Electrifying Nigeria: the Household-Level Impact of Access to Electricity on Consumption, Education and Employment

Enrico Nano

The Graduate Institute
Geneva

Abstract

This paper aims at providing a better understanding of the effect of electricity access on consumption, education and employment outcomes at the household level in Nigeria. The country hosts the second largest population without access to electricity in the world after India, but has received so far very little attention in this respect from the academic community. The literature also does not generally agree on the impact of access to electricity on the aforementioned outcomes. The results show that, once the possible endogeneity in the relationships under investigation is tackled and that household-specific effects are taken into account, electricity access has indeed a significant impact on both household consumption, girls' education and employment of men. The paper discusses also some of the mechanisms that can lead to the observed findings, and provides heterogeneous regressions along the wealth, education and urban-rural axes.

Keywords

Energy Access, Electrification, Development, Labour Market, Education, Consumption, Nigeria

JEL codes

O13, E20, I25, J22, Q12

1 Introduction

Electricity is a critical enabler. Every advanced economy has required secure access to electricity to underpin its development and growing prosperity. In developing countries, access to affordable and reliable electricity is fundamental to reducing poverty and improving health, increasing productivity, enhancing competitiveness and promoting economic growth. This is because electricity is essential for the provision of clean water, sanitation and healthcare, and provides great benefits to development through the provision of reliable and efficient lighting, heating, cooking, mechanical power, transport and telecommunication services. The burden of lacking electricity is carried especially by women and children, because of the time spent collecting traditional fuels such as coal and biomass, cooking with unsafe methods and because of indoor pollution. An estimated 4 million people – mostly children under 5 – die each year from illnesses related to household air pollution caused by burning these fuels (WHO, 2016).

According to the 2017 World Energy Outlook, 1.1 billion people were lacking access to electricity in 2015, but their geographical distribution is uneven across the world: more than half live in Sub-Saharan Africa (SSA), mostly in rural areas. According to the 2030 projections, while the overall number of people without electricity will drop thanks to current and planned policies, in SSA it will actually increase to more than 600 million, or 90% of the world's total, because of population growth. These numbers explain the increasing attention paid to Africa's rural electrification, but the yearly investment devoted to electrification by 2030 is still less than half of what is needed (IEA, 2017).

The international community has only recently recognized the central role of modern energy solutions, such as electricity, for sustainable development and poverty alleviation. Excluded from the Millennium Development Goals adopted by the United Nations (UN) in 2000, the role of energy in fostering development only gained international recognition in 2011, with the launch of the UN Sustainable Energy for All initiative. Then, in 2015, to "ensure access to affordable, reliable, sustainable and modern energy for all" ultimately became one of the 17 Sustainable Development Goals (SDGs) adopted by the UN in the framework of the 2030 Agenda for Sustainable Development.

The international academic community has also been rather slow in assessing the relationship between access to modern energy solutions and development. Impact evaluation studies shedding light on the causal relationship between access to electricity and labour market and welfare outcomes have indeed only emerged since 2011. As the literature review will show in the next sections, these studies have analysed several country cases spanning from Africa (e.g. South Africa, Ethiopia, Rwanda, Zanzibar, Kenya), Asia (e.g. India, Vietnam) and Latin America (e.g. Brazil, Nicaragua, El Salvador, Colombia). A notable gap in this list of countries is represented by Nigeria, which was not covered by any prior study. This gap is particularly relevant if considering that, with 98 million people (World Energy Outlook, 2016) still lacking access to electricity, Nigeria ranks second - after India - in the world's list of countries with the highest number of people lacking access to electricity.

With this paper, we seek to further contribute to the reduction of this gap in the literature, by providing a quantifiable assessment of the impact of electrification on consumption, education and employment in Nigeria. More specifically, we achieve this through the application of FE (Fixed Effects) and IV (Instrumental Variables) modelling technique on the panel component of the General Household Survey (GHS) run by the National Bureau of Statistics of Nigeria between 2011 and 2013. Our results show that access to electricity has a positive and significant impact on all three dimensions. The remainder of the paper is organised as follows: section 2 provides a review of the literature and a background of the energy situation in Nigeria; section 3 illustrates the methodology; section 4 describes the data and the summary statistics; section 5 provides the results and their discussion; section 6 concludes.

2 Literature review and background

2.1 Literature review

Although the last few years have witnessed an increased recognition of the role of energy access and reliability in fostering economic development, academic studies on the subject are still scarce. Those existing focus on the obstacles to and effect of accessing either clean cooking technologies or electricity. Of the two strands of literature, only the second is relevant to our case (for a recent in-depth review we refer the interested reader to Bonan, Pareglio and Tavoni, 2017). Figure 1 shows the theoretical pathways between energy supply and wealth generation and poverty reduction. Clearly, the relationship goes in both directions leading to reverse causality bias. In this paper we focus on the first and the second channels, and address the endogeneity concerns that would bias our causal estimates.

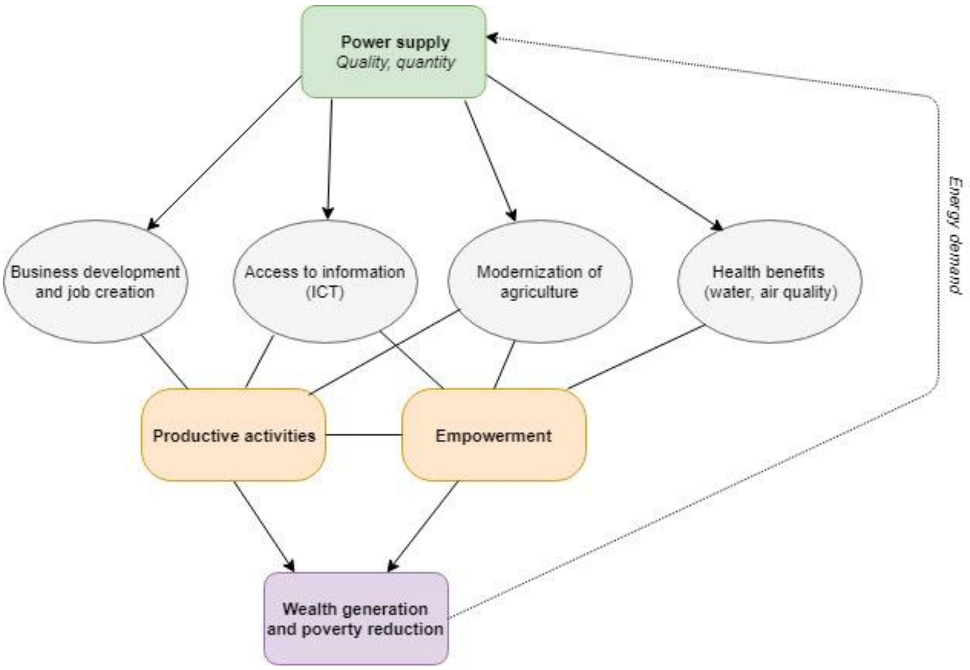


Figure 1. Theoretical framework relating power supply and poverty reduction. Source: own elaboration.

The majority of studies looking at electricity access are focused on its effect on either employment outcomes (Dinkelman, 2011; Lipscomb et al., 2013; Grogan and Sandanand, 2013; Khandker et al., 2013; Chakravorty et al., 2014; Bernard and Torero, 2015; Salmon and Tanguy, 2016), firm productivity (Peters et al., 2011; Alby et al., 2012; Rud, 2012; Abeberese, 2012; Fisher-Vanden et al., 2015; Allcott et al., 2016), household welfare and education (Bensch et al., 2011; Khandker et al., 2014; Bridge et al., 2016; van de Walle et al., 2017) or health and fertility (Fetzer et al., 2013; Burlando, 2014; Barron and Torero, 2015; Fujii et al., 2018). While the techniques applied, the geographical focus and the robustness of the results vary amongst these papers, the effects of electrification on the outcome of interest generally tend to move in similar directions.

For the case of labor markets, most studies find that expanding electricity access increases time spent in income generating activities, especially outside of the agricultural sector. This effect seems to hold for both formal and informal (self) employment across urban and rural areas, particularly for women, although the relative strength of these effects varies from region to region. The evidence of a substantial effect of electricity access on wages is instead less conclusive. In investigating the connection between electricity access and firm productivity, most studies have focused on the reliability of electricity supply more than access per se, although there are also some studies covering the latter. There is broad agreement in the literature: expanding access in rural areas has been linked to an increase in the number of manufacturing firms and, particularly in India and in Sub-Saharan Africa, low quality of electricity supply and frequent power outages negatively impact firm revenues, productivity and investment. For a comparison of the findings of previous studies on the impact of electrification on employment outcomes, refer to Table A1 in the Appendix.

A positive impact of electricity access has also been found with regard to welfare and health. Most of these effects are connected to a change in lighting and cooking behavior within households, with less time having to be allocated for the collection of biofuels which can then be directed to productive activities or studying. The substitution of wood and kerosene with electricity in cooking and lighting also has a direct impact on the health status of household members through a reduction of respiratory diseases connected with indoor pollution. Furthermore, indirect improvements in household health could also stem from rural villages being connected to the grid and experiencing an increase in the quality of their health infrastructure.

Finally, little attention has so far been directed towards understanding what prevents households from being connected to the grid. Some studies have found that the price of connection itself, although often subsidized in many developing countries, remains too high for many of the poorest households, with significant differences in connection behavior observable among different wealth quintiles. The decision of a household to connect has also been linked to their neighbors' decision to connect, both because of the gain in social status associated with access to electricity and the increased understanding of the many benefits that can be derived from being connected.

2.2 Nigerian electricity background

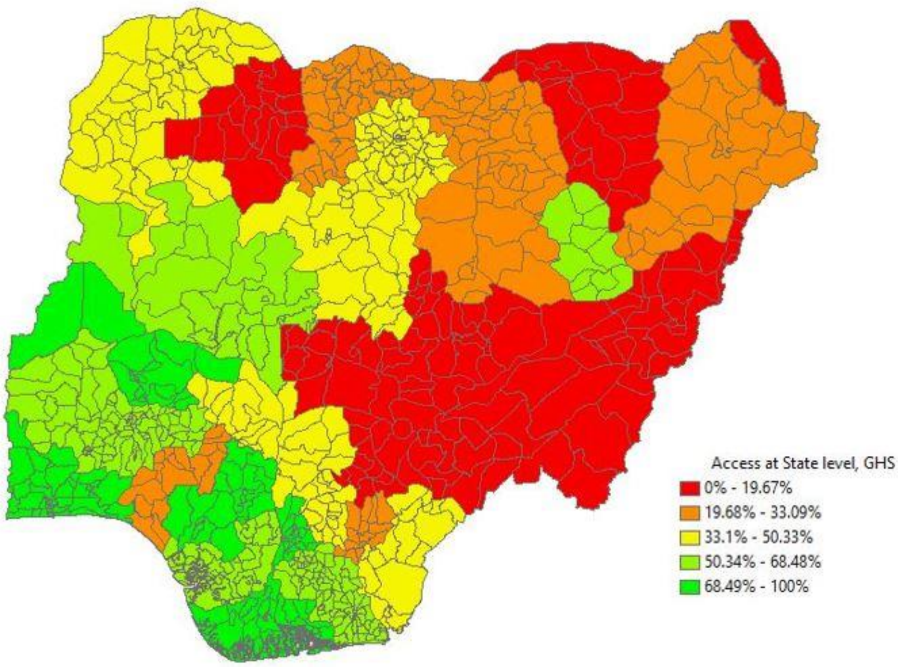


Figure 2. Average electricity access by state in the General Household Survey, 2015.
Source: Nigerian General Household Survey 2015.

As of 2016, 45% of the Nigerian population had access to electricity, with the access rate standing at 55% and 36% in urban and rural areas respectively (see Figure 2 for the sample average at the local government area level). That is, 98 million people still lacked access to electricity in the second biggest economy in the Sub-Saharan African region (World Energy Outlook, 2016). With an average of 146 kWh in the 2010-14 period, electricity consumption per capita is also particularly low for both continental (494 kWh in Sub-Saharan Africa) and regional (232 kWh in Ivory Coast, 336 kWh in Ghana) standards (World Bank Development Indicator). Given the current trends, it is unlikely that the goal of attaining an overall access rate of 75% by 2020, as stated in "Nigeria Vision 2020"[1], will be met.

Furthermore, the unreliability of electricity supply in the country has historically been one of the main obstacles for the successful development of productive activities. In the last wave of the World Bank Enterprise Survey (WBES) conducted in Nigeria in 2014, more than 77% of firms experienced at least one power outage during the previous financial year, and amongst these the average number of black outs was 32 per month, with an average length of more than 11 hours. The average loss due to electrical outages has been self-reported to be more than 15% of annual sales. Indeed, a study from 2003 (Adenikinju, 2003) reported already that 82% of the surveyed firms in the manufacturing sector identified in the quality of the electricity supply their main constraining factor with 66% reporting that they had to increase the working day to offset frequent outages.

The WBES carried out in 2014 also allows for a comparison of the situation more than ten years later: approximately 50% of firms still identify electricity as "major" or "very severe" obstacle for their operation (see Figure 3a) and more than 30% state that is "the" main obstacle for their operation (see Figure 3b). The problem is likely to be even more pronounced in rural areas, given the finding of a recent study covering six randomly selected villages (Olatomiwa et al., 2015) that electricity from the grid was unavailable for more than 18 hours per day.

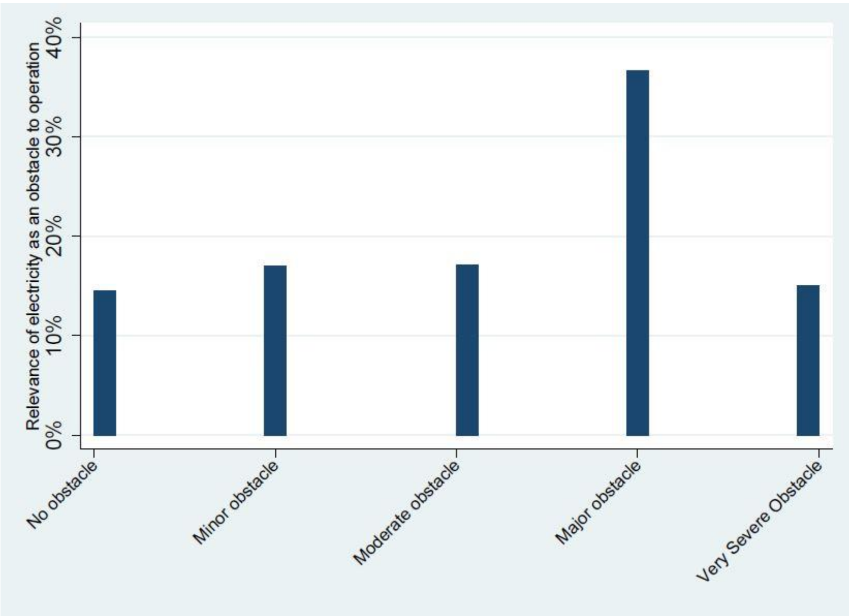


Figure 3a. Relevance of electricity as obstacle for firms' operation, 2014.

[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.

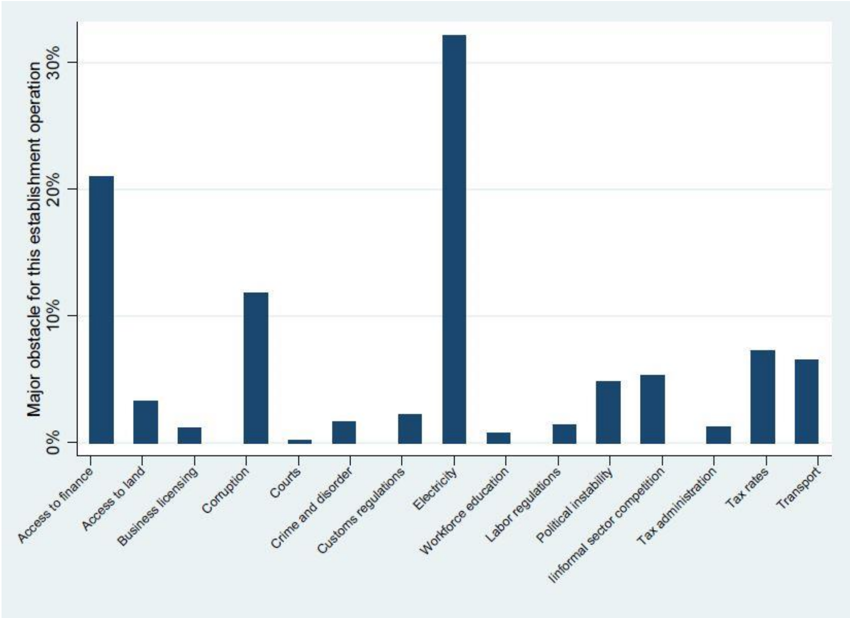


Figure 3b. Major obstacle for firms' operation, 2014.
Source: World Bank Enterprise Survey, Nigeria 2014.

In the last two decades there have been various attempt by the government to solve or at least to reduce the problems of the power sector. The Electric Power Implementation Committee was created by the government in 2000 and prepared both the National Electric Power Policy of 2001 and the National Energy Policy of 2003. These two policy documents had the overall objective of rationalising the utilisation of Nigeria's vast fossil and renewable energy resources. Increasing the participation of the private sector in energy generation and distribution, both through incentivising independent power producers and through the privatization of the National Electric Power Authority (NEPA), was deemed a necessary step. A special body, the National Integrated Power Project (NIPP), was created in 2004 to fast-track government-backed independent power projects to increase generation capacity, while the following year the Electric Power Sector Reform Act was promulgated to push forward the incorporation of NEPA (Usman and Abbasoglu, 2014; Ogunleye, 2016).

While by 2007 funds in excess to $13 billion were mobilised towards 10 different projects under the NIPP initiative, the privatization of NEPA proved to be a much longer process, starting in 2010 and finishing in 2013. Although the implicit complexity of unbundling a utility which comprised six generation companies, eleven distribution companies and one national transmission company must not be undervalued, a particular challenge was also represented by the overhaul of the fiscal and regulatory regime which the reform required (for an in-depth analysis of the reform process see Ogunleye, 2016). The second part of the privatisation process, currently underway, requires the government to sell the majority stake in the 10 power projects developed under the NIPP. However, also this second wave of privatisation is taking longer than expected, with problems this time related to gas shortages and delays in executing gas supply agreements affecting the bankability of the projects.

3 Methodology

In our 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 our main explanatory variable of interest. It would be then naïve to employ a simple least square regression model:

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

where y_{it} is, e.g., consumption of household *i* at time *t*, E_{it} is household's access to electricity, $\boldsymbol{x_{it}}$ is a vector of covariates, μ_i are unobserved time-invariant household effects, ϑ_t are year fixed effects and u_{it} is 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 error term, thus biasing our estimates of β, the coefficient of interest. Therefore, we exploit the panel nature of our data through a within transformation of the variables, which 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.

$$(2)\quad (y_{it} - \bar{y}_i) = \beta(E_{it} - \bar{E}_i) + \gamma'(\boldsymbol{x_{it}} - \bar{\boldsymbol{x}}_i) + (\vartheta_t - \bar{\vartheta}) + (u_{it} - \bar{u}_i)$$

Clearly, covariates in $\boldsymbol{x_{it}}$ which are time-invariant will be wiped out together with the individual effects and the constant term. For each econometric specification we perform a Durbin-Wu-Hausman test which allows us to decide whether to use model (1) estimated by random effects, or, in case of rejection of the null hypothesis of no correlation between covariates and error term, model (2) by "fixed effects".

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, a household's 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, e.g. the proportion of household members having a job. This simultaneity issue would lead to wrongly estimating the effect of access to electricity (see Duflo and Pande, 2007; Roller and Waverman, 2001; Rud, 2012; Grogan and Sadanand, 2013). We nevertheless test in each regression for the endogeneity of access to electricity using the Hausman test.

To tackle this type of endogeneity bias, called reverse causality, we employ an instrumental variable (IV) 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. In our analysis, we have access to four of them: household distance to the grid, household distance to the nearest power plant, land gradient and average solar radiation intensity at the site of the household (Dinkelman, 2011; Grogan and Sadanand, 2013; Bridge at al., 2016; Van de Walle et al., 2017).

However, of these four variables only one satisfies the instrument validity conditions in our case. The household distance to the grid may not satisfy the exogeneity condition, given that the extension of the grid to particular areas of the country is usually driven by political and economic motivations at least as much as by technical ones, and hence could favour household more likely to have better outcomes. The household distance to the nearest power plant is more plausibly exogeneous, but it does not vary much over time, becoming useless in a panel setting whether one uses a first difference or a within transformation approach. Land gradient is more defendable as an exogenous instrument, but it suffers from the same issue, being time-invariant.

Solar radiation intensity, instead, is the most plausibly valid IV as it does not directly affect the outcome variables, it varies over time and is correlated with access to electricity. Our first stage estimates show that solar radiation positively and significantly affects the access to electricity of a household. Two are the reasons for this to happen. First, total solar radiation is negatively correlated with land gradient, which in turn is negatively correlated with access to electricity: it is more difficult to reach and to erect an electricity pole on higher-slope terrains, and solar radiation intensity is less intense on non-flat surfaces. Second, in areas with more intense solar radiation, solar panels are more likely to be installed, benefitting households through mini-grid or off-grid solutions.

However, the validity of the exclusion restriction is never completely out of question. For example, land gradient might be correlated with agricultural productivity, as the slope of the terrain could influence the type of crops grown, in turn affecting consumption and/or employment. Thus, being correlated with land gradient, solar radiation intensity could have a channel through which to violate the exclusion restriction. To account for this possibility, we include in all regressions the population density at the local government authority (LGA) level as well as the distance to the nearest road and to the nearest market, which should control for plot dimension and reflect local labour market condition (Grogan and Sadanand, 2013).

A household without access to electricity may still benefit from connected households in the local community. We took into account these potential spillover effects by including in the regressions a measure of the degree of electricity use in the area surrounding the household, using NASA's night light data. Specifically it is the average of night-time light intensity in a radius of 5 km around the household site. In addition, we included a proxy for electricity reliability, given by a dummy for experiencing blackouts every day, as well as other standard covariates at the household (e.g. demographics) and community (e.g. population density) levels.

At the household level, beyond reverse causality, there is another source of endogeneity of electricity access, namely the presence of unobservable household characteristics correlated with both the decision to connect and the employment status (Rud, 2012). Richer households might be both more likely to be employed and to have acquired grid connection: not controlling for income would bias our coefficients upwards. At the same time, not all households looking for electricity access might do so for its productive use. Leisure motives are more likely to be predominant for wealthier households, potentially biasing our coefficients downwards.

To prevent us from biased coefficients because of this reason, we include a wealth index 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. We performed the principal component analysis separately for urban and rural households and subsequently mapped it to a national index as in Rutstein (2008). Moreover, all regressions also include the other "usual suspects": age and education of the household head[2], number of kids in the household, proportion of working-age household members that are employed, as well as a dummy variable for urban areas and for each year.

All our panel IV regressions are performed using the commands xtivreg2 in STATA, which also reports both the results of under-identification and weak identification tests, as well as the value of the F-statistics of our first and second stages. Given the survey nature of our data, in all regressions we also make use of population weights, which are provided by the World Bank, in order for our findings to be representative at the national level. All regressions are reported using heteroscedasticity-robust standard errors, but

[2] Time invariant covariates such as gender of the household head are excluded from the regressions because of the panel nature of the analysis.

4 Data and descriptive statistics

4.1 Data description

The main source of the data for the study is the General Household Survey (GHS) run by the National Bureau of Statistics of Nigeria and implemented together with the WB Living Standard Measurement Study and a series of other agencies of the federal government of Nigeria. The overall GHS usually covered 22,000 households across Nigeria, with 10 households sampled for each enumeration area and 60 enumeration areas identified in each of the 37 states of Nigeria. Although the general survey was repeated over time, since 2010 5,000 households were selected from 500 enumeration areas to be included in a new panel component of the GHS to be repeated every 2 to 3 years. These households were selected so to be representative of all geopolitical zones of Nigeria at both the rural and urban level, and the questionnaire normally used for the GHS were upgraded to include further information on both agricultural and non-agricultural income generating activities as well as household income and expenditure.

Of the 5,000 households initially sampled, 4,917 responded to the questionnaire in the first wave of 2010-2011. As families move to other regions and states over time, they cannot always be tracked. Thus, by the third wave of 2015-2016 only 4,581 households of the original households have remained in the sample (for the second wave in 2012-2013 we have 4,753 households). Furthermore, during the last wave of GHS-Panel a tracking visit was conducted after both post-planting and post-harvesting visit so to identify and interview as many of the households who moved following one of the previous waves or in between visits as possible. To avoid attributing to electricity access changes in the outcome variable which were connected to migration choices, in the robustness checks we control for those households who moved in between waves.

For one of the main dependent variables of interest (consumption) and for one of the main explanatory variables (electricity use in the area surrounding the household) we only have data for the first two waves, 2011 and 2013. Moreover, in the last wave (2015) some of the questions asked in the survey have slightly changed, potentially inducing a different understanding of the questions and different responses. For these reasons we have decided to focus our attention on the first two waves, excluding the 2015 one from the analysis. For each wave, all households were visited twice, once between August-October at the end of the planting season and once between February-April after the harvest. Although certain variables of particular interest such as labour allocation within the household or food consumption and expenditures were collected in both visits, we use the post-harvest visit for consistency given that an explicit question about the electricity connection status of the household was included also in the post-planting questionnaire only in the third wave.

The outcomes of interest in our study are related to consumption, education and employment. All the dependent variables are measured at the household level, since both the panel identifier and consequently our analysis is at the household level. We use consumption instead of income, since it is a dimension less affected than income from transitory shocks, it is more reliable and more representative of the overall household welfare. We use the expenditure data compiled by the World Bank and in particular the per-capita household non-food expenditure, which is deflated taking into account regional prices and discounted taking into account the period of the year in which the survey was conducted. As for the educational outcomes, we look at the proportion of children in schooling age (between 5 and 15 years old) within the household that are actually enrolled in school. As for the employment outcomes, the dependent variable is the proportion of people in working age (15-64) within the household that are employed, overall and in the non-agricultural sector. Members of the household who are studying and not working are excluded from the calculation of the proportion of people employed in the household, i.e. they are considered neither employed nor unemployed.

The explanatory variable of main interest is a dummy variable for access to electricity, which we obtained from the GHS survey, taking a value of 1 if the household is connected to the electricity grid. As mentioned, our instrumental variable is the solar radiation intensity, measured in KWh/m^2, in the area surrounding the household. In particular, the data are yearly means of the shortwave incoming solar radiation (SIS), which is the radiation flux density reaching a horizontal unit earth surface in the 0.2-4 μm wavelength range. It is usually also called global irradiance or solar surface irradiance, and is the sum of direct irradiance and diffuse horizontal irradiance, thus depending on the slope of the terrain to which it is directed. We obtained the data from the Satellite Application Facility on Climate Monitoring (CM SAF) of EUMETSAT.

4.2 Descriptive statistics

Due to the impossibility of tracking some households between one wave and the other one and to the non-response rate for certain covariates, our final sample includes 4,177 out of the 4,753 available households. These are fairly evenly divided across the 6 geopolitical areas included in the survey, with the highest share being located in the North Western area (19.17%) and the lowest share in the North Eastern area (13.49%).

Table 1 presents the summary statistics of the variables utilized for the years 2011 and 2013, including their mean, overall, between and within standard deviation, minimum and maximum and number of observations. Since the analysis exploits the variation within individuals and across time, it is important that our main variables of interest have enough within standard deviation in relation to the overall one. That is indeed the case for our dependent variables (per capita household expenditure, proportion of kids enrolled at school and of members in working age that are employed) and for the access to electricity dummy variable.

The average age of the household head in the overall sample is 51.5 years, with very little variation across geopolitical areas; on the other hand the education of the household head varies quite significantly, ranging from 4 years in the North West to 8.4 years in the South Central area (with a sample average of 6.4). Similar variation can also be noted in the number of kids per household (with the North West area averaging 3.8 and the South East at around 1.7 kids), as well as in the average wealth quintile distribution, with again the lowest value found in the North West (2.10), while the highest value found is that of households in the South West (3.75). Relevant differences across geopolitical areas exist also with regard to urbanisation levels, ranging from 18% of households in the North Eastern area to 71.2% in the South Western one, with an overall share of 32.5%.[3] The vast majority of households is headed by a male component (82.8%).

With regard to electricity access, the sample average stands at 51.3%, with significant differences between urban (53.7%) and rural households (44.1%). The figures for overall, urban and rural access are very close to those reported in the World Energy Outlook 2016 (45%, 55% and 36% respectively). Large differences can be found particularly across geopolitical areas, with a minimum overall access equal to 24.8% of households in the North Eastern area and a maximum of 68.4% in the Southern Central area.

[3] The North-Western region is also the part of Nigeria most affected by the jihadist militant organization known as Boko Haram.

Table 1. Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Expenditure	overall	9.901494	0.9780461	6.645674	14.47076	N = 9233
	between		0.9275356	7.329137	14.30948	n = 4798
	within		0.3323729	8.185427	11.61756	T = 1.92434
Enrolled	overall	0.8506539	0.3225567	0	1	N = 9419
	between		0.2966608	0	1	n = 3958
	within		0.181191	0.1839872	1.517321	T-bar = 2.37974
HH employment	overall	0.7780231	0.3127235	0	1	N = 13897
	between		0.2430031	0	1	n = 4918
	within		0.2044857	0.1113564	1.44469	T-bar = 2.82574
Electricity	overall	0.5130258	0.4998479	0	1	N = 14241
	between		0.4498088	0	1	n = 4967
	within		0.2203111	-0.1536409	1.179692	T-bar = 2.86712
Radiation	overall	232.695	24.6528	181.5833	275.6667	N = 14414
	between		24.52767	182.6667	274.125	n = 5000
	within		2.343786	205.3617	278.0561	T-bar = 2.8828
Blackouts	overall	0.2536303	0.4351038	0	1	N = 14186
	between		0.3294817	0	1	n = 4967
	within		0.2888684	-0.4130363	0.920297	T-bar = 2.85605
Nightlights	overall	8.50E-10	1	-0.6141775	4.266367	N = 9801
	between		1.004942	-0.6141775	4.25942	n = 5000
	within		0.1080834	-2.359356	2.359356	T = 1.9602
Head age	overall	51.48829	15.13635	0	110	N = 14172
	between		14.2971	15	103	n = 4967
	within		5.411157	3.82162	85.82162	T-bar = 2.85323
Head education	overall	6.407436	5.737229	0	16	N = 11808
	between		5.712358	0	16	n = 4302
	within		0.4594601	-4.259231	16.40744	T-bar = 2.74477
Number of kids	overall	2.661644	2.344616	0	19	N = 14269
	between		2.197521	0	14.66667	n = 4968
	within		0.8349927	-5.005023	10.16164	T-bar = 2.87218
Wealth quintile	overall	2.999858	1.414264	1	5	N = 14047
	between		1.328441	1	5	n = 4962
	within		0.4996083	0.6665243	5.666524	T-bar = 2.83091
Distance to road	overall	8.887416	13.16442	0	115.2	N = 14413
	between		9.858284	0	57.25667	n = 5000
	within		8.85674	-36.67258	77.93408	T-bar = 2.8826
Urban	overall	0.3249864	0.4683857	0	1	N = 14696
	between		0.4643334	0	1	n = 5000
	within		0.0646923	-0.3416803	0.9916531	T = 2.9392
Year = 2013	overall	2013	1.633048	2011	2015	N = 15000
	between		0	2013	2013	n = 5000
	within		1.633048	2011	2015	T = 3

In Figure 4, the Kernel density estimates of mean electricity access by Local Government Authority show that, in our sample, the average LGA connection rates increased over time, particularly between 2011 and 2013. Figure 4 also shows there are many LGAs with basically zero or almost complete (above 80% of households) access to electricity. This suggests that electrification is likely to take place homogeneously at the LGA level, potentially for peer-pressure, while the differences across LGAs are due to both their differential rates of urbanisation, their economic status, as well as the non-homogeneous unfolding of the national electrification strategy.

On the other hand, there are also several LGAs with a proportion of electrified households between 20% and 80%. This is explained by the fact that access to electricity can happen through various channels. The most common is the expansion of the national grid, followed by rural electrification programs via mini-grid and off-grid solutions (e.g. powered with solar panels). Alternatively, households can purchase their autonomous source of energy, for instance generators and solar panels. In any case, it is an important investment for the household, as also in the case of connection to grid there is a one-off fee to be paid. In general, the National Electric Power Authority represents the largest source of electricity, having connected more than 80% of households in our sample.

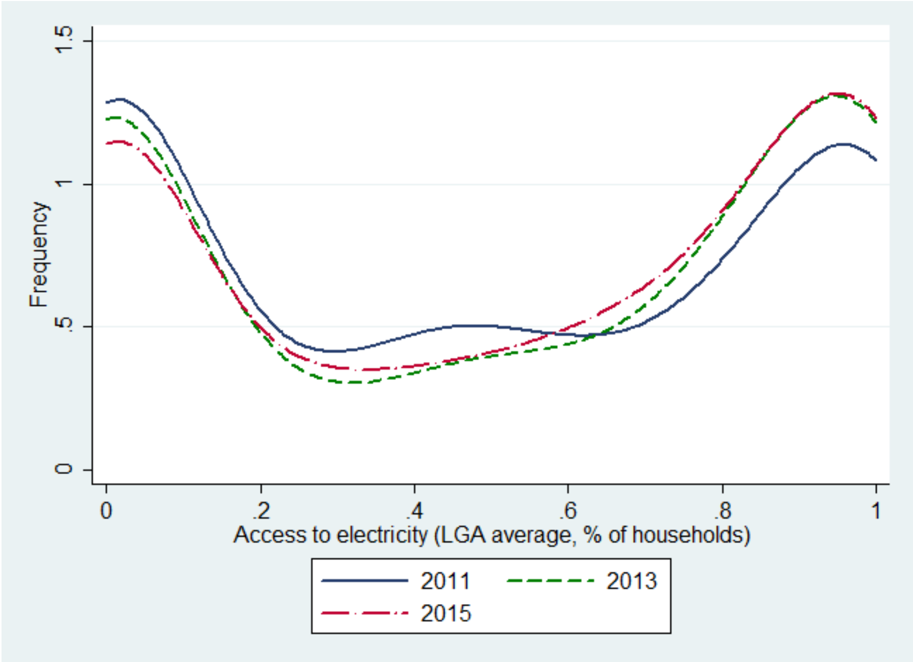
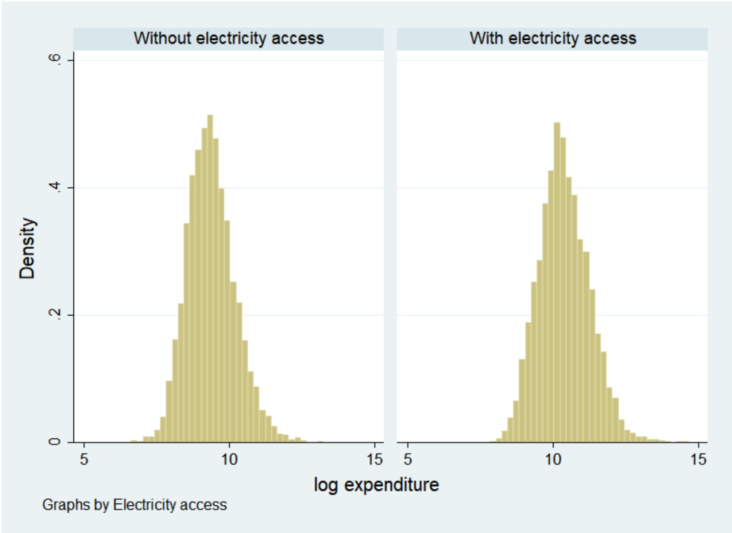


Figure 4. Kernel density function of average access to electricity in Local Government Authorities. Source: Nigerian General Household Survey 2011-2015.

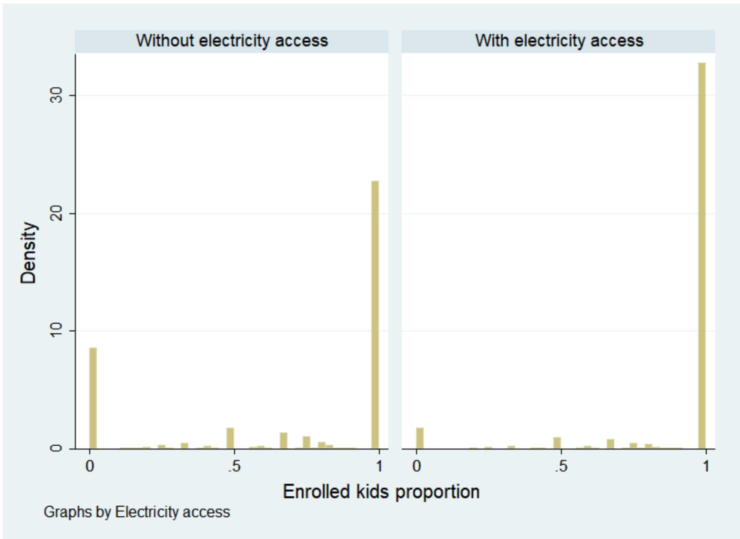
Our instrumental variable, solar radiation intensity, varies between 182 and 276 with both mean and median at around 230. It does not have a lot of within variation, but as shown in the next section it has a strong predictive power with respect to access to electricity in the first stage regressions. Among households with access to electricity, 25% experience blackouts every day, thus representing a strong indicator of quality of electricity. As expected, the proportion of households without access to electricity present an average luminosity close to zero in the 5km radius much higher than those with access to electricity. This hints again to the almost dichotomic result of Figure 6: households without access to electricity are surrounded by other households without access, but those with access are likely to be in an area where almost all other households are connected.

Figure 5 presents histograms of the three main dependent variables, by access to electricity. The logarithm of per capita household expenditure has a high degree of normality, with a distribution much more shifted to the right for connected households (see panel a). Similarly, the latter present right-shifted distributions also for the proportion within the household of kids enrolled at school (more than 30% of connected households have all kids enrolled, see panel b) and of employed people in working age (although to a lesser extent, see panel c).

Panel a: (log) per capita household expenditure



Panel b: household proportion of kids enrolled



Panel c: proportion of employed members of the household

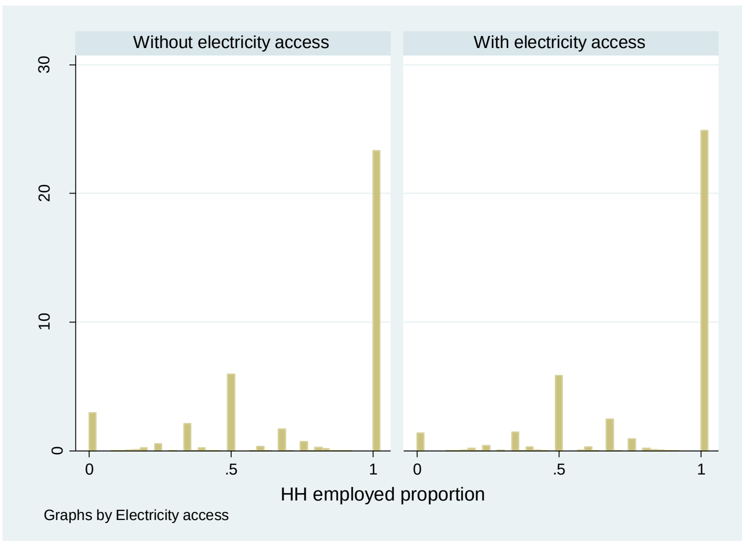


Figure 5. Histograms of the dependent variables by access to electricity. Source: Nigerian General Household Survey 2011-2013.

5 Results

5.1 Access to electricity and household consumption

As mentioned in the Methodology section, the three most relevant caveat in this type of studies are (1) time-invariant unobservable characteristics correlated with the error term, (2) omitted variable bias and (3) reverse causality of the access to electricity dummy. Our econometric strategy consists in subsequently tackling each of these issues. Let us start with the first two.

Table 2. Per capita household expenditure (FE estimates)

	(1)	(2)	(3)	(4)
DV: pc expenditure	FE1	FE2	FE3	FE4
Electricity access	0.094***	0.109***	0.126***	0.120***
	(0.035)	(0.038)	(0.041)	(0.042)
Blackouts		-0.021	-0.002	-0.025
		(0.029)	(0.028)	(0.028)
Nightlights		0.145*	0.195**	0.257**
		(0.088)	(0.093)	(0.101)
Urban area		-0.479***	-0.578***	-0.634***
		(0.127)	(0.153)	(0.137)
HH head age			-0.003	-0.003
			(0.002)	(0.002)
HH head education			0.040	-0.012
			(0.034)	(0.019)
Kids number			-0.087***	-0.091***
			(0.012)	(0.012)
HH employed ratio				0.155***
				(0.043)
Distance to road				0.000
				(0.001)
Distance to grid				-0.012
				(0.072)
Wealth quintile = 2				0.062
				(0.038)
Wealth quintile = 3				0.132***
				(0.049)
Wealth quintile = 4				0.230***
				(0.056)
Wealth quintile = 5				0.358***
				(0.065)
Year (1=2013)	0.020	0.009	-0.014	-0.020
	(0.013)	(0.015)	(0.017)	(0.019)
Overall p-value	0.024	0.000	0.000	0.000
Number of hhid	4,366	4,366	3,651	3,618

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In Table 2, four fixed effects (FE) regressions of log household expenditure per capita are presented, each with additional covariates included. Already in the first regression (FE1), which includes just the main explanatory variable together with the household- and year-specific effects, the fixed effects specification is preferred over the random effects one since the Hausman test rejects the null hypothesis of no correlation between the error term and the regressors with a p-value of 0.000.

In the subsequent columns the coefficient on electricity access does not change much, in particular in the last one with the inclusion of the wealth quintile dummies. With the inclusion of all covariates (FE4), the coefficient increases by about 20% with respect to the basic model (FE1), thus hinting at the fact that omitted variable bias might not be that much of an issue. On the other hand, the Hausman test rejects (p=0.000) the random effects model for all four specifications, suggesting that the error term is correlated with the regressors.

Next, we turn our attention to the endogeneity of access to electricity. As explained in the Methodology section, there are several reasons for doubting the exogeneity of this dummy variable. Indeed, in all four specifications, the Hausman test rejects the null hypothesis that access to electricity is exogeneous, with a p-value ranging between 0.01 and 0.08 depending on the specification. For this reason we consider biased the estimates in Table 2 and adopt an instrumental variable strategy, using solar radiation intensity as an IV for access to electricity.

In the Appendix, Table A2 shows the first stage regression using the equivalent of model FE4, i.e. the full model with all covariates. The coefficient on radiation is significant at the 1% level (p=0.001) and large in magnitude: an increase in radiation intensity by one standard deviation (25)[4] is associated to an increases in the probability of having access to electricity of 25.3%. Moreover, both the under-identification test (with the Kleibergen-Paap LM statistic) and the weak identification test (using the Cragg-Donald Wald F statistic) reject the null hypotheses that, respectively, the first stage regression is under- or weakly identified. Similar results are obtained with the progressive exclusion of covariates.

Table 3 presents the second stage reduced form regressions, after the instrumentation of access to electricity. The coefficient on the latter is much larger than in Table 2: having access to electricity increases per capita household expenditure by more than 170% (p-value=0.030) in the full model of column IV-FE4. This specification takes into account all three major issues that could bias our coefficient estimates, namely omitted variable bias, correlation between error term and covariates and endogeneity (particularly reverse causality) of access to electricity. This is thus our preferred econometric model that we will also use with other dependent variables in the next sections, if the tests for endogeneity and correlation between regressors and error terms confirm the appropriateness of such specification.

There are interesting findings with respect to the other covariates as well. Not surprisingly, quality of electricity matters: experiencing blackouts everyday (for those who have access to electricity) is a significant predictor of lower household consumption. Conversely, living in an area with more dense night lights (i.e. with more neighbours having access to electricity) is a strong predictor of higher household consumption. This happens because there are spill over effects, and even if a household is not connected, it can benefit from the connection of neighbouring households.[5]

[4] Solar radiation intensity ranges between 184 and 272.
[5] Nightlight satellite imagery is an common way to study regional poverty (see Sutton and Costanza, 2002).

Table 3. Per capita household expenditure (IV-FE estimates)

	(1)	(2)	(3)	(4)
DV: pc expenditure	IV-FE1	IV-FE2	IV-FE3	IV-FE4
Electricity access	1.258	1.255*	1.641**	1.709**
	(0.767)	(0.676)	(0.765)	(0.787)
Blackouts		-0.314*	-0.362**	-0.411**
		(0.173)	(0.182)	(0.191)
Nightlights		0.246**	0.293**	0.456***
		(0.119)	(0.134)	(0.162)
Urban area		-0.489***	-0.678***	-0.782***
		(0.183)	(0.213)	(0.196)
HH head age			-0.004	-0.004
			(0.003)	(0.003)
HH head education			0.056	-0.003
			(0.042)	(0.024)
Kids number			-0.084***	-0.088***
			(0.015)	(0.015)
HH employed ratio				0.136**
				(0.055)
Distance to road				0.001
				(0.001)
Distance to grid				0.157
				(0.125)
Wealth quintile				0.068***
				(0.024)
Year (1=2013)	-0.010	-0.014	-0.047*	-0.062**
	(0.024)	(0.022)	(0.026)	(0.031)
Overall p-value	0.088	0.012	0.000	0.000
Number of hhid	4,217	4,177	3,433	3,259

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Neither the age nor the educational level of the household head are significant predictors of consumption and their coefficient estimates are close to zero. Same applies to the distance of the household site from the nearest road and the nearest grid.[6] This is not surprising given that these variables change very little over time and thus have insufficient within variance. Conversely, number of kids negatively affects *per capita* expenditure so that in households with more kids each member consumes less. On the other hand, household with a larger share of members in working age that are employed enjoy larger per capita expenditure. As expected, richer households (i.e. belonging to a higher wealth quintile) also consume more. Finally, in all specifications, the F-test with null hypothesis of no overall significance of the model is rejected and all standard errors are robust to heteroskedasticity.[7]

[6] Adding to the specification distance to the nearest market or population density as regressors does not lead to any difference in the results and their estimates are insignificant and close to zero. Moreover, the variables are highly correlated. For these reasons we present only results with distance to road as regressor.

[7] We also estimated the same regressions but specifying standard errors clustered at the LGA (Local Government Authority) level and by Bootstrapping standard errors. Results are consistent with those reported, with minor differences in terms of coefficient significance. Regression tables are available upon request.

5.2 Access to electricity and kids' education

Using the same specification of the full model with all covariates, we estimate the effect of access to electricity on the household proportion of kids enrolled at school. In Table 4 we present estimates for all kids, only girls and only boys, using both a simple fixed effects strategy as well as with instrumentation of the main explanatory variable using solar radiation intensity.

Table 4. Kids' school enrolment rate (FE and IV-FE estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
DV: school enrolment	FE all	FE boys	FE girls	IV-FE all	IV-FE boys	IV-FE girls
Electricity access	0.035*	0.027	0.002	0.406	0.371	0.712*
	(0.021)	(0.024)	(0.027)	(0.358)	(0.776)	(0.386)
Blackouts	-0.011	-0.005	0.017	-0.104	-0.094	-0.156
	(0.015)	(0.019)	(0.017)	(0.089)	(0.200)	(0.097)
Nightlights	0.066	0.019	0.147**	0.100*	0.022	0.240**
	(0.041)	(0.054)	(0.057)	(0.059)	(0.061)	(0.102)
Urban area	-0.094	-0.041	-0.160	-0.107	-0.047	-0.192
	(0.067)	(0.040)	(0.185)	(0.098)	(0.071)	(0.197)
HH head age	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
HH head education	-0.008	-0.008	0.001	-0.007	-0.008	-0.003
	(0.008)	(0.009)	(0.002)	(0.006)	(0.007)	(0.004)
Kids number	-0.012*	-0.002	-0.014	-0.013*	-0.002	-0.018*
	(0.006)	(0.007)	(0.009)	(0.007)	(0.007)	(0.011)
HH employed ratio	0.027	0.001	0.019	0.029	-0.001	0.019
	(0.028)	(0.037)	(0.032)	(0.029)	(0.037)	(0.039)
Wealth quintile	0.003	0.006	0.004	-0.003	0.007	-0.007
	(0.010)	(0.012)	(0.013)	(0.013)	(0.012)	(0.018)
Distance to road	0.000	0.001	-0.001	0.000	0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance to grid	0.016		0.026	0.057		0.103**
	(0.011)		(0.028)	(0.041)		(0.051)
Year (1=2013)	-0.005	0.003	-0.034**	-0.013	0.001	-0.053**
	(0.011)	(0.013)	(0.015)	(0.014)	(0.015)	(0.021)
Observations	4,871	3,736	3,607	4,140	3,018	2,840
Number of hhid	2,801	2,227	2,187	2,070	1,509	1,420

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

As with expenditure as dependent variable, the IV-FE estimates are much larger than the FE ones and the Hausman test favours a fixed effects versus random effects specification. However, with these dependent variables, not in all cases the endogeneity test rejects the null hypothesis of conditional exogeneity of the access to electricity regressor. In particular, it is not rejected for the all-kids and only-boys cases, while in the only-girls case an IV strategy is called for. For completeness we report the IV-FE estimates for the other two cases as well.

The estimates for kids' enrolment are much more imprecise than those for expenditure as explanatory variable, but the message is that all estimates are positive and some are significant, suggesting a positive effect of electricity access on kids' education. Notably, the IV-FE estimates for girls' enrolment are particularly large and statistically significant (at the 10% level), pointing at an increase by more than 70% of the proportion of girls enrolled in the household.[8] The usual explanation is that thanks to lighting kids have the possibility to study in the dark, increasing their attendance and performance at school (van de Walle et al., 2017; Khandker et al., 2014; Bensch et al., 2011). Unfortunately we cannot test this mechanism with our data.

Although with larger standard errors, we can see that the other covariates share the same coefficient sign (in some cases also significantly) with the estimates of the previous subsection. Blackouts and the number of kids negatively affect kids' enrolment, while the proportion of employed household members and a higher average level of nighttime lights in the neighborhood are positive (and significant) predictors.

5.3 Access to electricity and employment

We use two different sets of definitions for the employment outcome variables. First, we present ratios of household members that are employed, counting all people in working age (15-64 years old) and separately for females and males, both for all type of employment and specifically for non-agricultural employment. Second, we specify the outcome variables as dummies for the household head, spouse and both of them being employed, again for all type of employment or just for non-agricultural employment.

Since in all cases both the Hausman test rejects the random effects specification and the endogeneity test for access to electricity does not reject exogeneity (p-value between 0.38 and 0.84, well above 0.05), in Table 5 we present just the fixed effects estimates. Notice that in all these regressions we have eliminated the household employment ratio as a regressor, which would be collinear with the dependent variable or highly endogenous. The only significant effect found is the positive one on the male employment ratio: having access to electricity increases employment in the household by 3.3%.

[8] This result is unchanged if standard errors are clustered at the LGA level.

Table 5. Household employment rate (FE estimates)

DV: hh employment	(1) FE all	(2) FE female	(3) FE male	(5) FE all non-agr	(6) FE fem non-agr	(7) FE male nonag
Electricity access	0.016	-0.012	0.033*	0.017	-0.005	0.063**
	(0.019)	(0.028)	(0.020)	(0.021)	(0.030)	(0.028)
Blackouts	-0.006	0.014	-0.004	0.015	0.026	0.017
	(0.014)	(0.020)	(0.015)	(0.014)	(0.021)	(0.016)
Nightlights	0.033	0.021	0.004	0.057*	0.040	0.023
	(0.030)	(0.051)	(0.026)	(0.031)	(0.049)	(0.027)
Urban area	-0.040	0.103	-0.142	0.027	0.138	-0.114*
	(0.084)	(0.092)	(0.103)	(0.059)	(0.092)	(0.068)
HH head age	0.001	0.000	-0.000	-0.001	0.000	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head education	-0.005	-0.022*	0.002	0.001	-0.010	0.002
	(0.005)	(0.011)	(0.007)	(0.009)	(0.019)	(0.007)
Kids number	0.013**	0.012	0.011**	0.006	0.007	-0.003
	(0.005)	(0.008)	(0.005)	(0.006)	(0.008)	(0.007)
Wealth quintile	0.009	0.017*	0.013*	0.031***	0.041***	0.030***
	(0.007)	(0.010)	(0.007)	(0.008)	(0.011)	(0.011)
Distance to road	-0.001*	-0.001	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Distance to grid	-0.003	0.006**	-0.008	-0.001	0.008*	-0.007
	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Year (1=2013)	-0.009	-0.001	-0.010	0.009	0.025**	0.002
	(0.008)	(0.011)	(0.008)	(0.009)	(0.012)	(0.010)
Constant	0.805***	0.642***	0.994***	0.492***	0.215	0.861***
	(0.106)	(0.130)	(0.117)	(0.122)	(0.176)	(0.126)
Overall p-value	0.168	0.128	0.120	0.004	0.001	0.001
Number of hhid	3,653	3,506	3,257	3,653	3,505	3,259

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Interestingly, it seems that this effect is driven by non-agricultural jobs: the effects doubles when looking at the last column.[9] Non-agricultural employment is indeed the usual suspect when it comes to the positive effects of electrification: households can start a small business (as a new or additional job), for instance a barber shop or selling cold beverages by owning a fridge, which requires electricity. This thus seems to suggest a reallocation of men's labour from the agricultural (typically household farms) to the non-agricultural sector (wage labour or self-employment). We will look into this in more detail in the next section.

As a robustness check, in Table A3 of the Appendix we look at the second definition of employment, i.e. using dummies for employment of the household head and spouse. The results confirm those of Table 5: access to electricity significantly although only slightly affects the employment of the household head. Given that 85% of household heads are male, it is not surprising that the results of the two employment variable definitions are similar. Again, the effect is driven mostly by the non-agricultural productive activities.

[9] The specular regressions using agricultural employment as a dependent variable show that there is zero or a negative and non-significant effect of access to electricity. Results available upon request.

6 Discussion

6.1 Migration

Households may obtain access to electricity by migrating to an electrified – normally urban – area. Such households should be carefully analysed, since they are also likely to gain access to better infrastructures or employment opportunities. For this reason, we re-estimated all regressions excluding households that have migrated between waves as well as including a dummy for having migrated in the full sample regressions.

Table 6. Migrated households

	year	
migrated	2011	2013
No	4,917	4,844
Yes	-	73
Total	4,917	4,917

The results are all identical to the original ones, given that there are very few households (73 out of 4917) that have migrated between the first and the second wave, as shown in Table 6. As a result, migration is not a concern in our analysis.[10]

6.2 Heterogeneity

Claiming that the average effect of access to electricity is the same for all households is clearly an unrealistic statement. We thus looked at different segments of our population to study how the impact of our variable of interest changes along two dimensions, wealth and average years of education within the household. The rationale for this choice is that the effect on consumption may well differ for poorer and richer households as well as between the more and less educated ones. A priori it is not obvious which group should be able to reap the largest benefits. For both these variables, we divided the households into three equally populated categories and ran a separate regression in each category. Finally, we also ran the consumption equation separately between urban and rural households.

As Table 7 shows, the impact of access to electricity on consumption is positive for every wealth group and stronger for poorer families. This could be a surprising finding: someone might have thought that to reap the largest benefits of electricity would have been the richest families, since they have more means to exploit it. Conversely, it seems that poorer family enjoy access to electricity the most, perhaps thanks to the reduced time needed for house production (e.g. collection of firewood, see next subsection) and the possibility of running additional remunerating activities, as seen in the previous section. Unfortunately, the smaller sample sizes do not allow us to precisely identify such effects for all categories, except the average wealth one.

[10] Full regression tables are available upon request.

Table 7. Per capita household expenditure by wealth category

	(1)	(2)	(3)
DV: pc expenditure	Low wealth	Average wealth	High wealth
Electricity access	2.944	1.564*	1.038
	(2.142)	(0.811)	(1.149)
Blackouts	-1.980	-0.469*	-0.079
	(1.413)	(0.269)	(0.121)
Nightlights	-0.633	0.397	0.361**
	(0.732)	(0.385)	(0.170)
HH head age	-0.007	0.006	-0.005
	(0.005)	(0.006)	(0.007)
HH head education	0.073	-0.014	-0.043*
	(0.045)	(0.019)	(0.025)
Kids number	-0.074**	-0.060*	-0.080**
	(0.030)	(0.034)	(0.039)
HH employed ratio	0.038	0.013	0.186**
	(0.125)	(0.130)	(0.090)
Wealth quintile	0.103	0.042	0.131*
	(0.063)	(0.051)	(0.073)
Distance to road	0.001	-0.000	0.002
	(0.001)	(0.003)	(0.003)
Distance to grid	0.000	0.000	0.043
	-	-	(0.085)
Urban area	-0.350	-0.802***	-0.897***
	(0.826)	(0.298)	(0.264)
Year (1=2013)	0.031	-0.076	-0.033
	(0.073)	(0.052)	(0.037)
Overall p-value	0.001	0.012	0.000
Number of hhid	757	639	887

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Similarly to the analysis above, we examined the impact of access to electricity on three categories of average education in the household. Although the larger standard errors again do not allow us to make any definite statement, the results in Table 8 mimic those for the wealth categories. Households in all three categories reap the benefits of access to electricity, but the poorly educated ones about three times more than the highly educated ones (although only the latter is statistically significant). Given the high correlation between wealth and education (r = 0.602), these and the previous findings suggest that expanding access to electricity is a "pro-poor" policy. Everyone gains from such an intervention, but the low wealth-low education households to a larger extent.

Table 8. Per capita household expenditure by average education category

DV: pc expenditure	(1) Low education	(2) Average education	(3) High education
Electricity access	2.468	1.655*	0.646
	(2.919)	(0.988)	(1.145)
Blackouts	-1.220	-0.376*	-0.079
	(1.399)	(0.228)	(0.161)
Nightlights	0.418	0.632**	0.235
	(1.465)	(0.255)	(0.151)
HH head age	0.004	-0.005	-0.005
	(0.010)	(0.004)	(0.007)
HH head education	0.000	-0.052**	-0.047
	-	(0.023)	(0.080)
Kids number	-0.124***	-0.050**	-0.108***
	(0.037)	(0.023)	(0.034)
HH employed ratio	0.086	0.068	0.226**
	(0.137)	(0.093)	(0.113)
Wealth quintile	0.038	0.100***	0.094**
	(0.065)	(0.034)	(0.039)
Distance to road	-0.000	0.001	0.002
	(0.002)	(0.002)	(0.003)
Distance to grid	0.000	0.154	-0.016
	-	(0.221)	(0.073)
Urban area	-0.413	-1.179***	-0.920***
	(0.349)	(0.413)	(0.083)
Year (1=2013)	-0.061	-0.092**	0.024
	(0.164)	(0.041)	(0.039)
Overall p-value	0.014	0.000	0.000
Number of hhid	903	1,231	682

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Given these results, one might expect that rural households would present larger estimates of the impact of access to electricity on consumption, given the fact that low-wealth and low-education households are concentrated in rural areas. The first two columns in Table 9 show that this is not necessarily the case. Although the coefficient on access to electricity is significant only in the urban column, this is larger than the rural column estimate. This interesting finding questioned whether access to electricity should be thought as just one development tool complementary to other ones, particularly other types of infrastructure to which households living in urban areas have easier access.

We thus re-ran our baseline consumption specification by adding interaction terms between access to electricity ("a2e") and distance of the household to the nearest road as well as distance to the nearest population center. Table A4 in the Appendix shows that both interaction terms are negative and significant, whether they are added alone or together. This implies that, for households having access to electricity, there is an additional positive effect from being closer to the nearest road or nearest population center. This is also the reason why the coefficient on access to electricity alone is reduced in size: in previous specifications it incorporated the interaction effects.

Columns 3 and 4 of Table 9 report the same regressions as in columns 1 and 2 with the addition of the interaction terms. As expected, the latter are all negative although the distance to road one is not significant. Interestingly, the coefficient on electricity access is now significant also for the rural area households and larger than the urban area one (although the difference between the two is not statistically significant).

Moreover, as in Table A4, the size of the effect of being connected to electricity *per se* is reduced in size for both the rural and urban specifications. This suggests that development policies should not be conceived as stand-alone, but as a comprehensive "policy package": access to electricity, for instance, should be promoted in conjunction with access to other types of infrastructure.

Table 9. Per capita household expenditure by urban-rural area

DV: pc expenditure	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Electricity access	1.311	1.513*	0.977*	0.904**
	(0.872)	(0.847)	(0.508)	(0.453)
Distance to road*a2e			-0.006	-0.009
			(0.006)	(0.008)
Dist popul center*a2e			-0.013*	-0.032**
			(0.008)	(0.015)
Blackouts	-0.488	-0.192*	-0.250*	-0.088*
	(0.342)	(0.103)	(0.137)	(0.051)
Nightlights	0.303*	0.608**	0.252*	0.603***
	(0.173)	(0.257)	(0.133)	(0.219)
HH head age	-0.007**	0.005	-0.006**	0.003
	(0.003)	(0.007)	(0.003)	(0.006)
HH head education	0.039	-0.052**	0.030	-0.049***
	(0.030)	(0.021)	(0.025)	(0.018)
Kids number	-0.065***	-0.119***	-0.071***	-0.114***
	(0.017)	(0.028)	(0.015)	(0.025)
HH employed ratio	0.105	0.195**	0.120**	0.153*
	(0.068)	(0.094)	(0.058)	(0.079)
Wealth quintile	0.073***	0.092**	0.085***	0.079**
	(0.024)	(0.043)	(0.018)	(0.039)
Distance to road	0.000	-0.002	0.000	0.005
	(0.001)	(0.003)	(0.001)	(0.006)
Distance to pop center	0.001	0.003	0.004*	0.030**
	(0.001)	(0.003)	(0.002)	(0.012)
Distance to grid	0.000	0.121	0.000	0.049
	-	(0.119)	-	(0.087)
Year (1=2013)	-0.039	-0.097**	-0.032	-0.098**
	(0.036)	(0.046)	(0.028)	(0.043)
Overall p-value	0.000	0.000	0.000	0.000
Number of hhid	2,259	1,000	2,259	1,000

Note: robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

6.3 Time use and item ownership

If the main channel through which electrification affects employment is reducing the time needed for house production, we should see this through a change in time use. In our data, the only thing that we can test is related to the time spent collecting firewood. We thus construct a dummy variable that takes value equal to 1 if any member of the household has collected firewood in the day before the survey interview and 0 otherwise.

Secondly, as electrification allows the usage of electrical appliances, owning specific items can be a channel for improving health, knowledge, productivity and so on, and in turn education, employment and consumption. For instance, if a household owns a fridge it will have access to better conserved food and consequently better health, as well as the possibility of trading fresh food and beverages. Owning instead a television, besides its leisure use, is a means to access information.

Table 10. Collection of firewood and item ownership by access to electricity

Electricity	firewood	fridge	TV
No	69.1%	3.3%	12.6%
Yes	43.3%	26.9%	64.6%
Total	56.2%	15.2%	38.9%

As shown in Table 10, households with access to electricity are much less likely (by 26 percentage points) to have to collect firewood. This is typically an activity performed by women and kids, thereby freeing up more of their time for both labour or education purposes, e.g. by allowing kids to study in the dark. Similarly, connected households are more likely to own a fridge and a television, with an even larger difference with respect to non-connected households.

A concern could be that these conditional means, not controlling for other covariates in a regression setting, could just reflect the fact that richer households both have access to electricity and own electrical appliances. We thus repeat the same exercise by wealth and expenditure quantiles, separately. Clearly, richer households are better off and are in general more likely to own a fridge or a television, and less likely to have to collect firewood. Interestingly though, in each quantile we find the same pattern as in the aggregate case: households having access to electricity have higher ownership rates and lower firewood collection rates, regardless of their economic status.

7 Conclusions

The analysis in this paper aims to provide a better understanding of the effects of electricity access on consumption, education and employment outcomes in Nigeria, which hosts the second highest population without access to electricity in the world after India. We assess this impact in particular on the per capita household non-food expenditure, on the school enrolment rate of kids and on different definitions of employment of household members. We take into account the potential correlation between time-invariant unobservable effects and regressors through a fixed effects strategy and we tackle the possible endogeneity in the relationships under investigation through an IV procedure. Before applying these methodologies, in each specification we test for their appropriateness. The results show that, even in a short time frame of two years, electricity access has indeed a relevant impact on all three dimensions, although with different degrees of magnitude and statistical significance of the estimated coefficients.

Specifically we show that, for households with access to electricity, per capita expenditure increases by 170%, that school enrolment rate of kids increases, particularly for girls (by almost 70%), and that the employment rate within the household increases for men (or for the household head, which is a man in most cases). There is also evidence that, thanks to electrification, there is a reallocation of labour from the agricultural to the non-agricultural sector. Conversely, we did not find evidence for an effect of access to electricity on the school enrolment rate of boys, nor on the overall employment ratio and on that of women or spouses. There is strong evidence in favour of the presence of spill over effects of neighbours having access to electricity, as well as of the role played by the quality of electricity, exemplified by the frequency of blackouts.

While migration does not seem to play a role in our sample, households that are characterised by lower wealth and education levels seem to reap larger benefits than the richer and more educated ones. This suggests that, while expanding access to electricity favours every group, it is likely to be a "pro-poor" policy. Taking into account the interactions between access to electricity and access to other types of infrastructure, the effect on rural and urban households is similar and the role of the interactions themselves seems to be prominent. Finally, connected households are likely to enjoy more time to be spent on education or on other productive activities, and are more likely to own a fridge or a television, suggesting that gains might not be limited to the ones described in this paper.

The findings have important policy implications, as they show that the expansion of the electricity access to households which are not yet connected to the grid could play a relevant role in increasing both labour market participation, educational level and consumption, particularly for the poorest and least educated. This in turn can push households out of poverty more quickly and help the transformation of the Nigerian economy away from agricultural activities. Moreover, if combined with other development policies such as the construction of roads, the impact of electricity access can be unleashed even more. Further research is needed on the mechanisms to understand the causal pathways driving these findings, as well as on other outcome variables, particularly the health ones. A comparison across countries would also be desirable to better quantify the impact of electrification at the household level.

Appendix

Table A1. Previous impact evaluation studies on employment outcomes

Reference	Year(s) under analysis	Country/region	Methodology/type of study	Outcome variable	Estimated effect
Barron and Torero (2014)	2009-2013	El Salvador	RCT	Female employment	Women 45.8% more likely to be engaged in non-farm employment
Bernard and Torero (2015)	2-period survey (1 year)	Ethiopia	Panel RCT	Labour supply	No short run effect of rural electrification on time spent on income generating activities
Burlig and Preonas (2016)	2001-2011	India	Regression discontinuity design	Labour supply	Reject changes in male labour allocation larger than 1.3%
Chowdhury (2010)	2004-2005	Bangladesh	Cross-sectional dataset with IV and structural model to cope with endogeneity	Female employment rate and labour supply	Availability of electricity has large and statistically significant influence on women's paid work and a negative effect on unpaid work burden. No statistically significant effect of employment rate.
Dasso and Fernandez (2015)	2006-2012	Peru	DID and FE	Labour supply	Small increase in hours worked for men, no effect on women. Decrease in probability to be self-employed for women (nothing for men). Decrease in the likelihood of having more than one job among males
Dinkelman (2011)	1996 and 2001	South Africa	DID with IV	Employment rate	+9-9.5% increase for women; no significant effect for men
Grogan (2008)	2000	Guatemala	Cross-sectional OLS and probit	Employment rate	Mostly for women, being younger at the time of community electrification has a strong positive effects on labour force participation
Grogan and Sadanand (2013)	1998-2005	Nicaragua	Panel data with IV, tobit regression, recursive bivariate probit	Labour supply	+23% propensity of rural Nicaraguan women to work outside the home. No impact on male employment.
Khandker et al. (2014)	2005	India	Cross-sectional with IV	Labour supply	+ 17 % employment hours for women and only +1.5% percent for men
Libscomb et al. (2013)	1960-2000	Brazil	FE – IV	Employment rate	A county that goes from 0 to full electrification would experience a 17–18% increase in probability of employment
Rathi and Vermaak (2017)	-	India and South Africa	Cross-sectional with IV; PSM; panel data with FE	Employment rate and labour supply	In India access decreases the probability of being employed for men by a 0.2 margin, while it increases that for women. However, annual earnings increase only for men and increased paid employment hours for both genders.
Salmon and Tanguy (2016)	2010-11	Nigeria	Panel-data with IV, copula-based bivariate hurdle model	Labour supply	Electrification increases working time of both household spouses when assessment is separated; however, joint HH-level analysis highlights a positive effect only for men
Van de Walle et al. (2017)	1981-1999	India	Panel data with IV	Labour supply	Growth in regular wage work for men and more casual wage work for women

Table A2. Household consumption: first stage estimates

	First stage
DV: access to elec	
Radiation	0.010***
	(0.00)
Blackouts	0.244***
	(0.02)
Nightlights	-0.112**
	(0.05)
Urban area	0.085
	(0.10)
HH head age	0.001
	(0.00)
HH head education	-0.004
	(0.01)
Kids number	-0.002
	(0.01)
HH employed ratio	0.010
	(0.02)
Distance to road	-0.000
	(0.00)
Distance to grid	-0.106***
	(0.02)
Wealth quintile	0.012
	(0.01)
Year (1=2013)	0.050***
	(0.01)
Constant	-0.072
	(0.78)
F test	19.62
R2	0.14
Number of groups	3618

Note: Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table A3. Employment: alternative outcome variable definition

DV: employed dummy	hh head empl FE	hh spouse empl FE	head&spouse empl FE	head nonagr FE	spouse nonagr FE	head&spouse noag FE
Electricity access	0.025*	-0.004	0.003	0.040*	0.005	0.033
	(0.01)	(0.03)	(0.04)	(0.02)	(0.04)	(0.04)
Blackouts	-0.012	0.016	0.004	0.015	0.031	0.021
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Nightlights	-0.017	-0.053	-0.057	0.008	-0.046	-0.034
	(0.02)	(0.05)	(0.05)	(0.02)	(0.04)	(0.04)
HH head age	-0.001	0.001	-0.000	-0.004***	0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HH head education	-0.004	-0.010	-0.015	0.010	-0.004	-0.016
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Kids number	0.004	0.006	0.006	0.000	0.000	-0.003
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wealth quintile	0.006	0.023**	0.029**	0.025**	0.038***	0.043***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Distance to road	-0.001**	-0.001	-0.001	-0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Distance to grid	-0.005	0.002*	-0.001	-0.004	0.005	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Urban area	-0.045	0.083	0.141	0.010	0.098	0.133
	(0.08)	(0.10)	(0.11)	(0.06)	(0.08)	(0.08)
Year (1=2013)	-0.008	0.013	0.006	0.002	0.031**	0.014
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	1.079***	0.622***	0.707***	0.730***	0.221	0.339*
	(0.10)	(0.12)	(0.17)	(0.13)	(0.16)	(0.20)
Overall p-value	0.245	0.224	0.314	0.042	0.007	0.050
Number of groups	3599	2882	2843	3598	2881	2842

Note: Robust standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table A4. Household consumption with interaction terms

DV: pc expenditure	Road+Pop center	Dist to road	Popul center
Electricity access	1.157***	1.239**	1.307**
	(0.43)	(0.49)	(0.53)
Distance to road*a2e	-0.008*	-0.015*	
	(0.00)	(0.01)	
Dist popul center*a2e	-0.017**		-0.022**
	(0.01)		(0.01)
Blackouts	-0.204***	-0.275**	-0.237**
	(0.08)	(0.11)	(0.10)
Nightlights	0.416***	0.359***	0.464***
	(0.13)	(0.13)	(0.15)
HH head age	-0.003	-0.003	-0.003
	(0.00)	(0.00)	(0.00)
HH head education	-0.008	-0.007	-0.007
	(0.02)	(0.02)	(0.02)
Kids number	-0.090***	-0.091***	-0.088***
	(0.01)	(0.01)	(0.01)
HH employed ratio	0.138***	0.138***	0.136***
	(0.05)	(0.05)	(0.05)
Wealth quintile	0.080***	0.076***	0.078***
	(0.02)	(0.02)	(0.02)
Distance to road	0.001	0.005*	-0.002
	(0.00)	(0.00)	(0.00)
Distance to grid	0.074	0.104	0.086
	(0.09)	(0.10)	(0.09)
Distance to pop center	0.007***	-0.000	0.010**
	(0.00)	(0.00)	(0.00)
Urban area	-0.723***	-0.784***	-0.708***
	(0.15)	(0.17)	(0.15)
Year (1=2013)	-0.045*	-0.053**	-0.046*
	(0.02)	(0.03)	(0.02)
Overall p-value	0.000	0.000	0.000
Number of groups	3259	3259	3259

Note: Robust standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Bibliography

1. Abeberese, A. B. (2017) "Electricity cost and firm performance: Evidence from India", *Review of Economics and Statistics*, 99(5), 839-852.

2. Adenikinju, A. F. (2003) "Electric infrastructure failures in Nigeria: a survey-based analysis of the costs and adjustment responses", *Energy Policy*, *31*(14), 1519-1530.

3. Alby, P., Dethier, J. and Straub, S. (2012) "Firms operating under electricity constraints in developing countries", *The World Bank Economic Review*, 27(1), 109-132.

4. Allcott, H., Collard-Wexler, A. and O'Connell, S. (2016) "How do electricity shortages affect productivity? Evidence from india", *American Economic Review*, 106(3), 587-624.

5. Barron, M., and Torero, M. (2017) "Household electrification and indoor air pollution", *Journal of Environmental Economics and Management*, *86*, 81-92.

6. Bensch, G., Kluve, J. and Peters, J. (2011) "Impacts of rural electrification in Rwanda", *Journal of Development Effectiveness*, 3, 567-588.

7. Bernard, T. (2010) "Impact analysis of rural electrification projects in sub-Saharan Africa", *The World Bank Research Observer*, *27*(1), 33-51.

8. Bernard, T. and Torero, M. (2015) "Social interaction effects and connection to electricity: experimental evidence from rural Ethiopia", *Economic Development and Cultural Change*, 63(3), 459-484.

9. Bernard, T., and Torero, M. (2013) "Bandwagon effects in poor communities experimental evidence from a rural electrification program in Ethiopia", mimeo.

10. Bonan, J., Pareglio, S. and Tavoni, M. (2017) "Access to modern energy: a review of barriers, drivers and impacts", *Environment and Development Economics*, 22(5), 491-516.

11. Bridge, B. A., Adhikari, D. and Fontenla, M. (2016) "Household-level effects of electricity on income", *Energy Economics*, *58*, 222-228.

12. Burlando, A. (2014) "Power outages, power externalities, and baby booms", *Demography*, 51(4), 1477-1500.

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

14. Chowdhury, S. K. (2010) "Impact of infrastructures on paid work opportunities and unpaid work burdens on rural women in Bangladesh", *Journal of International Development*, *22*(7), 997-1017.

15. Dasso, R., and Fernandez, F. (2015) "The effects of electrification on employment in rural Peru", *IZA Journal of Labor & Development*, *4*(1), 6.

16. Dinkelman, T. (2011) "The effects of rural electrification on employment: new evidence from South Africa", *American Economic Review*, 101(7), 3078-3108.

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

18. Emodi, N. V., and Yusuf, S. D. (2015) "Improving electricity access in Nigeria: obstacles and the way forward", *International Journal of Energy Economics and Policy*, *5*(1), 335.

19. Fetzer, T., Pardo, O. and Shanghavi, A. (2013) "An urban legend?! Power rationing, fertility and its effect on mothers", CEP Discussion Paper 1427.

20. Fisher-Vanden, K., Mansur, E. and Wang, Q.J. (2015) "Electricity shortages and firm productivity: Evidence from China's industrial firms", *Journal of Development Economics*, 114, 172-188.

21. Fujii, T., Shonchoy, A. S., and Xu, S. (2018) "Impact of electrification on children's nutritional status in rural Bangladesh", *World Development*, 102, 315–330.

22. Grogan, L. and Sadanand, A. (2013) "Rural electrification and employment in poor countries: evidence from Nicaragua", *World Development*, 43, 252-265.

23. Heckman, J.J. (1978) "Dummy Endogenous Variables in a Simultaneous Equation System", *Econometrica,* 46(4), 931-959.

24. International Energy Agency (2017). *World Energy Outlook 2017*, OECD/IEA 2017.

25. Khandker, S.R., Barnes, D.F. and Samad, H.A. (2013) "Welfare Impacts of rural electrification: a panel data analysis from Vietnam", *Economic Development and Cultural Change*, 61, 659-662.

26. Khandker, S. R., Samad, H. A., Ali, R., and Barnes, D. F. (2014). "Who benefits most from rural electrification? Evidence in India", *The Energy Journal*, 75-96.

27. Lipscomb, M., Mobarak, A.M. and Bharam, T. (2013) "Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil" *American Economic Journal: Applied Economics*, 5, 200-231.

28. Ogunleye, E.K. (2016) "Political economy of Nigerian power sector reform", *WIDER Working Paper* 2016/9.

29. Peters, J., Vance, C., and Harsdorff, M. (2011) "Grid extension in rural Benin: Micro-manufacturers and the electrification trap", *World Development*, 39(5), 773-783.

30. Roller, L. H., and Waverman, L. (2001) "Telecommunications infrastructure and economic development: A simultaneous approach", *American Economic Review*, *91*(4), 909-923.

31. Rud, J.P. (2012) "Electricity provision and industrial development: Evidence from India", *Journal of Development Economics*, 97, 352-367.

32. Rutstein, S. (2008) "The DHS Wealth Index: Approaches for Rural and Urban Areas", retrieved 8/10/2017 from http://dhsprogram.com/publications/publication-wp60-working-papers.cfm

33. Salmon, C. and Tanguy, J. (2016) "Rural electrification and household labor supply: Evidence from Nigeria", *World Development*, 82, 46-68.

34. Sutton, P. C., and Costanza, R. (2002) "Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation", *Ecological Economics*, *41*(3), 509-527.

35. Van de Walle, D., Ravallion, M., Mendiratta,V. and Koolwal, G. (2017) "Long-term gains from electrification in rural India", *The World Bank Economic Review*, 31(2), 385-411.