reach them is higher.

The country has low levels of electricity consumption per capita, averaging at 146 kWh during the 2010-14 period, against both similar countries in the region (336 kWh in Ghana and 232 kWh in Ivory Coast) and the sub-Saharan African average of 494 kWh.[2] This is the result of both low generation capacity and a very unreliable supply of electricity, which has historically been one of the main obstacles for the successful development of the country. In 2014, according to the World Bank Enterprise Survey (WBES), among firms that experienced at least one blackout during the year (77.6% of the total), the average number of power outages is 32 per month, with an average length of 8 hours. More than half of surveyed firms, in fact, identify electricity as a "very severe" or "major" obstacle

[2]World Bank Development Indicators.

for their operations and more than 30% state that it is the main obstacle (Alby et al., 2013; Emodi and Yusuf, 2015).

The relevance of this problem can be easily extended to education. For instance, without electricity, kids cannot study during dark hours, thereby reducing the number of potentially productive hours and creating a conflict with other activities (such as working on the field or helping with household chores). This in turn can have an impact both on school performance and on the likelihood that a kid actually enrols at school. As explained in the next subsection, the availability of reliable electricity can also activate other channels that impact the extensive and intensive margins of education, such as access to information, increased health status and time endowment. Furthermore, the relevance of these matters tends to be even more pronounced in rural areas.

The past two decades have witnessed several attempts by Nigerian policymakers to tackle or at least mitigate the issues of the electricity sector. The government created the Electric Power Implementation Committee in 2000, which drafted two key policy documents: the 2001 National Electric Power Policy and the 2003 National Energy Policy. They had the overarching goal to better exploit and optimize the use of Nigeria's vast fossil and renewable energy resources. Some of the milestones of these programs related to the private sector's increased role in energy generation and distribution, such as by privatizing the National Electric Power Authority (NEPA) and by incentivising independent power producers to enter the Nigerian market. Moreover, in 2014, the government created National Integrated Power Project (NIPP), a special body to push forward government-backed independent power projects to increase generation capacity and then, in 2015, it promulgated the Electric Power Sector Reform Act to fast-track the incorporation of NEPA (Ogunleye, 2017).

These initiatives had different outcomes. While 10 different projects for about

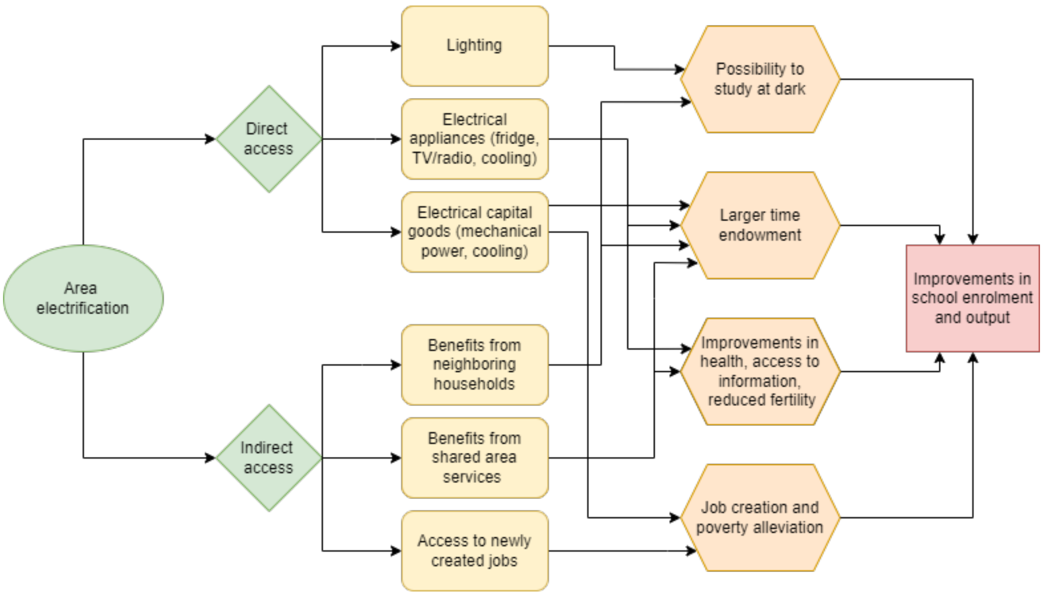
$13 billion were already initiated through the NIPP initiative by 2007, the privatization of NEPA, which started in 2010, was only completed by 2013. Clearly, unbundling such a large public utility firm was a complex operation. The NEPA was in fact composed by six generation companies, one national transmission company and eleven distribution companies. Moreover, this reform involved also the modernization of the associated regulatory and fiscal regimes (see Ogunleye, 2017). Currently, the government is completing the second wave of the privatization reform, by selling its stakes in the ten power projects developed through the NIPP. Also this process is taking more time than planned, since delays and issues related to gas supply have negatively impacted many of these projects' bankability. During the COVID-19 pandemic, within its recovery plan, the government approved a plan which aims to connect 25 million people with access to electricity through incentives to off-grid solar businesses and financing of solar home systems (International Energy Agency, 2016b).

2.2 From electrification to schooling outcomes

Regardless of the research design or intervention analysed, most studies in the literature surveyed at the beginning of this section have a similar conceptual framework. Access to electricity and sometimes its qualifiers (quality of the electricity received, connection costs, etc.) affect some development outcomes (e.g. consumption, income, labor supply, business creation or educational outcomes) through channels enabled by the use of electricity via some appliances or services. This kind of conceptual framework can be applied to the case of kids' schooling, as outlined in Figure 2.

A household can have access to electricity through three main sources: connection to the national grid, to mini/off-grid systems and via autonomous solutions (like generators and solar panels), or any combination of these options. The focus

Figure 2: Conceptual framework relating area electrification and education outcomes



Source: author's own elaboration.

on this paper is on the first two solutions, which both imply the electrification also of the area - at the minimum the village - in which the household lives. This is key for the instrument choice, as lightning strikes can affect the proper functioning of either the powerplants, generators or transmission lines involved in both the grid and mini/off-grid solutions, as explained more in detail in the next section. In fact, the vast majority of surveyed households (86.5%) get electricity directly from the grid and 7.1% of the sample from mini/off-grid solutions. Some households use a combination of the national or decentralized grid and generators (5.6%), while the exclusive use of autonomous solutions is instead a residual option, represented by less than 1% of the sample under study (see Table 1).

In the sample, as shown in Table 2, 45.6% of households have their village connected. Among these, 78.3% of households have a direct access to electricity, having paid the connection fee and bills for their consumption. This number hinders heterogeneity along the wealth axis, with households in the richest quin-

Table 1: Household sources of electricity

Source	Frequency	Percent	Cumulative
NEPA only	3,033	86.5	86.5
NEPA/generator	165	4.7	91.2
Rural electrification	246	7.1	98.3
Rural electricity/ generator	31	0.9	99.2
Private generator only	26	0.7	99.9
Solar panel	4	0.1	100
Total	3,505	100.0	

Source: Nigeria's General Household Survey 2010-2016.

tile twice as likely to be connected than households in the poorest quintile. The remaining 21.7% of households in connected villages, while not having direct access to electricity, can potentially enjoy partial benefits from the village being connected, due to sharing and stealing of electricity, and other spillovers from the area's electrification. To include these hardly quantifiable effects in the analysis, I use as the main explanatory variable the village rather than the household electrification status.[3] This also estimates the average treatment effect (ATE) on all households, as the policymaker's goal is ultimately to quantify the overall benefits of extending access to electricity to the part of the population that is not yet connected.

Figure 2 presents the case for both households with direct and indirect access to electricity, and how they are linked to the improvements in the extensive and intensive margins of education, here represented by school enrolment and output measures. The literature identified four main channels. Lighting is the most obvious one: thanks to electricity kids can increase their study time in dark hours, as shown by Kanagawa and Nakata (2008), Barron and Torero (2014) and Kudo et al. (2019). The second channel relates to the higher time endowment for study-

[3]For a comparison of the village and household access to electricity effects, see section 6.1.

Table 2: Household-level and village-level access to electricity

Household connected	Village connected 0	Village connected 1	Total
0	5,258	966	6,224
	(54.1%)	(9.9%)	(63.9%)
1	34	3,478	3,512
	(0.3%)	(35.7%)	(36.1%)
Total	5,292	4,444	9,736
	(54.4%)	(45.6%)	(100%)

Source: Nigeria's General Household Survey 2010-2016.

ing that kids, especially girls, gain from saving time on other household chores, such as fuel wood collection (Khandker et al., 2014; Arraiz and Calero, 2015). The third one relates to the improvements in health, nutrition, access to information and fertility reduction brought about, among other things, by the ownership of electrical appliances (Burlando, 2014; Grogan, 2016; Fujii et al., 2018). The fourth channel is linked to the job creation and welfare enhancements derived from electrification: this channel may both raise the financial means of households to send kids to school or increase the opportunity costs of education and thus child labor (Squires, 2015; Bridge et al., 2016; Kumar and Rauniyar, 2018).

3 Methodology

3.1 Specification

In the analysis of the impact of electricity access, there are two sorts of issues that need to be taken into account: unobserved time-invariant heterogeneity and endogeneity of the main explanatory variable of interest. It would be then naïve to employ a simple least squares regression model:

$$y_{it} = \alpha + \beta E_{it} + \gamma' \boldsymbol{x_{it}} + (\mu_i + \theta_t + u_{it}) \tag{1}$$

where y_{it} is the outcome variable for household i in year t (the proportion of kids enrolled at school or the average grade-for-age gap), E_{it} is household's access to electricity and x_{it} is a vector of covariates. Then there is the error term, composed by μ_i, the unobserved time-invariant household effects, θ_t the year fixed effects and u_{it}, the residual error term.

As households' access to electricity can be correlated with the household-specific effects, it produces a correlation between the explanatory variable and the unobserved error term, thus biasing the estimates of β, my coefficient of interest. Therefore, I exploit the panel nature of the data through a fixed effects (FE) model, which operates a within transformation of the variables. This is equivalent to performing a least square estimation on model (1) after that all variables have been demeaned using the individual means across time periods, as in (2).

$$(y_{it} - \overline{y_i}) = \beta(E_{it} - \overline{E_i}) + \gamma'(\boldsymbol{x_{it}} - \boldsymbol{\overline{x_i}}) + (\theta_t - \overline{\theta}) + (u_{it} - \overline{u_i}) \tag{2}$$

Clearly, covariates in x_{it} that are time-invariant will be wiped out together with the individual fixed effects and the constant term, so only covariates that have some degree of variation over time are included. For each econometric specification I also perform a Durbin-Wu-Hausman test which, by rejecting the consistency of the random effects model in all instances, confirms the soundness of employing the fixed effects model.

Still, in this type of studies, the estimate of β is not free from concerns, namely the endogeneity bias. As identified in most of the literature on the socioeconomic impact of electrification, access to electricity cannot be considered exogenous to many outcomes of interests. Grid extension, the choice of villages targeted by the roll-out of electrification programs and the decision by a household to pay for the connection may in turn depend on the outcome variables, or the two can be co-determined by other factors. This simultaneity issue would lead to wrongly estimating the effect of access to electricity (Roller and Waverman, 2001; Duflo and Pande, 2007; Rud, 2012; Grogan and Sadanand, 2013). I nevertheless test in each regression for the endogeneity of access to electricity using the Hausman test with a null hypothesis of no correlation between covariates and error term.

3.2 Identification

To tackle the endogeneity concerns, I employ an instrumental variable procedure. A valid instrument is a variable that is correlated with the endogenous explanatory variable (access to electricity) but that has no direct effect on the dependent variable after controlling for the covariates. Several instruments have been proposed in the literature, from solar radiation intensity to a time series of hypothetical electricity grids based solely on geographic cost considerations (Lipscomb et al., 2013; Salmon and Tanguy, 2016). In the survey data I have access to four of them which are relevant to this set up: household distance to the grid, household distance to the nearest power plant, population density at the local government authority level and land gradient at the site of the household (Dinkelman, 2011; Grogan and Sadanand, 2013; Chakravorty et al., 2014; Van de Walle et al., 2017).

However, of these four variables only one satisfies the instrument validity and relevance conditions in this context. The household distance to the grid may not satisfy the exogeneity condition, given that the extension of the grid to different areas of the country is often driven by political and economic motivations, hence its endogenous placement could favour households more likely to also enjoy better socioeconomic characteristics. Land gradient has also been criticized as an exogenous instrument (see Bensch et al., 2020) and it is time-invariant, making it useless in a panel setting, whether one uses a first differences or a within transformation approach. LGA population density may directly affect other development outcomes as well (such as job availability), and if used as an ex-ante characteristic it would also not have any within variation. The household distance to the nearest power plant is a more plausibly exogeneous IV, as the location of power plants depends on the presence of energy sources rather than on the distance to the areas that will be electrified. I employ this as an auxiliary instrument in some regressions, but its low variation over time does not make it the ideal candidate to be employed in the main identification strategy.

I use as primary instrument for access to electricity the average monthly frequency of lightning strikes in the area surrounding the household, also called flash density. To the best of my knowledge, it has never been used as an instrument in the microeconomic literature studying the development impacts of household electrification. It was first introduced by Andersen et al. (2012) who examine labor productivity growth in US states and argue that a higher flash density is associated with lower speed of IT diffusion, by causing voltage instability and thus damaging digital equipment. It was then employed by Andersen and Dalgaard (2013) to instrument power outages and study their impact on economic growth in cross-country regressions across sub-Saharan Africa. The only micro-level evidence is Millien (2017), who establishes the link between households' decision to connect to the grid and lightning intensity through its effect on electricity supply reliability. Using lightnings as an instrument for power outages severity, he finds a 0.67 elasticity between the likelihood of a household to connect to the grid and electricity reliability.

As a geoclimatic variable, it varies over time and space (see section 4.2) and is strongly correlated with access to electricity, both at the village and household level, regardless of the set of covariates employed (see section 6.1). With also relatively high Kleibergen-Paap Wald F-statistics, the IV thus satisfies the relevance property, which is further proved with the robustness checks in section 5.2. The first stage relationship is negative and strong: a higher intensity of lightning strikes in the area around the household geolocation increases the likelihood of damaging generators and transmission lines and, as a result, decreases connection rates (Andersen and Dalgaard, 2013). This happens because lower expected quality and reliability of electricity supply may negatively influence the likelihood both of households to connect to the grid and of grid extension to the village or area by the planner, which is in line with the evidence from Kennedy et al. (2019) and Millien (2017). A similar argument applies to mini- and off-grid solutions, which anyway represent only 8% of total sample connections.

Lightning density is also an arguably exogenous instrumental variable since it does not directly affect the outcome variables, conditional on covariates. It is definitely an external instrument in the sense of Deaton (2010). However, to be a valid instrument it needs to fulfil the exclusion restriction of zero correlation with the error term. Despite being to a large extent a random climatic phenomenon, a threat to validity could come from its potential correlation with other geoclimatic factors (e.g. rainfall), which can in turn affect agricultural output and then schooling outcomes. I therefore control, in the full specification, for other key geoclimatic variables at the household area level: annual mean precipitations, annual mean temperature and a potential wetness index created by World Bank experts. Interestingly, when adding these covariates, neither the coefficient of lightning strikes in the first stage regressions nor the coefficient on access to electricity in the reduced form regression of both outcome variables are significantly impacted, with both point estimates and significance levels remaining almost identical (see section 5.1).

Additionally, one could hypothesize that other unobservable socioeconomic factors correlated with both the instrument and the outcome variables may become a source of endogeneity. For instance, richer households could live in areas where the negative impact of lightnings on electricity supply and reliability, and therefore on schooling outcomes, is less pronounced (e.g. due to the quality of transmission cables). First, to have any effect, these factors should vary within the time span of 3 years (the distance between panel waves), otherwise they would be wiped out by the within transformation. Second, they should be uncorrelated with the other time-varying household-level demographic and socioeconomic covariates I control for. Besides the “usual suspects" such as age of the household head, number of kids, proportion of female and of employed household members, I include a wealth index to account for household economic status.[4] Moreover, I also control for whether the household owns a generator, given its importance as a replacement power source, as well as for the distance to the nearest market and to the nearest population centre, which reflect local labor market conditions (Grogan and Sadanand, 2013).

However, the validity of the exclusion restriction is never completely out of question. To provide further proof of the soundness of my identification strategy I perform several robustness checks in section 5.2. In particular, employing

[4]The wealth index is based on a principal component analysis (PCA) over the ownership of 16 household goods not requiring electricity, the possession of a bank account, the source of drinking water, the type of toilet accessible in the household, the quality of the walls and the number of people per room, following Rutstein (2008).

household distance to the nearest powerplant as a second exogenous instrument, I test whether the validity of the main IV is rejected using the Sargan-Hansen overidentification test. Secondly, I implement Nevo and Rosen (2012) imperfect instrumental variable inference test, which relaxes the IV exogeneity assumption. Thirdly, I perform a placebo test by randomly permuting the count of lightning strikes across households to check whether first stage regressions are actually driven by random geographic noise. The identification strategy survives all robustness tests. Finally, with respect to inference, all regressions are reported using heteroscedasticity-robust standard errors clustered at the household level. I also check whether bootstrapping or jackknifing standard errors alters the significance of the main results, and section 5.2.5 confirms that it remains virtually unaffected.

4 Data and descriptive statistics

4.1 Data

The main source of data for this paper is the General Household Survey implemented by the World Bank under the Living Standard Measurement Study (LSMS) series, together with the National Bureau of Statistics of Nigeria. Since 2010, the panel component of the GHS surveyed 5,000 households selected from 500 enumeration areas, to be repeated every 2 to 3 years. These households were selected to be representative of all geopolitical zones of Nigeria at both the rural and urban level, and were visited twice, once between August-October at the end of the planting season and once between February-April after the harvest. Given that all variables of interest are included in the post-harvest visits, I employ the latter as the main dataset and replace missing observations with post-planting information whenever available. Households are fairly evenly divided across the six geopolitical zones, with the highest share being located in the North Western area (19.2%) and the lowest share in the North Eastern area (13.5%).

Of the 5,000 households initially sampled, 4,917 responded to the questionnaire in the first wave of 2010-2011. From these, I restrict the focus to the 3,380 households living in rural areas, where the analysis is more compelling. As families move to other regions and states over time, they cannot always be tracked so that, by the third wave of 2015-2016, only 3,171 households of the original rural households were still present in the sample (in the second wave in 2012-2013 there are 3,369 rural households). Furthermore, during the last wave, a tracking visit was conducted after both post-planting and post-harvesting visit so to identify and interview as many households as possible among those who moved following one of the previous waves or in between visits. Overall, the attrition rate is quite low, at 3.9%, especially if compared to other household surveys in similar countries. To avoid attributing to electricity access changes in the outcome variable which are connected to migration choices, in the robustness checks I control for those households who moved in between waves.

The main outcomes of interest of this paper capture two key dimensions of kids' schooling: enrolment rate for the extensive margin and grade-for-age gap for the intensive margin of education. Both dependent variables are measured for kids in schooling age (between 5 and 15 years old) and at the level of household, which are both the panel identifier and the unit of analysis. In fact, this helps capturing intra-household dynamics, as choices related to kids' schooling are interdependent. Consequently, the enrolment rate is the proportion of kids within the household that are enrolled at school in the current year. Similarly, the grade-for-age gap is the average difference in years, across kids in a household, between the grade in which the kid should be enrolled given his/her age and the actual grade in which he/she is enrolled. For instance, as mandatory schooling in Nigeria starts at the age of 6, a 7-years-old kid enrolled in the first grade will have a grade-for-age gap of 1 year, and the higher the gap the worse. This measure incorporates information on grade repetition as well, and thus indirectly reflects school performance which is not available in the survey data (Islam and Choe, 2013).

The main explanatory variable of interest is access to electricity at the village level, obtained from the GHS survey, which is a dummy variable taking value 1 if the village is connected to an electricity grid (NEPA or a decentralized one) and 0 otherwise. In a robustness check I also employ the household-level access to electricity as explanatory variable, but the village access is preferred for most specifications since, as explained, it incorporates potential spill over effects, including the sharing and stealing of electricity, and it better captures the ATE. For data on the other electricity-relevant variables, namely household distance to the grid and to the nearest powerplant, I rely on external data sources. Specifically, information on the transmission grid network of medium and high voltage lines is from the West African Power Pool GIS database, accessible through the energy-data.info portal, while power plant location information comes from Platts.

My main instrumental variable is the flash density, measured as the average monthly number of lightning strikes in the area surrounding the household in the two years preceding the survey. The time window has been chosen to incorporate seasonal fluctuations and to be long enough to potentially influence factors affecting grid expansion and households' decision to connect. The land surface over which lightning strikes are counted is the area defined by a 30 kilometres radius around the household geolocation. This choice is both data driven, to maximize the first stage regressions' strength, and defined to include the average household distance from the grid. In a robustness check I also vary this radius to 20 and 50 kilometres. The lightning data have a 0.05°x0.05° spatial resolution and have been manipulated using the NASA's Earthdata API. They were obtained from the Science Data of NASA's Lightning Imaging Sensor (LIS), a space-based lightning sensor aboard the Tropical Rainfall Measuring Mission (TRMM) satellite, which has high detection efficiency, is capable of removing the background signal and has a millisecond precision (Blakeslee, 1998).

4.2 Descriptive statistics

Table 3 presents the summary statistics of the main variables utilized in the analysis, thus for all rural households, including their number of observations, mean, standard deviation, minimum and maximum. As mentioned in section 2, the sample average of the village electricity access stands at 45.6%, while the household-level access is somewhat lower, at 36.1%, both with significant variation across the sample. The latter figure is remarkably close to the 2013 rural electrification access rate reported for Nigeria in the 2015 World Energy Outlook, 36.5% (International Energy Agency, 2016a). With respect to the outcome variables, the enrolment ratio of household kids averages at 0.81, while the grade-for-age gap (which is available for slightly fewer households) at 1.87, and also their sample variation is relatively high.

Table 3: Descriptive statistics

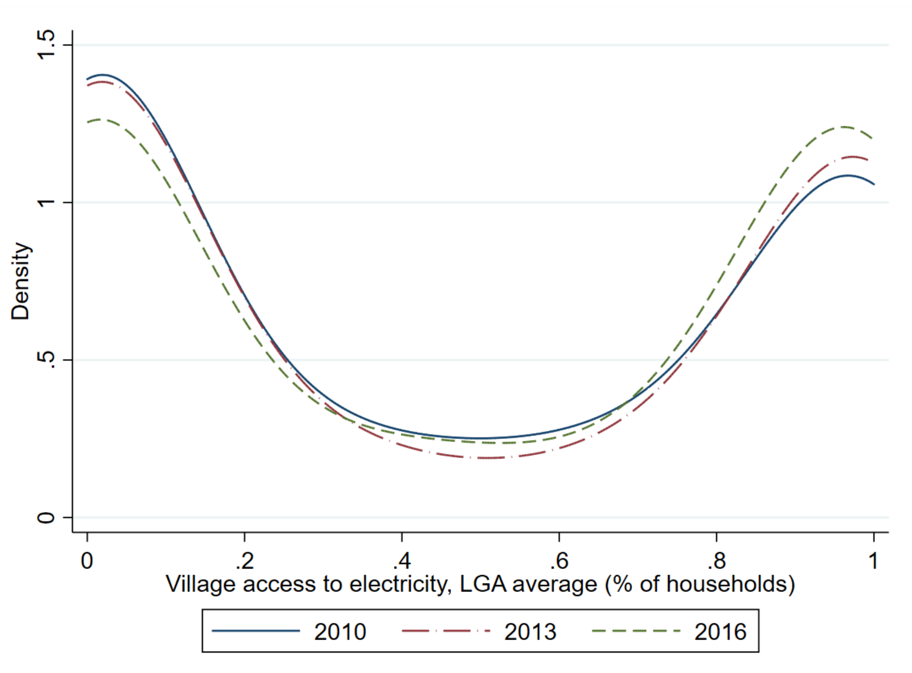
	N	**Mean**	**SD**	**Min**	**Max**
Village electricity access	9,738	0.46	0.50	0	1
HH electricity access	9,736	0.36	0.48	0	1
Enrolled ratio	6,672	0.81	0.36	0	1
Grade-for-age gap	5,327	1.87	1.14	0	7.8
Blackouts	3,490	2.69	0.62	1	3
Lightnings	9,812	5.42	3.03	0.08	17.6
Distance to grid	9,812	24.5	24.6	0.01	133.3
Distance to powerplant	9,812	130.3	97	2.13	465.6

Source: Nigeria's General Household Survey 2010-2016.

As expected, the average frequency of blackouts among households with access to electricity is quite high (this categorical variable ranges from 1 for households never or rarely experiencing power outages, to 3 for blackouts happening every day). 78.4% of sample households have power outages at least every week and only 3% of households never experience them, which indicates the low level of the quality of electricity received in Nigeria. The average monthly number of lightning strikes in the 30-kilometres radius area around households in the two years preceding the survey is 5.4, and it ranges between 0.1 and 17.6. As mentioned, the radius employed to obtain this instrumental variable has been chosen also to include the average household distance from the grid, which is 24.5 kilometres. The average household distance to the nearest powerplant, the additional IV used in some specifications, is much larger, at 130.3 kilometres.

Figure 3 presents the Kernel density estimates, for each year, of the average electricity access by local government authority, in terms of the proportion of households whose village is connected. The figure shows that, in my sample, the average LGA connection rate increased over time, both between 2010 and 2013 and between 2013 and 2016. Figure 3 also shows that there are many LGAs with close-to-zero or almost complete (above 80% of households) access to electricity. This suggests that electrification is likely to take place in a relatively homogeneous way within local government authorities, potentially for peer effects between households (Bernard and Torero, 2015). Conversely, the differences across LGAs are due to both their average economic status and other household characteristics, as well as the non-homogeneous unfolding of the national electrification strategy, factors that I aim to account for with the identification strategy outlined in section 3.

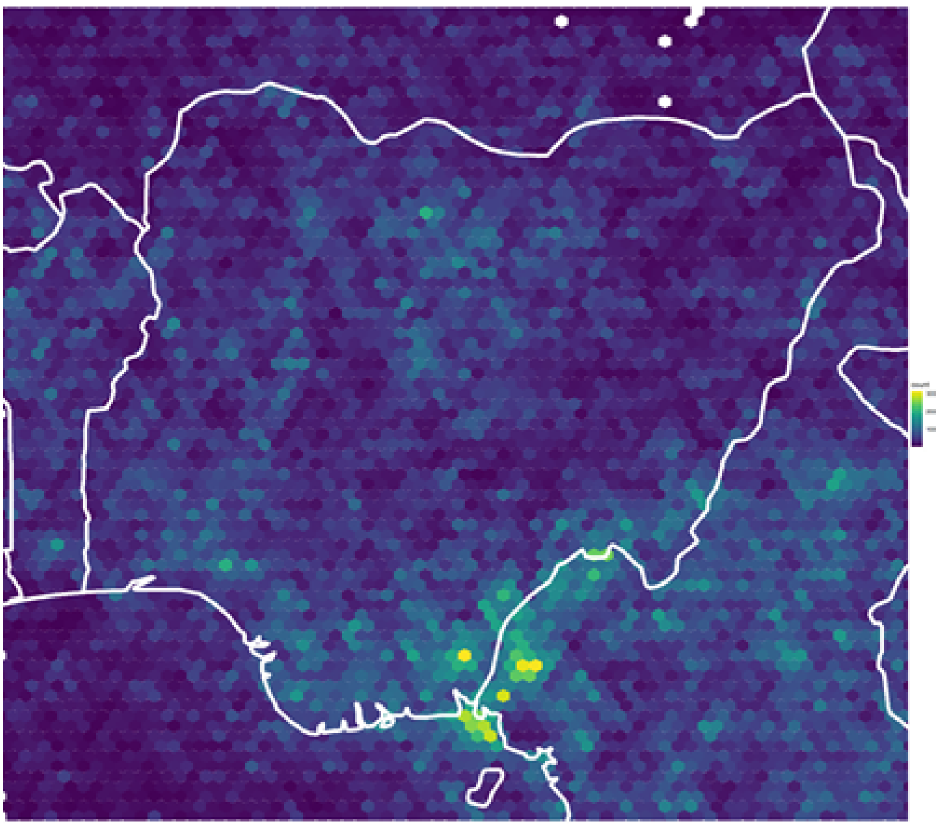
Figure 3: Kernel density function of average access to electricity in LGAs



Source: Nigeria's General Household Survey 2010-2016.

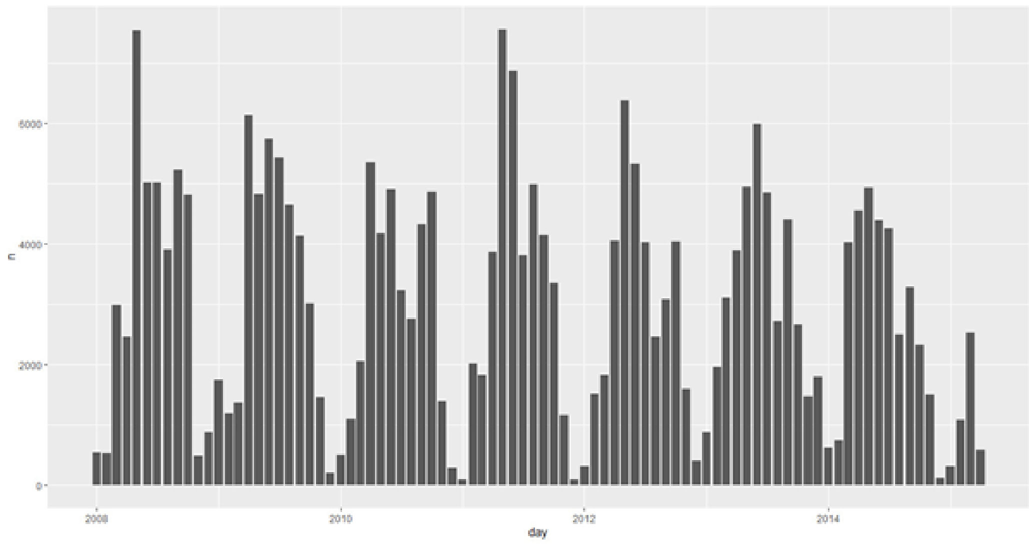
Figure 4 and Figure 5 show the geographic and time variation of the lightning strikes instrument. The number of flashes varies across the country's surface, with a more intense activity in the southern, western and central northern areas. There is also large lightning variation across time, mainly due to seasonal cyclicality (each bar of Figure 5 is a month), but year patterns are also somewhat different from each other. This explains the choice of aggregating this variable across the two years preceding the survey year, together with the need to be a significant timeframe for influencing economic agents' decisions. In fact, as shown in the next section, this instrument has a strong predictive power with respect to both village-level and household-level access to electricity in the first stage regressions.

Figure 4: Geographic distribution of lightning strikes (average 2008-2015)



Source: TRMM-LIS Data Science, NASA.

Figure 5: Monthly distribution of lightning strikes in Nigeria (2008-2015)

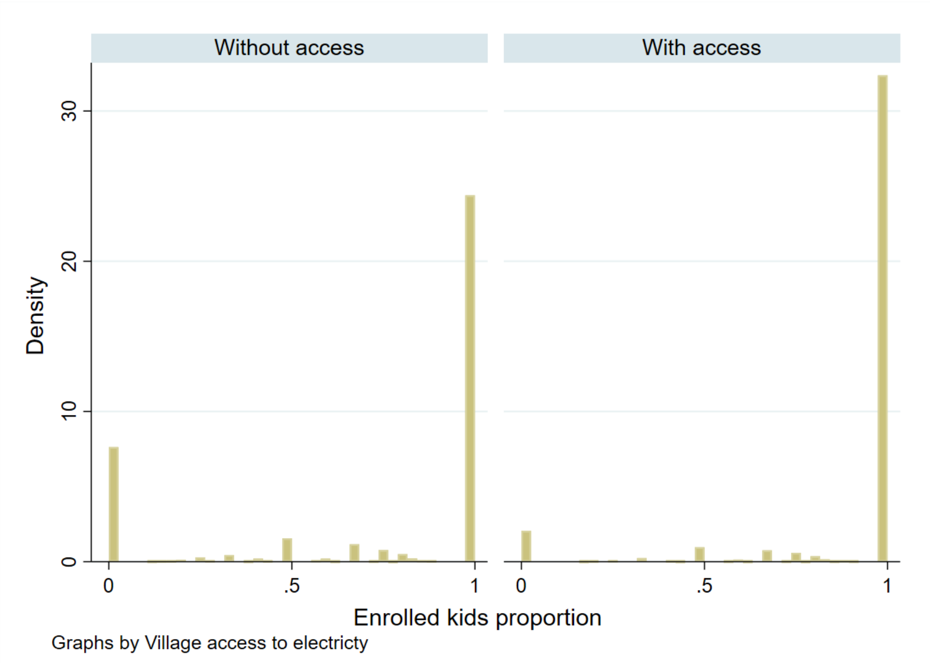


Source: TRMM-LIS Data Science, NASA.

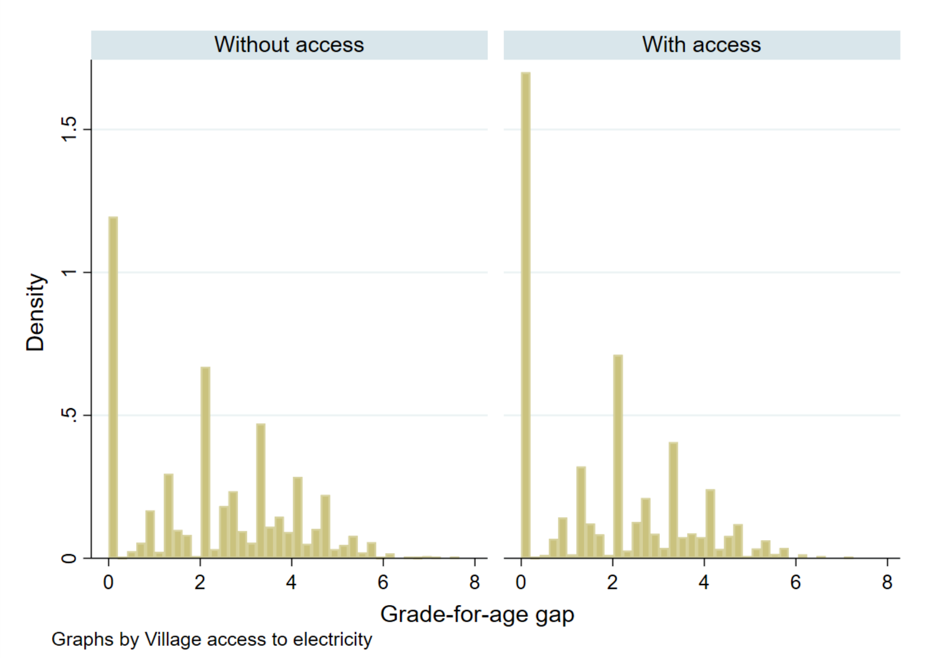
Figure 6 presents histograms of the two main dependent variables, by village-level access to electricity. These charts already present the essence of the main results of this paper, although at a very descriptive level. The school enrolment rate of kids in households whose village is connected to electricity is on average higher than that of households whose village is not connected, with a larger share of households having all their kids enrolled at school in the former than in the latter (see panel a). Similarly, the average grade-for-age gap is lower in households whose village is connected to electricity, with a larger share of households in which kids have no grade-for-age gap against households in non-connected villages (see panel b). The next section analyses more thoroughly these relations.

Figure 6: Histograms of the dependent variables by village access to electricity

(a) Panel a: household proportion of kids enrolled at school



(b) Panel b: average household kids' grade-for-age gap



Source: Nigeria's General Household Survey 2010-2016.

5 Results

5.1 Main results

Following the methodology described in section 3, Table 4 presents the main IV-FE results with the proportion of household kids enrolled at school as dependent variable. Each specification adds a set of covariates to the previous one to show the evolution of coefficients, of their statistical significance and of some other statistics. Column 1 only contains the instrumented main explanatory variable, village access to electricity, besides household and year fixed effects. Column 2 adds the demographic covariates (age of the household head, share of female components of the household and number of kids), while column 3 includes other household-level socioeconomic variable (share of employed household members, wealth index quintile, whether the household owns a generator, distance to the nearest market and to the nearest population centre). Column 4, the full specification, also adds the geoclimatic covariates (annual precipitations, annual mean temperature and potential wetness index).

The Hausman test clearly rejects the simple fixed effects regressions, with p-values below the 1% level in all specifications, indicating that village access to electricity is endogenous and instrumentation is thus necessary. Table 4 presents a negative and statistically significant first stage relation, implying that a higher density of lightning strikes negatively affects village electrification.[5] The strength of the first stage regressions is supported by high Kleibergen-Paap F-statistics, above 20 in the last two specifications, and is also reinforced by additional robustness checks presented in the next subsection. Despite the addition of key covariates and a drop of about 3% of observations in the sample between the first and last column, first stage coefficients are remarkably stable across specifications. Similarly,

[5] Full regression tables are available from the author upon request.

Table 4 also reports stable and statistically significant second stage regression coefficients (p-values are around 0.013). The relation is positive and, taking the full specification as preferred, the point estimates indicate that village-level access to electricity increases the household enrolment rate by about 55%. This a sizeable effect on the extensive margin of schooling, which suggests that on average the lack of rural electrification is a binding constraint for the human capital accumulation of households.

Table 4: IV-FE results: school enrolment rate of household kids

	(1)	(2)	(3)	(4)
Dependent Variable	Enrolled at school			
Village access	0.587**	0.578**	0.539**	0.548**
	(0.246)	(0.246)	(0.219)	(0.220)
	First stage - DV: village access			
Lightnings	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Year and household FE	YES	YES	YES	YES
Demographic covariates	NO	YES	YES	YES
Socioeconomic covariates	NO	NO	YES	YES
Geoclimatic covariates	NO	NO	NO	YES
Observations	6,215	6,189	6,016	6,016
Number of households	2,328	2,323	2,277	2,277
First stage R-squared	0.007	0.011	0.024	0.027
K-P F-statistics	17.4	17.2	20.9	20.1
Hausman test (p-value)	0.006	0.007	0.007	0.006

Note: robust standard errors clustered at household level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

Table 5 presents the IV-FE results for the grade-for-gap, a proxy for school output, as outcome variable. It follows the same structure as in Table 4. Hausman tests indicate the presence of endogeneity of the electrification variable, first stage relations are strong and statistically significant, and Kleibergen-Paap F-statistics are well above the standard threshold of 10. The reduced form coefficients, as expected, indicate that village electrification decreases the grade-for-age gap, by about 1.2 years on average (column 4). This negative effect, which implies an improvement of the intensive margin of schooling, has a p-value of 0.014.

Table 5: IV-FE results: grade-for-age gap of household kids

	(1)	(2)	(3)	(4)
Dependent Variable	Grade-for-age gap			
Village access	-1.196**	-1.292**	-1.234**	-1.220**
	(0.530)	(0.555)	(0.499)	(0.494)
	First stage - DV: village access			
Lightnings	-0.008***	-0.008***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Year and household FE	YES	YES	YES	YES
Demographic covariates	NO	YES	YES	YES
Socioeconomic covariates	NO	NO	YES	YES
Geoclimatic covariates	NO	NO	NO	YES
Observations	4,737	4,715	4,591	4,591
Number of households	1,801	1,796	1,763	1,763
First stage R-squared	0.008	0.012	0.027	0.029
K-P F-statistics	15.7	14.9	17.6	17.8
Hausman test (p-value)	0.006	0.004	0.003	0.003

Note: robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

5.2 Robustness

This section discusses several robustness checks associated with the main results presented above. First, I ran the baseline results varying the radius of the area considered for the lightnings instrumental variable. I then examine the IV validity via an overidentifying restriction test with the help of an auxiliary instrument. The third robustness check corroborates the evidence on the instrument's robustness, including a random permutation of lightning strikes, followed by a test on whether migration drives the main results. The fifth one relates to inference, where I check whether bootstrapping or jackknifing standard errors modifies the statistical significance of my estimates. In all instances I use the full specification from the previous section.

5.2.1 IV radius

As mentioned in section 4, the choice of the IV radius is both driven by logical reasons and data driven. As for the former, the logic is to select a radius that is close to the mean household distance to the grid (24.5 kilometres), without extending it beyond what would be the relevant area driving the decisions to expand and connect to the grid. Here I present the data argument, which is based on the relative strength of each instrument in the respective first stage regressions. Moreover, it can serve as a robustness check to test the sensitivity of the results to varying the radius.

As shown in Appendix A1, the Kleibergen-Paap F-statistics for the 30-kilometres radius first stage estimates are about twice as much the 20- and 50-kilometres radius ones. Both first stage and second stage regression estimates are qualitatively similar: the coefficient on lightnings is always negative and highly statistically significant, while the effect of village electrification is positive on enrolment and is negative on the grade-for-age gap. Also the point estimates tell a similar story to the baseline ones, from which are not statistically different, in particular using the 20 kilometres radius. The only not significant coefficient is from the grade-for-age gap second stage regression using the 50 kilometres radius, which is likely related to the excessive length of that radius.

5.2.2 IV validity

While the validity of an instrumental variable cannot be directly tested, if a second or auxiliary exogenous IV is available one can check whether the exogeneity of both of them is jointly rejected, i.e. one of the two IVs or both are correlated with the error term, using an overidentifying restriction test. In Appendix A2, I employ the Sargan-Hansen test and distance to the nearest powerplant as an auxiliary instrumental variable. In fact, differently from the endogenous grid placement, the location of powerplants depends on the presence of the relevant natural resources (gas, water, etc.) and not on the characteristics of the population served.

The p-values of the Sargan-Hansen test, whose null hypothesis is that the instruments are valid, are well above the standard 0.05 rejection threshold for both outcome variables, which does not prove but reinforces the identification strategy. Unfortunately, the distance to the nearest powerplant instrument is not strong enough to be employed in the baseline regressions, particularly with respect to the enrolment outcome variable, because it does not vary much over time. However, besides reporting the overidentifying restriction tests, Appendix A2 also confirms that the estimates remain qualitatively similar to the main ones both in terms of magnitude and statistical significance of the key coefficients.

In addition, I implement the method described by Nevo and Rosen (2012) to test the construction of bounds estimates in the hypothesis that the instrument is not valid. Their “Imperfect Instrumental Variable inference" is based on the idea to replace the assumption of zero correlation between the unobserved error term and the instrument with an assumption related to the sign of the correlation. It could be argued in favour of a correlation in both directions, but for each dependent variable I assume the sign that would risk to make the main results insignificant, i.e. negative for enrolment and positive for the grade-for-age gap. The imperfect IV test, implemented following Clarke and Matta (2018) with both robust and bootstrapped standard errors, leads to bounds estimates that clearly get closer to zero, but never include it. Therefore, even relaxing the IV exogeneity assumption, the general messages of this paper would hold.

5.2.3 IV robustness

Despite the strength of the first stage regressions already presented so far, an instrument obtained from a geoclimatic phenomenon like lightning strikes may still create weak instrument concerns. In this subsection I tackle the issue in two additional ways. First, I employ the weak IV robust test proposed by Olea and Pflueger (2013). This test computes the "Worst Case Bias" (WSB) in case of weak instrument, the critical values associated with different scenarios depending on how large the actual bias is compared to the WSB, and an effective F statistic. The latter is then compared to the critical values of each scenario (e.g. 10%, 20%, 30%, etc. of the WSB). For both outcome variables, the test indicates that the 20% bias scenario is rejected but not the 10% one. However, the effective F statistic is just slightly larger than the critical value associated with the 10% bias scenario, suggesting that lightnings can overall be deemed a strong instrument in this context.

The second approach is in the spirit Kelly (2019) and tests whether the first stage regressions are mostly identified by spatial noise from the instrument. I perform a permutation test by randomly assigning the lightning strikes observations to different households, re-run first stage and reduced form regressions, extract the relevant t-statistics from both and repeat these steps 1000 times. It is thus a placebo test in which I assume that the relations I find could be driven by any lightning density in my sample and check whether I do find statistically significant results in these replications. Appendix A3 presents the distribution of the t-statistics of four sets of replications based on the instrument permutation: for the lightnings coefficient in the first stage regressions (panels a and b) and for the access to electricity coefficient in the reduced form regressions (panels c and d), for each of the dependent variables.

The absolute value of a t-statistic above 1.96 indicates that the corresponding regression would have been significant at the 5% conventional level (2.58 for the 1% level and 1.645 for the 10% level). In the lightning permutations associated with the first-stage regressions (panels a and b), there are less than 5% of t-statistics above 1.96 or below -1.96. In the reduced form permutations (panels c and d), the percentage drops to zero for both outcome variables. This indicates that very few placebo first stage regressions and no placebo reduced form regressions would randomly be statistically significant, implying that the baseline results are not driven by random geographic noise.

5.2.4 Migration

It could be argued that households may migrate towards regions where electricity is available or away from areas in which the supply reliability is deemed too low. In this case, my results would be biased upwards by migration patterns. This can be tested in my sample, since households have been followed over time and a variable coding migration status is included in the survey data. In Appendix A4 I report the baseline regressions (columns 1 and 4), next to the results from the same specification with the addition of the migration dummy (columns 2 and 5) and with dropping migrated households (columns 3 and 6), for each dependent variable. The results in each set of regressions are substantially identical, with point estimates remaining very similar and unchanged significance levels. Even if the migration dummy is significant at the 10% level in the grade-for-age gap results, it has no meaningful effect on the access to electricity coefficient.

5.2.5 Inference

The statistical significance of the results could be biased by incorrectly specifying how standard errors are calculated. As Young (2019) shows, the normality and i.i.d. assumptions are often rejected in many IV applications and the bootstrap can reveal severely asymmetric confidence intervals. Moreover, jackknifing can show that the results, especially first stage ones, are sensitive to eliminating specific observations. I thus re-ran all baseline regressions in their full specification both jackknifing (in square brackets) and bootstrapping with 1000 replications (in braces) the standard errors. Appendix A5 presents the results: the conclusions about inference of the estimates are virtually the same, with no change in the significance levels and standard errors only marginally larger. In addition, I also cluster standard errors at the LGA level: some p-values become larger, but the main findings do not qualitatively change.[6]

[6] Results are available upon request from the author.

6 Discussion and mechanisms

6.1 Village and household access to electricity

The main analysis carried out so far assessed the impact of access to electricity at the village level to include potential spill over effects to non-connected households in connected villages (which are slightly more than one fifth of all households in electrified villages). However, it is clearly of interest to also learn what is the estimated effect for households that have direct access to electricity. The decision to connect obviously depends on the balance between benefits and costs (e.g. connection fee, consumption bills, etc.), but also on the expected quality and reliability of the electricity supply (see section 6.5 for a discussion on this). Therefore, lightnings strikes can be used as an instrumental variable also for the household-level access to electricity. Table 6 compares the results for each outcome separately using the two electrification explanatory variables and the full set of covariates.

As expected, the point estimates for household-level access to electricity are larger than the village-level ones, especially for the grade-for-age gap dependent variable. This suggests that kids in households with direct access enjoy larger benefits in terms of schooling outcomes than the average household in a connected village. It is important to note that the Kleibergen-Paap F statistics are lower in the household access results, especially in the grade-for-age gap case. This implies that the corresponding first stages are weaker than the village access ones, which are then better suited for the main analysis. Nevertheless, the first stage estimates are very close in the two specifications, with estimates just slightly lower in the household access one, and the significance levels for both first and second stage and for both outcome variables are exactly the same.

Table 6: Village-level and household-level access to electricity

	Enrolment		Grade-for-age gap	
Village access	0.548**		-1.220**	
	(0.220)		(0.494)	
Household access		0.638**		-1.718**
		(0.276)		(0.812)
	First stage - DV: village access			
Lightnings	-0.008***	-0.007***	-0.009***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Year and household FE	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES
Observations	6,016	6,014	4,591	4,590
Number of households	2,277	2,276	1,763	1,763
First stage R-squared	0.027	0.030	0.029	0.032
K-P F-statistics	20.1	14.9	17.8	8.5

Note: robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

6.2 Wealth heterogeneity

The impact of access to electricity may well differ by household economic status. On the one hand, it could be argued that richer households have the financial means to better exploit the advantages of electrification, for instance by being able to buy (better) electrical appliances. On the other hand, it could also be argued that poorer households can enjoy larger benefits from electricity access, as it makes a larger difference in a context of greater deprivation. In Table 7 I test whether the baseline results are heterogeneous along the wealth axis, by adding to the electrification dummy its interaction with the PCA-based wealth index and instrumenting both with the lightnings IV and the corresponding interaction with the wealth index. The interaction is significant only for enrolment and not for the grade-for-age gap, with a negative sign. This implies that larger benefits from access to electricity accrue to poorer households, who are then more likely to send their kids to school. In fact, at least for the extensive margin of education, this evidence supports the second hypothesis above, suggesting that electricity access is a pro-poor policy in the Nigerian context.

Table 7: Heterogeneous results along the wealth axis

Dependent Variable	(1) Enrolled	(2) Access	(3) Access*Wealth	(4) GFA gap	(5) Access	(6) Access*Wealth
Village electr	0.538**			-1.216**		
	(0.223)			(0.492)		
Village electr*Wealth	-0.096**			-0.085		
	(0.042)			(0.108)		
Lightnings		-0.008***	0.012***		-0.009***	0.008***
		(0.002)	(0.002)		(0.002)	(0.003)
Lightnings*Wealth		0.001	0.035***		0.002	0.036***
		(0.002)	(0.003)		(0.002)	(0.003)
Year and household FE	YES	YES	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES	YES	YES
Observations	6,016	6,016	6,016	4,591	4,591	4,591
Number of households	2,277	2,277	2,277	1,763	1,763	1,763
First stage R-squared		0.027	0.305		0.029	0.350

Note: robust standard errors clustered at the household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

6.3 Gender heterogeneity

Another dimension in which the literature found differential results is gender. Similarly to the previous subsection, in Table 8 I interact the village-level access to electricity variable with the proportion of girls in the households and add an interaction of the latter with the lightnings instrument. Also in this case the heterogeneity is present only for the enrolment results, although significant at the 10% level. Households with a higher share of girls enjoy lower enrolment increases due to electrification than households with more boys. To put it into perspective, on average, enrolment increases in girls-only households are almost a third lower than enrolment increases in boys-only households. The point estimate for the interaction in the grade-for-age gap results is not significant, so for this outcome there is no gender heterogeneity, but it also has the opposite sign of the main regressor's coefficient. This evidence suggests that boys seem to be the main beneficiaries of electrification's impact on the extensive margin of education.

Table 8: Heterogeneous results along the gender axis

Dependent Variable	(1) Enrolled	(2) Access	(3) Access*Girls	(4) GFA gap	(5) Access	(6) Access*Girls
Village access	0.619**			-1.231**		
	(0.242)			(0.541)		
Village access*Girls share	-0.197*			0.236		
	(0.105)			(0.263)		
Lightnings		-0.015***	-0.029***		-0.016***	-0.030***
		(0.003)	(0.002)		(0.003)	(0.002)
Lightnings*Girls share		0.014***	0.054***		0.013**	0.054***
		(0.004)	(0.004)		(0.005)	(0.004)
Year and household FE	YES	YES	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES	YES	YES
Observations	6,016	6,016	6,016	4,524	4,524	4,524
Number of households	2,277	2,277	2,277	1,741	1,741	1,741
First stage R-squared		0.030	0.176		0.033	0.185

Note: robust standard errors clustered at the household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

6.4 Child labor and time use

The evidence from the previous subsection may raise questions about what drives the heterogeneous results along the gender axis, and in general what behavioural mechanisms can explain the findings. Despite having some constraints on the availability of granular data, I can explore two possibilities related to the time use of kids. In Table 9 I regress the proportion of kids that are working, typically in the household field, and the share collecting firewood on the village access to electricity and its interaction with the proportion of household girls.

Table 9: Child labor and firewood collection

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Child labour	Access	Access*Girls	Collect firewood	Access	Access*Girls
Village access	0.163			-0.562**		
	(0.229)			(0.241)		
Village access*Girls share	-0.113			0.159*		
	(0.105)			(0.096)		
Lightnings		-0.015***	-0.026***		-0.012***	-0.027***
		(0.003)	(0.002)		(0.002)	(0.002)
Lightnings*Girls share		0.014***	0.049***		0.009**	0.050***
		(0.004)	(0.004)		(0.004)	(0.003)
Year and household FE	YES	YES	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES	YES	YES
Observations	6,127	6,127	6,127	6,867	6,867	6,867
Number of households	2,277	2,277	2,277	2,546	2,546	2,546
First stage R-squared		0.031	0.157		0.024	0.174

Note: robust standard errors clustered at the household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

The instruments are the same as in Table 8, and they are again all statistically significant. Interestingly, the estimated effects are not significant for child labor, but they are for the collection of firewood. In particular, village electrification reduces the proportion of kids collecting firewood, especially boys, since the interaction term is positive. As a result, the larger enrolment effects estimated for boys can be explained by a reduction of the time spent in household chores rather than in child labor.

6.5 Reliability of electricity supply

Access to electricity is thus important for education, but the quality of its supply is also key, especially in a context like Nigeria in which power outages are very frequent (see section 2.1). The issue of electricity reliability has been widely discussed in the context of firm performance (Adenikinju, 2003; Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018), but the literature did not extensively address it with respect to education outcomes (an exception is Chakravorty et al., 2014). I do not have detailed data about electricity supply and use, but the survey includes qualitative information on the frequency of blackouts experienced by households, which I recode into a three-step variable (respectively associated with the frequency of blackouts “never" or “few times a year", “few times a month" and “few times a week" or “everyday").

While the blackouts variable can be again instrumented with the lightnings IV, I also need to take care of a potential sample selection bias, since the power outages frequency is reported only by households with access to electricity. For this reason, Table 10 presents the results of a Heckman selection model in which I regress my two outcome variables on the usual full specification, the blackouts frequency variable and its interaction with the generator ownership dummy (both instrumented with lightnings and the corresponding interaction), as well as the inverse Mills ratio. The latter comes from a selection equation in which the village access to electricity is regressed on both lightnings and an auxiliary IV, the household distance to the nearest powerplant, using a panel Logit model.

The results of Table 10 suggest that the quality of electricity supply, proxied by the frequency of blackouts variable, significantly affects only the intensive margin of schooling and not the extensive one. In fact, a higher frequency of blackouts is associated with larger grade-for-age gaps. Intuitively, while the decision to enrol at school can be more easily linked with the availability of electricity, school performance and thus the grade-for-age gap have a tighter connection to home study time and therefore with the reliability of the electricity received. However, these findings must be interpreted with caution given the low significance level in the second-stage regressions and the more limited sample.

Table 10: Blackout frequency (Heckman selection model)

Dependent Variable	(1) Enrolled	(2) GFA gap	(3) Village access
Blackouts	-0.141	0.870*	
	(0.147)	(0.515)	
Lightnings			-0.120***
			(0.020)
Distance to powerplant			-0.223**
			(0.105)
Mills ratio	-0.863	0.987	
	(1.455)	(0.779)	
Year and household FE	YES	YES	YES
Demographic covariates	YES	YES	YES
Socioeconomic covariates	YES	YES	YES
Geoclimatic covariates	YES	YES	YES
Observations	1,875	1,641	1,975
Number of households	749	670	684

Note: robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

7 Conclusions and policy implications

This paper provides a better understanding of the effects of electricity access on kids' schooling outcomes in rural Nigeria, a country that hosts the second largest non-electrified population in the world. In particular, I study the village-level access to electricity since it allows to measure the average treatment effect relevant to policymakers and incorporates potential spill overs to non-connected households in connected villages. The outcomes, measured at the household level, are kids' school enrolment and average grade-for-age gap, respectively as proxies for the extensive and intensive margin of education. Using panel data, I employ a fixed effects strategy and instrument the access to electricity variable with the density of lightning strikes in the area surrounding the household, a novel instrument in this context.

I find large and positive impacts of rural electrification on both dimensions of education. Specifically, it increases enrolment by 55% and decreases the grade-for-age gap by 1.2 years within the span of three years. These results are robust to the addition of several demographic, socioeconomic, geographical and climatic covariates as well as to different tests and checks related to instrument validity, relevance and inference. I also find that households that have direct access to electricity enjoy greater benefits than the average households in connected villages and that the enrolment effects are larger for poorer households. The results for the extensive margin of education are also larger for boys than for girls. This seems to be driven by the time channel since kids, in particular boys, have more free time available from household chores like firewood collection, rather than from a reduction in child labor. Interestingly, the frequency of blackouts, a proxy for the quality of electricity supply, negatively affects only the grade-for-age gap after accounting for sample selection.

This evidence has significant policy implications as it shows that there are large education benefits from rural electrification, contributing to the ongoing academic debate on the topic. Importantly, as less wealthy households enjoy larger benefits, it also appears to be a pro-poor policy. Furthermore, despite in electrified villages the average access rate is almost 80% and there are spill over effects to non-connected households, governments should subsidize connection fees and electricity use. While the evidence on the effectiveness of subsidies is mixed (Abeberese, 2017; Lee et al., 2020b), the COVID-19 outbreak has increased the proportion of households under the poverty line and that cannot afford paying for the bills. As a result, the positive trends in terms of both electricity access and use have reverted in several sub-Saharan African countries, including Nigeria (International Energy Agency, 2016b).

There is actually a large potential for government intervention in connecting households that are “under-the-grid", i.e. close to an already present electricity grid but that lack the last mile hook up. Leo and Morello (2015) estimate that in several African countries the grid coverage rate is much higher than the household access rate, especially in rural areas. As shown in Appendix A6, this is quite striking for countries like Nigeria and Kenya, where the difference is above 50 percentage points. In particular, the authors estimate that about 31 million Nigerians, or 40% or those without access to electricity, live “under-the-grid". Before more capital-intensive investments like the national grid extension or mini-/off-grid systems, targeting the last mile hook up and subsidizing connection costs can be low hanging fruit policies for governments, together with improving service reliability to reduce power outages.

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A Appendix

A.1 IV radius

Table 11: Robustness check: varying the IV area radius

	Enrolment			Grade-for-age gap		
	20k	30k	50k	20k	30k	50k
Village access	0.584*	0.548**	0.975**	-1.648**	-1.220**	-0.883
	(0.317)	(0.220)	(0.406)	(0.835)	(0.494)	(0.605)
	First stage - DV: village access					
Lightnings	-0.010***	-0.008***	-0.003***	-0.011***	-0.009***	-0.003***
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
Year and household FE	YES	YES	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES	YES	YES
Observations	6,016	6,016	6,016	4,591	4,591	4,591
Number of households	2,277	2,277	2,277	1,763	1,763	1,763
First stage R-squared	0.024	0.027	0.024	0.026	0.029	0.026
K-P F-statistics	9.0	20.1	10.9	7.6	17.8	11.7

Note: robust standard errors clustered at the household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

A.2 IV validity

Table 12: Robustness check: two IVs and overidentifying restriction test

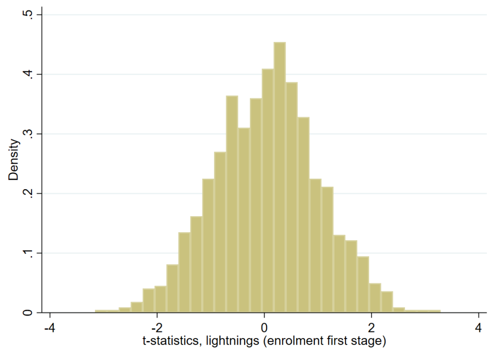
	(1)	(2)	(5)	(6)
Dependent Variable	Enrolled	Village access	GFA gap	Village access
Village access	0.632***		-0.975**	
	(0.232)		(0.418)	
Lightnings		-0.008***		-0.009***
		(0.002)		(0.002)
Distance to powerplant		-0.011		-0.026**
		(0.009)		(0.013)
Year and household FE	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES
Observations	6,016	6,016	4,591	4,591
Number of households	2,277	2,277	1,763	1,763
First stage R-squared		0.027		0.031
Sargan-Hansen test (p-value)	0.286		0.217	

Note: robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

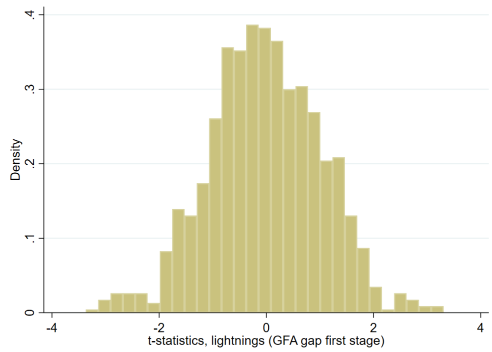
A.3 IV robustness

Figure 7: Robustness check: permutation of lightning IV, distribution of t-statistics

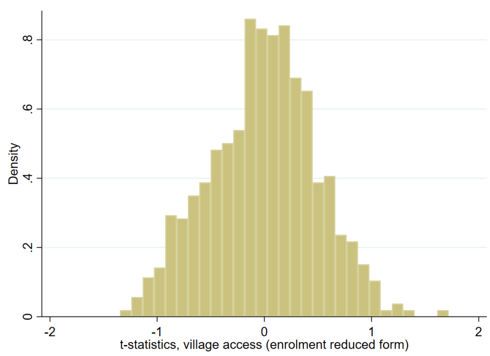
(a) Panel a



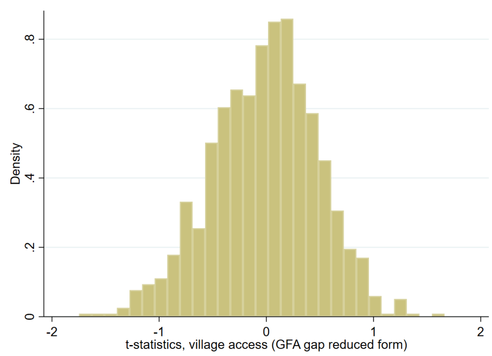
(b) Panel b



(c) Panel c



(d) Panel d



Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

A.4 Migration

Table 13: Robustness check: migration status

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		Enrolled			Grade-for-age gap	
Village access	0.548**	0.545**	0.562**	-1.220**	-1.214**	-1.214**
	(0.220)	(0.219)	(0.224)	(0.494)	(0.492)	(0.495)
Migrated		0.095			-0.479*	
		(0.158)			(0.247)	
Year and household FE	YES	YES	YES	YES	YES	YES
Demographic covariates	YES	YES	YES	YES	YES	YES
Socioeconomic covariates	YES	YES	YES	YES	YES	YES
Geoclimatic covariates	YES	YES	YES	YES	YES	YES
Observations	6,016	6,016	6,003	4,591	4,591	4,578
Number of households	2,277	2,277	2,274	1,763	1,763	1,759

Note: robust standard errors clustered at household level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

A.5 Inference

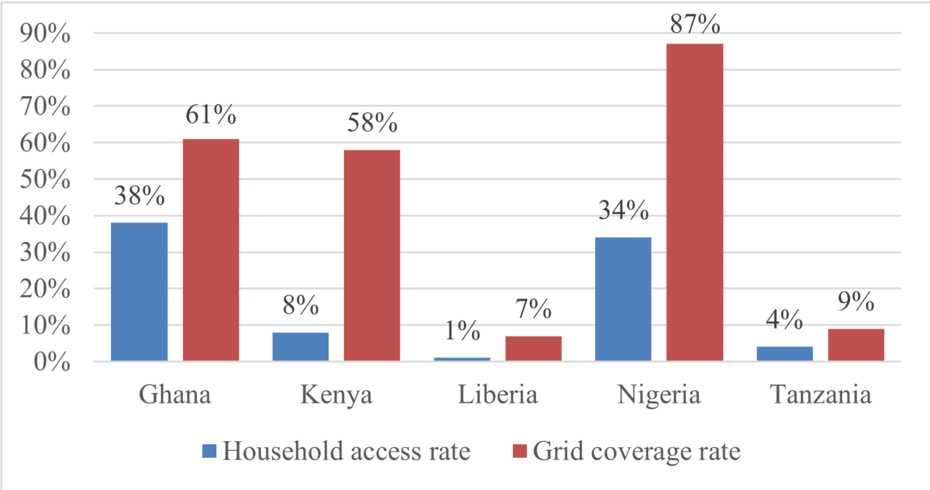
Table 14: Robustness check: jackknifing and bootstrapping standard errors

	Enrolment	GFA gap
Village access	0.548**	-1.220**
	(0.220)	(0.494)
	[0.221]	[0.500]
	{0.255}	{0.553}
	First stage - DV: village access	
Lightnings	-0.008***	-0.009***
	(0.002)	(0.002)
	[0.002]	[0.002]
	{0.002}	{0.002}
Year and household FE	YES	YES
Demographic covariates	YES	YES
Socioeconomic covariates	YES	YES
Geoclimatic covariates	YES	YES
Observations	6,016	4,591
Number of households	2,277	1,763

Note: robust standard errors clustered at household level in parentheses, jackknifed standard errors in square brackets and bootstrapped (1000 replications) standard errors in braces. *** p<0.01, ** p<0.05, * p<0.1. Source: Nigeria's General Household Survey 2010-2016, author's own elaboration.

A.6 Living under-the-grid

Figure 8: Household access rate and grid coverage rate in selected sub-Saharan African countries, rural averages



Source: Leo and Morello (2015).