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ORIGINAL PAPER

The impact of electrification on labour market outcomes in Nigeria

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Abstract
This article aims at providing a better understanding of the effect of electricity access onto labour market outcomes in Nigeria, a country which hosts the second largest population without access to electricity in the world after India, but which has received so far very little attention from the academic community. We assess, through a rigorous econometric analysis carried out employing probit, biprobit and propensity score matching, this impact on the proportion of employed working age components of a household. We consider both female and male employment as well as agricultural and non-agricultural employment separately, further disaggregating the effect between rural and urban households. Our results show that, once the possible endogeneity in the relationships under investigation is tackled, electricity access has indeed a relevant impact on particular labour market outcomes. Specifically, we show a consistent shift out of agricultural employment of around 7% and into non-agricultural employment of about 15%., with some evidence of a positive effect on overall labour participation. These findings show that the expansion of electricity access to households which are not yet connected to the grid could play a relevant role in both increasing labour market participation and in helping the transformation of the Nigerian economy away from agricultural activities.

Keywords Nigeria · Energy access · Electrification · Labour market · Development

1 Introduction

Electricity is a critical enabler. Access to electricity has underpinned the development and the growing prosperity of industrialised countries since the late nineteenth century: not only is electricity required by all industrial activities, it is also essential for the provision of clean water, sanitation and healthcare, as well as efficient lighting, heating, cooking, use of mechanical power, transport and telecommunication

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services (Rosenberg 1998; Elias and Victor 2005). However, 840 million people across the world continue to lack access to electricity. Sub-Saharan Africa remains the region with the largest access deficit: here, 573 million people—more than one in two—lack access to electricity (International Energy Agency et al. 2019). Access to affordable and reliable electricity is still one of the fundamental obstacles to reducing poverty, improving health, and promoting economic growth in many developing countries.

Indeed, electricity has long been recognised as fundamental to development and poverty alleviation. As early as 1917, Lenin recognised this potential when describing communism as Soviet power summed-up with the electrification of the entire country (Grogan and Sadanand 2013). In the 1930s, under Franklin D. Roosevelt, the Rural Electrification Administration in the United States oversaw huge public investment into the expansion of electricity grids across the country as part of the New Deal policies Fluitman (1983). Since the early twentieth century, such policies and programmes have operated under the accepted notion that "electricity would make households better off and increase the productivity of rural areas" Jiminez (2017). The role of energy in fostering development was however excluded from the Millennium Development Goals adopted by the United Nations (UN) in 2000. This changed in 2011, with the launch of the UN Sustainable Energy for All initiative. In 2015, ensuring 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.

Motivated by such public policy support, the academic community has for a long time investigated the relationship between access to modern energy solutions and development. Throughout the 20th Century, results tended to be inconclusive with estimation depending crucially on the country and context under investigation (Fluitman 1983; Attigah and Mayer-Tasch 2013). Establishing the direction of causality between energy expansion and economic growth has proven particularly difficult. Impact evaluation studies shedding light on the causal relationship between access to electricity and firm productivity, labour market outcomes, and general welfare in developing countries emerged in the 2000s. Such literature has been able to utilise more mature econometric techniques in order to better quantify causal relationships. A number of studies have analysed cases from several countries, spanning from Africa (e.g. South Africa, Ethiopia, Rwanda, Zanzibar, Kenya) to 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 study prior to 2016. This gap is particularly relevant when considering that Nigeria became the largest African economy in GDP term in 2014 and that, with 77 million people 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 International Energy Agency (2018).

With this article, we seek to further contribute to the understanding of the relationship between electricity and development, by providing a quantifiable assessment of the impact of electrification on labour market outcomes in Nigeria. More specifically, we achieve this through the application of two different modelling technique, namely probit/biprobit and propensity score matching. Our data come from the panel component of the General Household Surveys (GHSs) run by the National Bureau of Statistics of Nigeria between 2011 and 2015. We follow important advances in literature by looking to address concerns of endogeneity through exploiting a series of instruments (household distance to the grid, to the nearest power plant and slope of the household location's site). Our results show that access to electricity has a positive and significant impact on the proportion of household members employed, while also leading to a shift from agricultural to non-agricultural employment. Furthermore, our analysis confirms that the presence of endogeneity in the relationship between electricity access and economic growth (employment) must be indeed taken into account, but should not be uncritically assumed. We find evidence of its presence only with regard to overall and non-agricultural employment but not agricultural employment. We also find evidence of a stronger effect of electricity access in rural than in urban areas and for male rather than female headed households.

The remainder of the paper is organised as follows: Sect. 2 reviews the established literature in the field; Sect. 3 provides a background of the energy situation in Nigeria; Sect. 4 introduces the data and presents the summary statistics; Sect. 5 covers the methodology; Sect. 6 discusses the results; while Sect. 7 concludes.

2 Literature review

Academic studies on the role of energy access and reliability in fostering economic development focus on the obstacles to and the effects of accessing either clean cooking technologies or electricity. The second of these two strands of literature is relevant to our case [we refer the interested reader to Bonan et al. (2017) for a recent in-depth review].

Three types of potential impacts from electrification on development indicators stand out from past research. These can be grouped into social and educational, health and environmental, and economic (Cecelski and Glatt 1982). We illustrate a non-exhaustive list of the types of benefits that could be expected. Educational benefits may arise from increases in study time (due to improved and cheaper lighting), reduced burden on women (due to less time spent collecting alternative fuels), and improved communication (via telephone, television, and other electrical appliances). Health benefits may arise predominantly due to a decrease in respiratory diseases (a reduction in local air pollution as electric lights substitute for kerosene-based lights). Economic benefits stem from the ability to engage in new productive activities, which tend to be non-agricultural activities, as well as the ability to shift away from household production (due to labour-saving technologies such as electric lighting and water pumps). Explicit financial savings can also arise from lower energy costs.

Such benefits have been used as motivation for rural electrification programmes for the majority of the twentieth century in spite of a lack of consistent empirical evidence existing in their support (Davis 1998). Fluitman (1983), for instance, reviewed available literature in 1983 and concluded that the social benefits of electrification tended to be overestimated and the costs underestimated. Existing literature was criticised for being primarily descriptive and partial. The author comments that none of the available studies is capable of convincing a critic that rural electrification anywhere has been the key to meeting development objectives (Fluitman 1983). Future research was encouraged to address the concept of 'impact' in order to avoid methodological problems arising from reverse causality. The relationship between energy supply and wealth generation and poverty reduction clearly runs in both directions and hence reverse causality bias leads to endogeneity concerns which need to be addressed in any methodological approach.

Impact evaluation studies have indeed since been forthcoming in which authors have used more mature econometric techniques to establish causality. Nonetheless, as late as 2011, a review of the existing literature concluded that although there are more studies (numerically) showing positive effects of electrification on income generating activities the evidence is not strong enough to draw conclusions (Cook 2011). The author comments that the inconclusive nature of empirical results may be due to statistical inconsistencies, inappropriate methodologies, or different effects in different contexts.

Ozturk (2010) surveyed the literature on the energy-growth nexus between the years 1978 and 2009. The author concludes that there is not a consensus on neither the existence nor the direction of causality between energy consumption and economic growth. Some studies find causality running from energy to growth, others from growth to energy, whilst some others find no causality at all. However, country-specific studies focussed upon electricity expansion do tend to conclude that there exists a positive relationship. The paper describes commonly used methods in the literature as being based on common variables for different country and temporal realities (Ozturk 2010). Concluding remarks are therefore that future studies should not simply replicate this analysis but instead look to focus on new approaches, perspectives, and the uses of multivariate models.

More recently, Jiminez (2017) examined 50 impact evaluation studies published between 1983 and 2015. On average, the effects of electrification on school enrolment, employment, and income are all positive. However, there is still substantial variance among estimates, with several studies finding no effects. Lee et al. (2020) further support the idea that the notion of electrification improving development outcomes is highly contextual. They suggest different methodologies, different electrification interventions, as well as different regions as plausible reasons for divergences in existing country-specific research.

These papers highlight that the use of empirical techniques exploiting exogenous variation in an attempt to determine the causal relationship between electrification and economic outcomes has been an important area for exploration over the last couple of decades. We explore the methodologies and key findings from some of the most relevant papers for our work.

The majority of studies looking at electricity access or the quality of its supply are focused on its effect on either employment outcome (Dinkelman 2011; Bensch et al. 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; Alam 2014; Fisher-Vanden et al. 2015; Allcott et al. 2016; Cole et al. 2018), household welfare (Khandker et al. 2012; van de Walle et al. 2017) or health and fertility

(Fetzer et al. 2013; Burlando 2014; Barron and Torero 2015). The reported studies cover very different geographical areas, spanning from South America to Sub-Saharan Africa, and Asia. While the techniques applied 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 our research, we focus specifically on the case of labour markets and employment. Moreover, given the relatively short time span of our data, we are particularly interested in the short-term impact (i.e. over four years) on labour market outcomes.

One of the seminal papers in this strand of literature is Dinkelman (2011), which analyses the case of South Africa's mass roll-out of electricity to rural households. To generate exogenous variation in electricity roll-out to communities, the paper uses the instrument of household land gradient. The author finds that electrification significantly raises female employment within five years, as it releases them from home production and enables the establishment of microenterprises. Conversely, Dinkelman shows that electrification can also have a perverse effect in areas where electricity is rolling out, since it seems to increase the gender imbalance by reducing women's wages and increasing male earnings. A similar empirical strategy is adopted by Dasso and Fernandez (2015), who apply difference-in-differences and fixed effects approaches to the case of rural Peru and find that the electrification program under analysis increased the number of work hours and diminished the likelihood of a person having a second occupation, in particular among women. They also observe that each additional electrification project in a region increases the magnitude of the estimated impacts.

Khandker et al. (2012) work with household-level survey data from India to estimate the impact of rural electrification, focussing in particular on the heterogeneity of the effects across different population segments. They observe a number of significant and positive impacts of electricity access, including on time available, time allocated to education by young people, and schooling level. Positive effects are also found for labour supply, household per capita income, expenditure, and poverty reduction. On the other hand, they highlight that the bulk of benefits from village electrification accrue to richer households and that poorer ones exhibit only a limited consumption of electricity. In a following study, Khandker et al. (2013) test the validity of the electrification-development causality in Vietnam using panel data for two project years (2002 and 2005). The authors report that electrification increased total income by 28% and expenditure by almost 23%. Furthermore, the benefits of the program at the commune-level seem to exceed the benefits derived from households from their own connection. While in absolute terms household-level grid connection benefits upper-income groups more, lower-income groups benefit more from commune-level electrification.

Akpandjar and Kitchens (2017) use data from the 2000 and 2010 population census of Ghana. In 1989, the Ghanaian government introduced the National Electrification Programme (NEP) with the aim of achieving universal electricity access by 2020. The authors investigate whether the arrival of electricity affects the structure of employment. To overcome endogeneity arising from the NEP applying to non-randomly selected communities, they compare adults in the same district and in the same year. To overcome the endogenous problem of household selection within communities, they control for a set of observable pre-determined household-level characteristics which could plausibly influence the decision. If unobservable characteristics motivated adoption then they would still have biased estimates and hence they test for omitted variable bias. Their results suggest that individuals who have residential electricity access are more likely to operate a non-agricultural business, more likely to be employed, and have higher occupational scores on average. This increase in available time for productive activities stems from a reduction in the burden of household chores—such as water and wood collection – brought about by electricity access.

Grogan and Sadanand (2013) model the effects of household electrification on labour supply decisions in the household in Nicaragua. The authors are interested in investigating the channel through which extending light hours of the day may affect household labour allocation. Controlling for a range of observable characteristics, they find a strong positive association between having electricity and working for a salary. There also exists a strong negative association between electricity in the household and time spent in family agricultural activities or collecting firewood. Decomposing the effects shows that electrification causes an increase in the probability of rural woman to work outside the home by 23% but that no such effect exists for men. The suggestion is that electrification, and particularly just having electricity for lighting, significantly changes household resource allocation.

One clear hypothesis from the literature is thus that the electrification of a household reduces the amount of time required for certain household tasks and that this frees individuals (primarily women) to pursue and benefit from alternative employment opportunities [Lee et al. (2020)].

Positive effects are not however a universal finding. For example, an alternative empirical approach has been employed by Burlig and Preonas (2016) who use regression discontinuity design. This exploits the variation in two villages that are immediately above and below the cut-off threshold for a programme assignment, the national rural electrification programme in India, launched in 2005. They find no evidence of statistically significant impacts on village labour market or educational outcomes. Their results suggest that the causal impact of rural electrification on development indicators may be substantially smaller than previously thought.

Employing randomised control trials (RCTs) is the gold standard method to generate exogenous variation. It is outside the scope of this study but has been used previously in the literature (Lee et al. 2020). The authors implemented a RCT in rural Kenya. Selected clusters of households were provided with the opportunity to connect to the grid at subsidised prices. Between 16 and 32 months following electrification the average household showed no meaningful economic or noneconomic gains. However, by varying the price households must pay for electricity access they were able to investigate whether households who are willing to pay more for electricity make a larger use of it than those whose willingness to pay is lower. This may be correlated with other characteristics such as wealth, access to credit, or unobservable characteristics such as ambition or ability. Indeed, high price adopters appear to 'do more with electricity' as they spend more on electricity, experience greater savings on kerosene, and purchase a greater number of electrical appliances. Such adopters also enjoy more benefits: they are more likely to become employed and more likely to own a business. The authors caution that limited sample sizes mean results should only be treated as suggestive; however, the suggestion is that particular household characteristics, such as wealth and education, may be fundamental in driving the benefits that a household derives from electricity connection. The authors conclude that provision of electricity alone is not enough to improve economic outcomes substantially for the world's poorest citizens.

Through alternative mechanisms, longer term impacts on wealth could also arise due to improvements in education and human capital. For instance, Grogan (2008) shows electrification having a positive effect on skills development of children which one would expect to translate into increased income in future generations. Where electrification is also found to reduce fertility, whilst increasing the quality of education of children, a similar long-term wealth effect could be inferred. Grogan (2016) uses municipal level panel data built from microdata and combined with geographical and historical data from Colombia over the period 1973 and 2005. The author uses an instrumental variable strategy with distance between nearest hydroelectric dam and the municipality under question assumed to be positively correlated with the marginal cost of household electrification. Results suggest that household electrification has no measurable self- or waged- employment effects. Instead, household electrification is found to have reduced fertility and increased children's educational levels. This is conceptually understood as a shift toward quality rather than quantity of children. Longer term effects could therefore be expected to contribute towards larger employment and income effects over time. Such effects are however outside of the scope of our study which focuses upon short term and more immediate labour market effects.

In investigating the connection between electricity access and firm productivity, most studies[1] have focused on the reliability of the electricity supply more than access per se, although there also are a couple of studies covering the latter. Blalock and Veloso (2007), for instance, find significant positive effect of energy consumption on firm productivity for manufacturing enterprises in Indonesia, while Peters and Vance (2011) do so using a propensity score matching technique on firm level data in Benin. Similarly, Chauvet et al. (2018) find that access to electricity provided by the national power grid has a positive impact on firm profits in Myanmar.

There is a broad agreement in the literature on the connection between electrification and industrial development: expanding access to rural areas has been connected to an increase in the number of manufacturing firms in places as diverse as India (Rud 2012 and Benin Peters et al. 2011; studies on China Fisher-Vanden et al. 2012, India Rud 2012; Alcott et al. 2014) and the Sub-Saharan region (Bernard 2010; Cole et al. 2018) have shown how low quality of electricity supply and frequent power outages impact negatively firms' revenue, productivity and investment decisions.

[1] Refer *inter alia* to Alcott et al. (2014) for an estimation of how Indian textile plants respond to weekly electricity shortages and the level of the derived productivity losses; Alam (2014) for an investigation of the impact of power outages across industry types in India; Poczter (2016) for an instrumental variable approach based on district level solar irradiance to estimate change in electricity demand in Indonesia; Cole et al. (2018) for an analysis of the effect of black outs on firms' productivity in Sub-Saharan Africa.

Finally, little attention has so far been directed towards individuating the biggest obstacle to households' connection to the grid. The few studies (see e.g. Emodi and Yusuf 2015) which investigated the topic found that the price of connection itself, although often subsidised in many developing countries, remains too high for many of the poorest households, with significant differences observable in connection behaviour amongst different wealth quintiles. A household's decision to connect has also been linked to the neighbours' decision to connect, both because of the gain in social status implicit in access to electricity and the increased understanding of the many benefits that can be derived by the connection [refer to Bernard and Torero (2013)].

In spite of a general consensus beginning to emerge among country-specific studies, previous literature reviews have still found the existence of a wide range of estimates suggesting that contextual characteristics of the country and areas under question, as well as the methodology employed, are influential. The external validity of results from one country to another cannot be assumed. Peters and Sievert (2016) particularly suggest that results from America and Asia (which they view as widely confirming the poverty reduction impacts of electrification) may not be so easily transferable to the African context due to underlying structural differences. This present study is therefore motivated to follow in the steps of previous country-specific literature, by applying an instrumental variables approach in order to generate exogenous variation in the context of Nigeria.

3 Specific Nigerian electricity background

As of 2018, about 60% of the Nigerian population had access to electricity, with the access rate standing at 80% and 40% in urban and rural areas respectively (see Figs. 1 and 2 for the sample average access at state and local government area level respectively). Therefore, 77 million people still lacked access to electricity in the biggest economy in the Sub-Saharan African region International Energy Agency (2018). 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.[2] 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",[3] 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 76% of firms experienced at least one power outage during the previous financial year, and amongst these the average number of black outs was 33 per month, with an average length of more than 11 h. Indeed, a study from

[2] World Bank Development Indicators database, accessed in May 2019.

[3] "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.

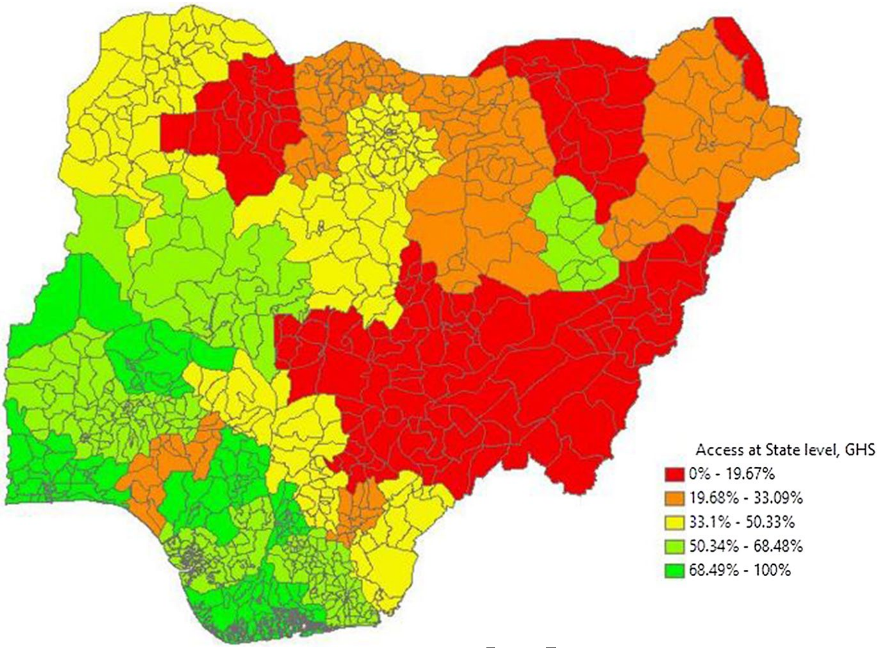

Fig. 1 Average electricity access by state in the General Household Survey, 2015. Map of Nigeria showing the proportion of households in the sample per state reporting to have access to electricity and receiving at least one hour of electricity from the grid over the week prior to the survey. Source: Nigerian General Household Survey 2015

2003 Adenikinju (2003) reported that 82% of surveyed firms in the manufacturing sector identified the quality of electricity supply as 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 a "major" or "very severe" obstacle for their operation (see Fig. 3) and more than 30% state that it is the main obstacle for their operation (see Fig. 4). 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 h per day.

In the last two decades there have been various attempts 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, both of which 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

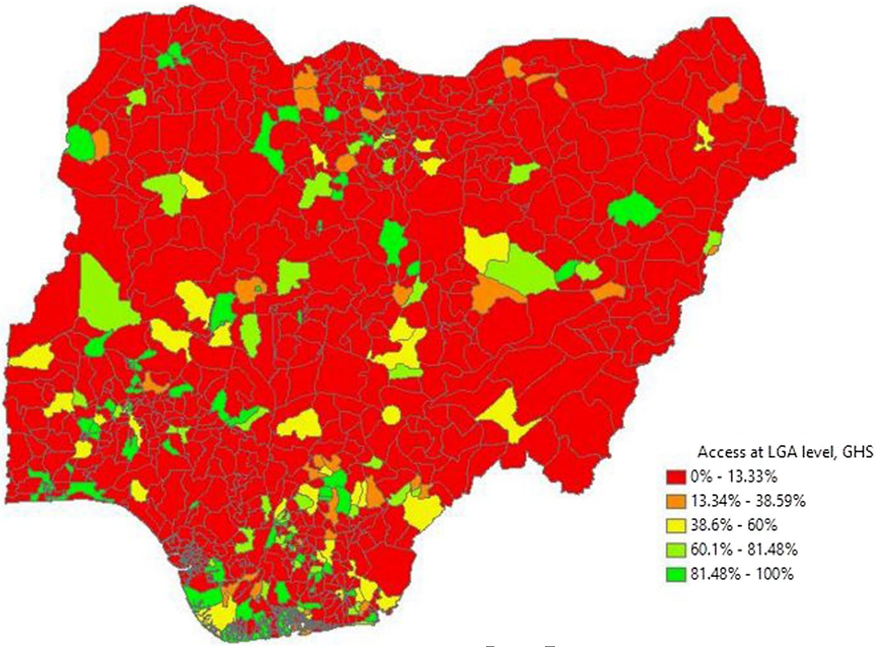

Fig. 2 Average electricity access by Local Government Authority (LGA) in the General Household Survey, 2015. Map of Nigeria showing the proportion of households in the sample per Local Government Authority reporting to have access to electricity and receiving at least one hour of electricity from the grid over the week prior to the survey. Source: Nigerian General Household Survey 2015

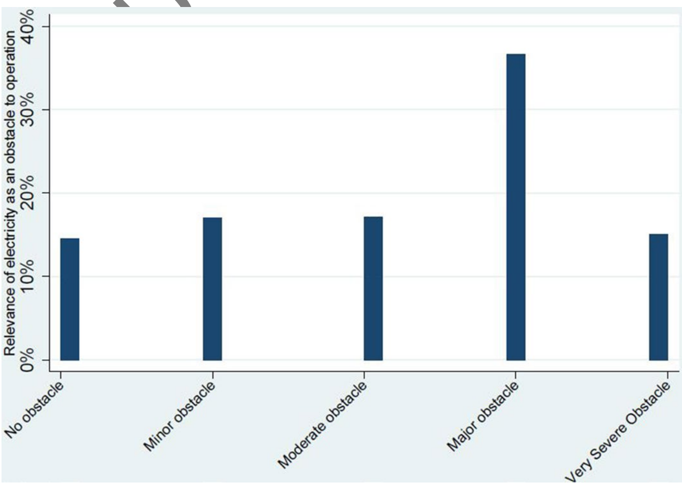

Fig. 3 Relevance of electricity as obstacle for firms' operation, 2014. Source: World Bank Enterprise Survey, Nigeria 2014.]

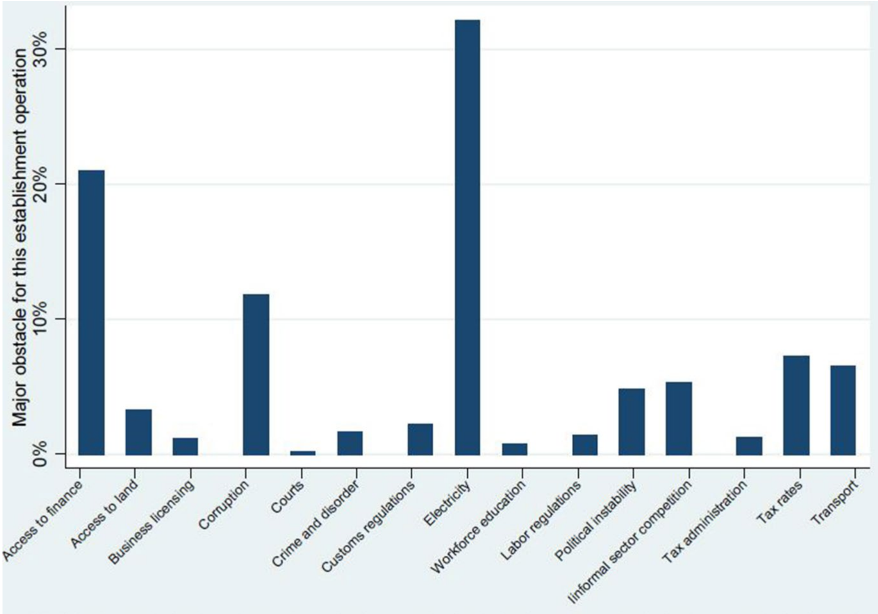

Fig. 4 Major obstacles for firms' operation, 2014. Source: World Bank Enterprise Survey, Nigeria 2014

government-backed independent power projects to increase generation capacity. 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 (see Ogunleye (2016) for an in-depth analysis of the reform process). 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, this second wave of privatisation is taking longer than expected, with problems related to gas shortages and delays in executing gas supply agreements affecting the bankability of the projects.

4 Conceptual framework

As we study the impact of electrification on employment specifically, we consider all potential pathways through which this relationship occurs. Our employment results are in fact driven by both an increase in labour supply and in labour demand, which in turn are driven by different channels stemming from both household and

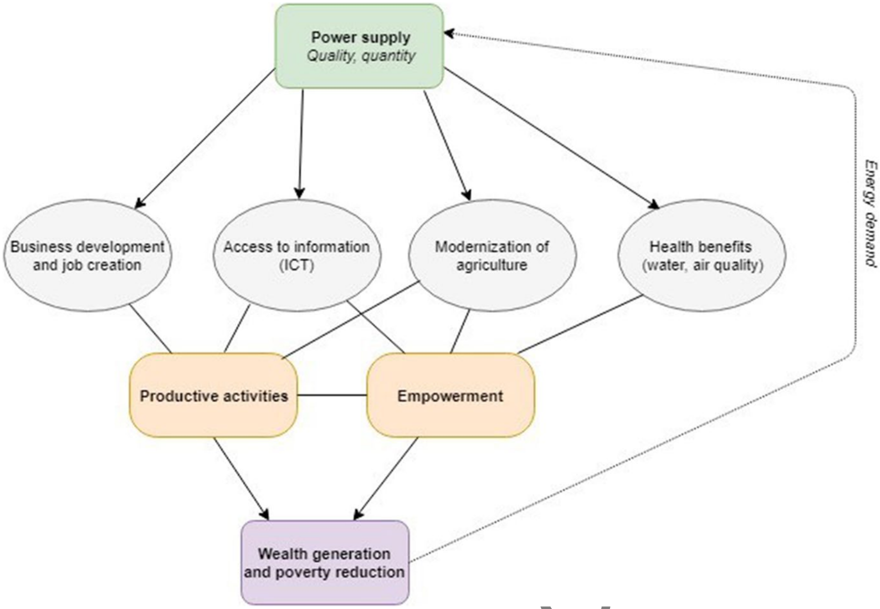

Fig. 5 Conceptual framework. Source: own elaboration, adapted from Salmon and Tanguy (2016)

area electrification. Figure 5 shows our conceptual framework, adapted from Salmon and Tanguy (2016), who limit their analysis to spouses' labour supply in rural households.

When an area is connected to the national grid, not necessarily all households will receive access to electricity, first and foremost because a connection fee is generally to be paid. Although in our sample the most commonly reported source of electricity is the national grid, household electrification may stem also from sources other than electricity grid expansion, such as mini-grids and autonomous solutions (e.g. solar panels). These are the reasons why household and area electrification are intertwined, but do not necessarily coincide. Household electrification may lead to both increases in labour demand and labour supply. Thanks to electricity, households have access to lighting, which drastically extends hours of activity, and to several electrical appliances (such as heating and cooling, refrigeration, radio and television), which bring about several benefits (Rathi and Vermaak 2017; Grogan and Sadanand 2013).

Connected households, for instance, have a lower need to fetch water and collect wood fuel for heating, cooking and lighting. This in turn reduces the burden of home production, but increases the time spent in non-market activities (e.g. education and leisure time). While the former will increase labour supply, the latter is likely to decrease it. However, while the theoretical prediction is uncertain, non-market activities are likely pushed after the end of the working day, given the extra time available for studying and leisure during hours without sunlight, thanks to lighting (see Van de Walle et al. 2017, and Dinkelman 2011). Moreover, a more educated population will at a later stage also increase the quality of labour supplied. In addition, labour supply may also increase through other channels affected by the availability of electricity, such as improvement of the health status, better access to information via access to media as well as increased empowerment and labour participation of women, who were previously relegated to home production activities.

Thanks to electrical appliances, households may also start small-scale business activities, such as a barber shop, local craft production or storing and re-selling cold beverages and food. This may happen either in parallel to the main household activity, typically in agriculture, or lead to a shift from agriculture to non-agriculture activities. Beyond employing household members, new businesses may also employ other people in the surrounding area, leading to positive spill-over effects and to a further increase in labour demand. Thanks to mechanical power, certain process in agriculture can be mechanized, generate an increase in productivity and competition, and in some cases even favour the development of new industries. Besides job creation, such developments also lower the marginal cost of energy inputs as well as lead to the adoption of new technologies. According to Akpandjar and Kitchens (2017), depending on the relationship between inputs, this has an ambiguous net effect on labour demand. On the one hand, it may decrease it by inducing a substitution between labour-intensive and energy-intensive inputs of production. On the other hand, if inputs are complementary in production or if the output increase is sufficiently large, the demand for labour may still witness an overall increase through this channel.

In sum, while the net impact of the described pathways from access to electricity to labour supply and demand is theoretically uncertain, our prior is that the overall effect is positive on both. An increase in labour supply and demand would then result in a rise in employment. We thus test in the data whether household electrification, also controlling for spill-overs from the nearby area, leads indeed to an employment increase.

5 Data and descriptive statistics

The main source of 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 GHS covers 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.

The general survey does not have a panel component, i.e. the same household has not been sampled repeatedly over time (or at least not on purpose and thus without a way to connect their observation over different years). However, since 2010 5000 households were selected from 500 enumeration areas to be included in a new panel component of the GHS to be repeated every 2–3 years. These households were selected so as to be representative of all geopolitical zones of Nigeria at both the rural and urban level. The questionnaire was upgraded to include further information on both agricultural and non-agricultural income generating activities as well as household income and expenditure.

Table 1 Distribution of samples households across geopolitical areas

Geopolitical areas	Num. of obs.	Share
North Central	2088	16.66%
North East	1691	13.49%
North West	2402	19.17%
South East	2178	17.38%
South Central	2082	16.61%
South West	2090	16.68%

The number and share of observations in the sample including surveyed households across three consecutive GHS waves. Source: Authors' calculation using data from the three rounds of the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

Of the 5000 households initially sampled, 4916 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 (the second wave was in 2012–2013) only 4581 households of the original households remained in the sample. 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, food consumption, and expenditure 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.

Furthermore, during the last wave of the GHS-Panel a tracking visit was conducted after both the post-planting and post-harvesting visit in order to identify as many of the households as possible who had moved following one of the previous waves or in between visits. We have decided to exclude from the analysis all households who moved in between waves. This is done in order to avoid attributing changes in the outcome variable which were connected to migration choices.

Due to the reasons explained in the previous sections and to the non-response rate for certain covariates our final sample includes 4397 out of the 4581 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%), see Table 1.

The average sample share of household components in working age who are employed, regardless of the nature of employment, is 78.4%, with the lowest share found in the North Eastern area (65.6%) and the highest share in the South Eastern area (85.8%). See Table 2 for the mean values of all dependent variables and selected covariates. For the overall sample, and for all but one geopolitical area (South Central), the proportion of employed male household members is higher than that of employed female members (85.9% and 71.9% respectively), although the difference is much more pronounced in the Northern areas.

The sample proportion of household members employed in non-agricultural activities is higher than that the proportion employed in agricultural activities

Table 2 Sample averages of dependent variables and selected covariates

Variable	Sample	Num. of obs.
Household employment	78.45%	12,274
Household employment, male	85.91%	10,647
Household employment, female	71.87%	11,506
Household employment, agriculture	39.32%	12,273
Household employment, agriculture, male	49.66%	10,645
Household employment, agriculture, female	31.52%	11,506
Household employment, non-agriculture	51.38%	12,274
Household employment, non-agriculture, male	53.32%	10,649
Household employment, non-agriculture, female	49.41%	11,507
Access to electricity	47.73%	12,531
Access to electricity, urban	80.90%	3,843
Access to electricity, rural	33.06%	8,688
Urban dwellers	30.66%	12,531
Male head of household	82.83%	12,531
Household head age	51.708	12,531
Household size	5.779	12,531
Wealth quintile	3.010	12,531

Based on the sample across three consecutive GHS waves. Source: Source: Authors' calculation using data from the three rounds of the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

(51.4% and 39.3% respectively), and this is true for all geopolitical areas except for the South Eastern area. The share of employed male household members occupied in agricultural activities is higher than that of female household members, both in the overall sample (49.7% of employed male household members against 31.5% of employed female members) and in most geopolitical areas, although this pattern is more common in Northern areas than in Southern ones. The difference in the share of employed male and female members employed in non-agricultural activities is much less marked (53.3% and 49.4%), and again this is true for both the overall sample and all geopolitical areas but the South Western one.[4]

With regards electricity access, the sample average stands at 47.7%, with significant differences between urban (80.9%) and rural households (33.1%) and across different geopolitical areas, with a minimum overall access equal to 22.6% of households in the North Eastern area and a maximum of 63.8% in the Southern Central area.[5] The figures for urban and rural access are very close to those reported by the International Energy Agency (2018) (i.e., 80% and 40% respectively), while there

4 The shares of male and female employed in agricultural and non-agricultural activities do not sum up to the shares of total male and female employed as each household member can be employed in more than one activity.

5 It must be noted that we consider households that received less than an hour of electricity from the grid over the previous week as having no access to electricity.

are relevant differences in the overall access rate (which stands at a much higher 60% in the International Energy Agency's World Energy Outlook). It must also be noted that this level of access across geopolitical areas is much more even amongst urban households (maximum of 83.8% in the North West and minimum of 75.5% in the North East) than it is among rural ones (maximum of 56.8% in the South Centre and minimum of 13.7% in the North East). Relevant differences across geopolitical areas exist also with regard to urbanisation levels, ranging from 14% of households in the North Eastern area to 70.3% in the South Western one, with an overall share of 30.7%.

Finally, the vast majority of households are headed by a male component, both in the overall sample (82.8%) and in all geopolitical areas, with a minimum share of 67.4% in the South Eastern area and a maximum of 96.9% in the North Western one. The average age of the household head in the overall sample is 51.7 years, with very little variation across geopolitical areas; on the other hand the maximum years of education of any member of the household varies quite significantly, ranging from 6.7 in the North West to 11.3 in the South Central area (with a sample average of 9.3). Some variation can also be noted in household size with the lowest average to be found in the South West (4.24) and the highest in the North East (7.51).Variation is again found in average wealth quintile distribution, with the highest value found in the South West (3.75) and the lowest in the North West (2.10).

6 Methodology

As identified in the literature on the socioeconomic impact of electrification, household's access to electricity cannot be considered exogenous to many outcomes of interests. The potential endogeneity of electricity access stems from different sources depending on the level of analysis, such as the roll-out of electrification programs, the choice of villages receiving grid extension or the unobserved decision by a household to pay for the electricity connection to name but a few (see Duflo and Pande 2007; Roller and Waverman 2001; Rud 012; Grogan and Sadanand 2013). For example, at the household level, the two main sources of endogeneity of electricity access with respect to employment outcomes are likely to be reverse causality and 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 therefore bias our coefficients upward. 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 downward.

To tackle the issue of endogeneity we employ an instrumental variable (IV) estimation strategy. For our analysis, we have access to three potential instruments all of which have been previously used in the literature: household distance to the grid, household distance to the nearest power plant, and land gradient at the site of the household (Dinkelman 2011; Grogan and Sadanand 2013; van de Walle et al. 2017). All of these three variables should plausibly satisfy the exogeneity condition.

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; while 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 could thus correlate with firms' concentration, hence impacting the likelihood of holding a non-agricultural job. To account for this possibility, we include in all regressions population density at the local government authority level, intended as a proxy for plot dimension, as well as distance to the nearest road and to the nearest market, which should reflect local labour market conditions Grogan and Sadanand (2013).

There are several models that can be implemented which allow for the use of IVs, depending on the distribution of the outcome variable and of the endogenous variable. When the outcome variable is the proportion of household members employed in a specific sector, using linear models such as two stage least square (2SLS) would yield biased estimates. Following Hutchinson and Wheelers (2006) and Nichols (2011), our choice of model has thus fallen on the bivariate probit (also called biprobit) model Heckman (1978), which is similar to IV probit but built explicitly for analyses where both the outcome and the endogenous regressor are limited between 0 and 1. An additional advantage over IV probit is that the first stage covariates do not necessarily need to be the same as those in the second stage regression.

For all biprobit estimations we calculate the Wald test of exogeneity, testing if the correlation between the estimated residuals from the first stage and those from the second stage (the "rho" coefficient) is significantly different from 0 Hutchinson and Wheeler (2006). If "rho" is equal to 0 then there are no common unobservable factors affecting both the access to electricity and the outcome variable, and the first and second stage equations can be treated as independent from one another. In this case a probit model would yield consistent and efficient estimates. On the other hand, when the test rejects the null hypothesis of exogeneity the correct approach would be bivariate probit. While we believe that all proposed instruments satisfy the required exclusion restriction and we are therefore inclined to include all of them, the biprobit routine of Stata does not include any automatic test of the overidentification restriction. Following the suggestion included in Guilkey and Lance (2014), we opt for indirectly testing it by including our instruments in the outcome equation and then performing a likelihood ratio test of the hypothesis that they are all jointly equal to 0. If the test yields a satisfactory result we include them all, otherwise we exclude any instrument which shows a significant effect on the outcome variable.

Alternatively, we also conduct the analysis using propensity score matching (PSM), specifically applying either nearest neighbour or Kernel matching techniques (Figs. 6 and 7). In the first case, we calculate the Abadie and Imbens (2006) standard errors, which have been shown to be superior to normal bootstrapping, while in the second case we have to rely on the former. The concurrent use of univariate—bivariate probit and PSM have precedent in both labour economics Morris (2006) and in the evaluation of the impact of health programs Hutchinson and Wheeler 2006; Babalola and Kincaid 2009). The reason for conducting the analysis using these two different methodologies lies in the diverse assumptions behind them. PSM creates comparable groups based on observable

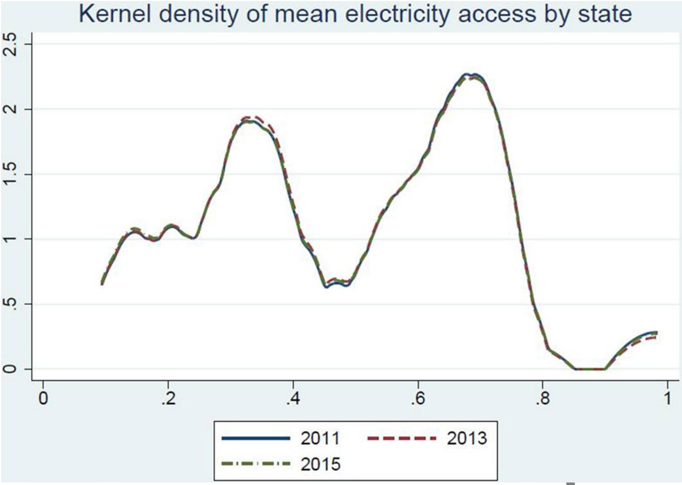

Fig. 6 Kernel density of mean electricity access by state. Source: Nigerian General Household Survey 2011–2015

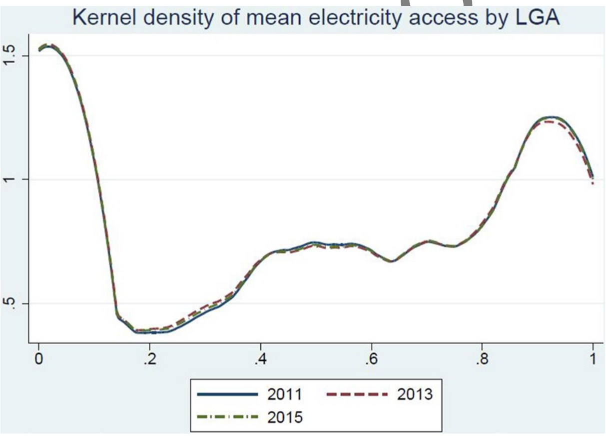

Fig. 7 Kernel density of mean electricity access by LGA. Note: Local Government Authority (LGA). Source: Nigerian General Household Survey 2011–2015

characteristics in order to assess the effect of the treatment on the outcome of interest, assuming that all unobserved characteristics can be ignored since they do not affect treatment or outcome if the model is correctly specified. Bivariate probit assumes that the correlation amongst unobservable characteristics affecting exposure to the treatment and the outcome of interest follows a joint normal distribution, simultaneously estimating the treatment and outcome equations to address the possibility that confounding variables in the latter are correlated with the treatment variable in the former even after controlling for the full set of observable characteristics.

Both techniques have advantages and disadvantages. With regard to PSM, one of the main advantages is that the relationship between treatment and outcome can take any functional form as it is not reliant on any parametric assumption. However, only observed heterogeneity is accounted for as the assumption is that all relevant characteristics are measured and, if not, that they can be ignored as not important enough to impact the internal validity of the estimates. That is, the more variance is explained by the model used to estimate propensity scores, the less substantial the possible bias from unobserved characteristics, although the bias can also be important when there is a relevant amount of unobserved heterogeneity between treated and non-treated (Shadish et al. 2002; Shen 2002). On the other hand, biprobit explicitly addresses the possible presence of unobserved characteristics leading to an endogenous relationship between treatment and outcome and generally yields relatively efficient estimates. Furthermore, it allows for the actual testing of the endogenous nature of said relationship. However, it only allows for the presence of two endogenous explanatory variables at once, and it can only be applied to situations where the outcome of interest is binary.

Furthermore, probit and bivariate probit estimations also allow for population weights, which are provided by the World Bank, and for intragroup correlation (clustering) of the standard errors. As it is the case in many empirical analysis using population surveys, the assumption that model errors will be uncorrelated at the individual level seems implausible. All regressions are then run with standard errors clustered at the local government authority level (LGA), thus allowing for correlation across error terms of individuals in the same LGA but assuming independence between individuals in different ones. Following Long and Freese (2006) and Williams (2012) we computed all reported marginal effects as average marginal effects, using the unconditional option which allows for heteroskedasticity or other violations of distributional assumptions among the observations.

The outcome of interest for our study is the proportion of people of working age (15–64) within the household that are employed. On top of overall employment level, we further divide this amongst male and female employment as well as agricultural and non-agricultural employment. Members of the household who are studying and without employment are excluded from the calculation of the proportion of people employed in the household, i.e. they are considered neither employed nor unemployed.

As previously stated, our three instrumental variables are the average slope of the terrain at the household site, the distance from the household to the nearest grid, and the distance from the household to the nearest power plant. Information about the household location and terrain slope were obtained from the General Household Survey. Data on the transmission grid network of medium and high voltage lines comes from the West African Power Pool GIS database, accessible through the *energydata.info* portal, and power plant location information comes from Platts. The explanatory variable of main interest is a dummy variable for access to electricity, which we obtained from the GHS. As we are interested in the impact of having access to electricity and not in that of having a connection per se, we did not consider households as being connected to the grid if less than one hour of electricity was obtained from the grid over the previous week.[6] Although the threshold might seem too low to be of any impact, 4% of the households included in the sample did not surpass it. The proportion of households below the threshold is as high as 7.8% in the Southern Central area.

All regressions include the usual covariates of interest: gender and age of the household head, household size, highest education attained by a household member, distance to the nearest road and to the nearest population centre, as well as a dummy variable for urban areas, categorical dummies for each of the six geopolitical zones and for each year. Finally, we also 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 Rutsetin (2008). The sample averages of the variables constituting the wealth index, and the mean and standard deviation of the rural and urban wealth index as well as the national mapping can be seen in Table 3.

7 Results and discussion

7.1 Probit and biprobit analysis

We begin the discussion by presenting the results of a probit (column 1) and a biprobit (column 2) regression. The dependent variable is the proportion of household members of working age who are employed, shown in Table 4. Column 1 shows that ignoring the potential endogeneity of the effect of electricity access leads to the conclusion that the latter has no effect on labour market participation. However, the results change significantly when employing a biprobit estimation (column 2): the negative and highly significant rho suggests that indeed the endogeneity concerns were well founded and that the insignificance of the coefficient in the probit regression was due to a downward bias in the estimation. Accounting for endogeneity, the coefficient on electricity access increases in order of magnitude and becomes highly significant, while the majority of the other coefficients remains of similar magnitude and significance. As the reported average marginal effect makes clear, acquiring access to electricity increases labour market participation at the household level by 8.1%. The effect though becomes indiscernible if one considers male and female labour market participation separately, as the coefficients on electricity access are insignificant in probit regressions and we do not find any evidence of endogeneity in the specific relations through biprobit estimation.[7]

[6] We also consider an alternative definition of having received at least one hour of electricity per day as a robustness check.

[7] Regression results not reported but available upon request.

Table 3 Sample averages of the variables constituting the wealth index and the mean and standard deviation of the wealth index in rural and urban areas as well as the mapped national index

Variable	North central	North East	North West	South East	South Central	South West	Total
Household owns one or more							
Mattress	93%	96%	97%	96%	96%	92%	95%
Bed	68%	91%	94%	84%	75%	79%	82%
Mattress	78%	95%	96%	77%	58%	63%	76%
Sewing machine	7%	11%	12%	10%	13%	11%	11%
Gas cooker	2%	1%	1%	6%	16%	8%	6%
Stove gas (table)	0%	0%	0%	1%	4%	5%	2%
Stove (kerosene)	39%	15%	14%	67%	67%	83%	51%
Bicycle	10%	28%	26%	23%	16%	1%	16%
Motorbike	44%	38%	39%	28%	26%	18%	31%
Cars and other vehicles	11%	6%	7%	12%	15%	18%	12%
Generator	28%	12%	10%	42%	47%	44%	32%
Fan	59%	73%	77%	62%	52%	51%	61%
Cassette recorder	12%	11%	7%	6%	6%	12%	9%
Iron	35%	31%	19%	45%	56%	56%	42%
Musical instrument	0%	1%	1%	1%	1%	1%	1%
Mobile phone	76%	61%	68%	87%	88%	86%	79%
Household has bank account	37%	22%	17%	49%	58%	61%	42%
Household has insurance	3%	1%	1%	4%	5%	7%	4%
Number of people per room	1.74	2.21	2.19	1.44	1.84	2.03	1.93
Main source of drinking water							
Pipe borne water treated	7%	8%	14%	4%	10%	11%	10%
Pipe borne water untreated	5%	2%	4%	4%	5%	2%	3%

Table 3 (continued)

Variable	North central	North East	North West	South East	South Central	South West	Total
Bore hole / hand pump	24%	28%	21%	59%	57%	40%	38%
Well /spring protected	24%	12%	20%	3%	4%	22%	15%
Well / spring unprotected	8%	28%	34%	6%	5%	3%	13%
River / spring	22%	13%	4%	9%	8%	8%	10%
Lake / reservoir	0%	1%	1%	1%	1%	0%	1%
Rain water	2%	0%	1%	1%	1%	1%	1%
Tanker / truck / vendor	5%	7%	2%	5%	0%	0%	3%
Satchet water	3%	1%	1%	7%	9%	12%	6%
Toilet facilities							
None	54%	17%	15%	24%	14%	26%	24%
Toilet on water	2%	1%	1%	1%	7%	4%	3%
Flush to sewage	10%	2%	2%	3%	13%	19%	9%
Flush to septic tank	8%	1%	1%	32%	28%	27%	17%
Pail/bucket	0%	0%	1%	2%	1%	1%	1%
Covered pit latrine	20%	49%	48%	31%	32%	20%	32%
Uncovered pit latrine	5%	28%	28%	7%	5%	2%	12%
VIP latrine	0%	2%	4%	1%	0%	1%	1%
Wall material							
Grass	1%	11%	6%	0%	0%	0%	3%
Mud	46%	56%	62%	9%	20%	10%	32%
Compacted earth	2%	2%	4%	1%	2%	0%	2%
Mud brick (unfired)	7%	3%	8%	1%	0%	3%	4%
Bunt bricks	2%	0%	1%	0%	0%	1%	1%
Concrete	10%	7%	3%	6%	13%	35%	15%

Table 3 (continued)

Variable	North central	North East	North West	South East	South Central	South West	Total
Wood	0%	0%	0%	0%	1%	1%	1%
Iron sheets	0%	0%	1%	0%	3%	1%	1%
Concrete or cement blocks	31%	20%	15%	83%	60%	48%	43%
Wealth index							
Rural							
Mean	− 1.09	− 1.87	− 2.22	− 0.16	0.10	− 0.18	-0.61
Standard deviation	1.80	1.64	1.79	1.89	1.99	1.72	1.96
Urban							
Mean	− 0.69	− 1.08	− 1.24	0.85	1.09	− 0.53	− 0.31
Standard deviation	1.76	1.42	1.17	1.91	2.18	1.79	1.95
National							
Mean	− 1.04	− 1.69	− 1.84	0.16	0.45	0.52	− 0.58
Standard deviation	1.85	1.45	1.31	1.85	2.06	2.06	2.04

Based on the sample across three consecutive GHS waves. Source: Source: Authors' calculation using data from the three rounds of the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

Table 4 Probit and biprobit regression coefficients of factors affecting household employment outcomes and marginal effects of access to electricity

	(1) Household employment	(2) Household employment
Access to electricity	0.03 (0.07)	1.02*** (0.28)
Household head gender	0.32*** (0.07)	0.34*** (0.06)
Household head age	− 0.00** (0.00)	− 0.00** (0.00)
Maximum education	0.01 (0.01)	0.00 (0.01)
Household size	0.06*** (0.01)	0.06*** (0.01)
LGA density of population	− 2.11 (3.90)	− 3.82 (3.85)
Distance to road	0.00 (0.00)	0.00 (0.00)
Distance to population centre	− 0.00 (0.00)	0.00 (0.00)
Urban area	− 0.03 (0.09)	− 0.20* (0.10)
Second wealth quintile	0.05 (0.08)	− 0.06 (0.09)
Third wealth quintile	0.19** (0.09)	− 0.12 (0.13)
Fourth wealth quintile	0.10 (0.10)	− 0.34** (0.16)
Fifth wealth quintile	0.23* (0.12)	− 0.22 (0.17)
Constant	1.32*** (0.20)	1.04*** (0.22)
Marginal effect: Access to Electricity	0.00 (0.01)	0.08** (0.04)
Distance to the grid (1st stage on electricity access only)		− 0.64** (0.27)
Slope at the household (1st stage on electricity access only)		− 0.01 (0.02)
ρ (Rho)		− 0.65*** 0.22
Number of obs.	11992	11992

Rho shows the correlation between the estimated residuals from the first and second stage regression (Wald test of exogeneity), Local Government Authority (LGA); Standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

Table 5 presents the results for the case in which the dependent variable is household employment in agricultural activities. In this case the data do not offer any confirmation of an endogenous relationship, neither for overall employment (column 1), nor for gender specific employment levels (columns 2 and 3). The coefficients are remarkably similar in all three cases and indicate that access to electricity decreases the proportion of household members employed in agricultural activities by about 7%, with a slightly stronger effect on male than on female employment. Moreover, the regressions clearly indicate a negative relationship between belonging to a higher wealth quintile, the density of population in the LGA, and being occupied in agricultural activities. While also in the case of wealth quintiles the effect seems to be stronger for male than for female household members, the opposite is true for population density.

In Table 6 we move onto considering the effect of electricity access on employment outside of the agricultural sector, with column 1 reporting the result

Table 5 Probit regression coefficients of factors affecting agricultural household employment outcomes and marginal effects of access to electricity overall and by gender

	(1) Employment, agri	(2) Male employment, agri	(3) Female employment, agri
Access to electricity	− 0.25*** (0.06)	− 0.24*** (0.06)	− 0.25*** (0.06)
Household head gender	0.45*** (0.07)	0.79*** (0.08)	0.04 (0.07)
Household head age	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Maximum education	− 0.01 (0.01)	− 0.01 (0.01)	0.01 (0.01)
Household size	0.05*** (0.01)	0.03*** (0.01)	0.02** (0.01)
LGA density of population	− 188.24*** (37.02)	− 200.61*** (38.01)	− 212.14*** (52.81)
Second wealth quintile	− 0.11* (0.06)	− 0.11* (0.06)	− 0.03 (0.06)
Third wealth quintile	− 0.36*** (0.08)	− 0.36*** (0.07)	− 0.20** (0.08)
Fourth wealth quintile	− 0.69*** (0.08)	− 0.73*** (0.09)	− 0.52*** (0.08)
Fifth wealth quintile	− 1.07*** (0.11)	− 1.10*** (0.11)	− 0.87*** (0.10)
Urban area	− 0.51*** (0.11)	− 0.52*** (0.11)	− 0.53*** (0.12)
Constant	0.01 (0.17)	− 0.25 (0.18)	− 0.36* (0.20)
Marginal effect: Access to Electricity	− 0.07*** 0.02	− 0.07*** 0.02	− 0.06*** 0.02
Number of obs.	11991	10427	11258

Local Government Authority (LGA); Standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01

Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

for overall employment and column 2 and 3 for male and female members of the household, respectively. Differently from previous cases, we only find significant evidence of endogeneity for overall and male household employment, with both cases showing a highly significant rho, while there is no indication that the same problem affects the relations between electricity access and female employment. Table 6 also shows that the level of wealth has a strong connection with employment outside the agricultural sector, conversely to that in the agricultural one. This relationship is shown explicitly in Fig. 8, graphing the marginal effect of electricity access across the different wealth quintiles, increasing employment outside of agriculture of 11.8% for families in the first wealth quintile, of 14.7% for those in the second, of 19.8% for those in the third and of a little more than 25% for those in the fourth and fifth.

The average marginal effect in both biprobit models are very similar and about thrice as big as in the probit model. Furthermore, the marginal effect for overall household employment in non-agricultural activities aligns almost perfectly with those relative to the two previous cases of overall and agricultural employment. That is, the 8% increase in the overall employment found in Table 1 masks a reallocation of household labour away from agricultural (− 7.3%, Table 2) and towards non-agricultural (+ 15.9%) activities.

Table 6 Biprobit and probit regression coefficients of factors affecting non-agricultural household employment outcomes and marginal effects of access to electricity

	(1) Employment, non-agri	(2) Male employment, non-agri	(3) Female employment, non-agri
Access to electricity	1.41*** (0.14)	1.23*** (0.15)	0.15*** (0.05)
Household head gender	0.07 (0.06)	0.54*** (0.10)	− 0.33*** (0.06)
Household head age	− 0.01*** (0.00)	− 0.01*** (0.00)	0.00 (0.00)
Maximum education	0.00 (0.01)	0.01* (0.01)	0.01 (0.01)
Household size	0.04*** (0.01)	0.02** (0.01)	0.03*** (0.01)
LGA density of population	1.60 (5.39)	− 0.35 (3.27)	− 10.51*** (2.38)
Urban area	0.15* (0.09)	0.24*** (0.08)	0.27*** (0.07)
Second wealth quintile	0.16*** (0.05)	0.22*** (0.05)	0.19*** (0.06)
Third wealth quintile	0.23*** (0.08)	0.37*** (0.08)	0.35*** (0.07)
Fourth wealth quintile	0.31*** (0.11)	0.50*** (0.11)	0.58*** (0.08)
Fifth wealth quintile	0.54*** (0.13)	0.62*** (0.13)	0.85*** (0.09)
Constant	− 0.57*** (0.17)	− 1.03*** (0.18)	− 0.49*** (0.17)
Marginal effect: Access to Electricity	0.16*** (0.02)	0.17*** (0.02)	0.05*** (0.02)
Distance to the grid	− 0.62** (0.25)	− 0.63** (0.25)	
Slope at the household	− 0.01 (0.02)	− 0.02 (0.02)	
ρ (Rho)	− 0.82*** (0.15)	− 0.66*** (0.12)	
Number of obs.	11992	10432	11259

Rho shows the correlation between the estimated residuals from the first and second stage regression (Wald test of exogeneity), Local Government Authority (LGA); Standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

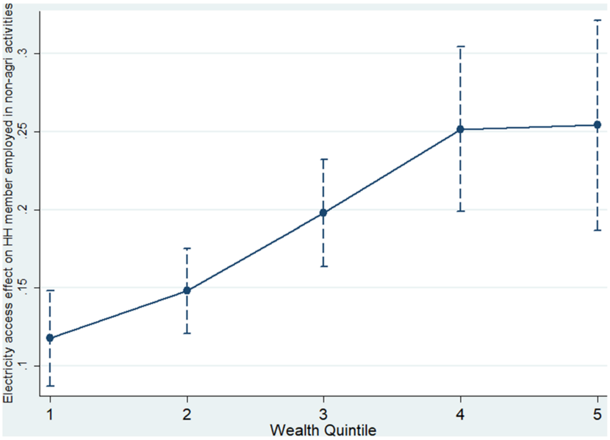

Fig. 8 Marginal effect of electricity access on non-agricultural employment across the wealth quintiles. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

7.1.1 Probit and biprobit robustness checks and expansions

Table 7 presents a series of further probit and biprobit specifications intended both as robustness checks and as a means to verify further hypotheses. The dependent variable is overall employment in columns 1, 2 and 3; agricultural employment in columns 4, 5 and 6; non-agricultural employment in columns 7, 8 and 9. To start with, in columns 1, 4 and 7 we include a dummy variable equal to 1 if the whole village in which the household is located is connected to the grid (self-reported), in order to check whether the effect we attribute to electricity access at the household level is instead due to spill-overs from other households.

It is indeed plausible that a household with access to electricity creates jobs for neighbouring non-electrified households (see Dinkelman 2011). We find evidence for this in our data as the connection dummy is significant regardless of the dependent variable and in the case of agricultural employment, household-level connection becomes insignificant. This is however the only situation in which our variable of main interests loses significance, as for both overall and non-agricultural employment the only variation from the main specification is a slight reduction in magnitude of both coefficients and marginal effects. This suggests that while spill-over effects from village level connection might be predominant in reducing the proportion of household members engaged in agricultural activities, household level connection still plays a relevant role in increasing the proportion of household members engaged in other type of activities, hence influencing overall employment decisions.

After verifying the absence of problems connected to excessive multicollinearity, we include one-period lagged electricity access in columns 2, 5 and 8, to then further add the one-period lagged value of our dependent variable in columns 3, 6 and 9. The inclusion of lagged electricity access gives us an indication of the timespan in which the effect of electricity access plays out, while including lagged employment

Table 7 Biprobit and probit regression coefficients of factors affecting overall, agricultural and non-agricultural household employment outcomes and marginal effects of access to electricity

	(1) Employment	(2) Employment	(3) Employment	(4) Employment, agri	(5) Employment, agri	(6) Employment, agri	(7) Employment, non-agri	(8) Employment, non-agri	(9) Employment, non-agri
Access to electricity	0.90*** (0.30)	0.80** (0.39)	0.84*** (0.30)	− 0.07 (0.07)	− 0.22*** (0.06)	− 0.20*** (0.06)	1.09*** (0.16)	1.29*** (0.16)	1.00*** (0.19)
Connection at village lvl	0.14* (0.09)			− 0.34*** (0.09)			0.37*** (0.07)		
Access to electricity lag		0.18** (0.08)	0.16** (0.08)		− 0.15** (0.06)	− 0.09 (0.06)		0.21*** (0.05)	0.13** (0.06)
Employment lag			0.95*** (0.11)			− 0.72*** (0.07)			1.56*** (0.09)
Household head gender	0.34*** (0.06)	0.34*** (0.08)	0.34*** (0.08)	0.44*** (0.07)	0.45*** (0.07)	0.46*** (0.06)	0.08 (0.06)	0.06 (0.06)	0.10 (0.07)
Household head age	− 0.00*** (0.00)	− 0.01*** (0.00)	− 0.00** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	− 0.01*** (0.00)	− 0.01*** (0.00)	− 0.00** (0.00)
Maximum education	0.00 (0.01)	− 0.00 (0.01)	− 0.00 (0.01)	− 0.00 (0.01)	− 0.01 (0.01)	− 0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
Household size	0.06*** (0.01)	0.07*** (0.01)	0.07*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.06*** (0.01)
LGA density of population	− 3.69 (3.83)	4.84 (7.21)	3.11 (7.32)	− 189.83*** (37.28)	− 199.53*** (40.81)	− 188.77*** (38.14)	1.56 (5.47)	9.87 (9.29)	3.92 (8.31)
Second wealth quintile	− 0.06 (0.09)	− 0.04 (0.10)	− 0.07 (0.09)	− 0.09 (0.06)	− 0.09 (0.07)	− 0.04 (0.07)	0.15*** (0.05)	0.09 (0.06)	0.04 (0.06)
Third wealth quintile	− 0.13 (0.13)	− 0.12 (0.16)	− 0.14 0.13)	− 0.31*** (0.07)	− 0.34*** (0.08)	− 0.22*** (0.08)	0.23*** (0.08)	0.16* (0.09)	0.05 (0.09)
Fourth wealth quintile	− 0.34** (0.16)	− 0.32* (0.19)	− 0.33** (0.16)	− 0.64*** (0.08)	− 0.65*** (0.10)	− 0.50*** (0.10)	0.33*** (0.11)	0.25* (0.13)	0.14 (0.12)

Table 7 (continued)

	(1) Employment	(2) Employment	(3) Employment	(4) Employment, agri	(5) Employment, agri	(6) Employment, agri	(7) Employment, non-agri	(8) Employment, non-agri	(9) Employment, non-agri
Fifth wealth quintile	− 0.22 (0.17)	− 0.21 (0.20)	− 0.19 (0.18)	− 1.03*** (0.11)	− 1.03*** (0.12)	− 0.84*** (0.12)	0.59*** (0.13)	0.47*** (0.15)	0.30** (0.14)
Urban area	− 0.21** (0.10)	− 0.18 (0.12)	− 0.16 (0.11)	− 0.48*** (0.11)	− 0.50*** (0.11)	− 0.45*** (0.11)	0.14 (0.09)	0.16 (0.10)	0.07 (0.09)
Constant	1.03*** (0.22)	1.19*** (0.25)	0.35(0.24)	0.06 (0.17)	0.09 (0.19)	0.40* (0.18)	− 0.61*** (0.17)	− 0.51** (0.19)	− 1.10*** (0.18)
Marginal effect: access to electricity	0.07** 0.04	0.06 0.04	0.06* 0.04	− 0.02 0.02	− 0.06*** 0.02	− 0.05*** 0.02	0.13*** 0.02	0.15*** 0.02	0.10*** 0.02
Distance to the grid	− 0.60** (0.27)	− 0.62** (0.30)	− 0.63** (0.29)				− 0.59** (0.25)	− 0.62** (0.27)	− 0.66** (0.29)
Distance to nearest power plant	− 0.08 (0.06)	− 0.03 (0.10)	− 0.03 (0.09)				− 0.09 (0.05)	− 0.02 (0.08)	− 0.00 (0.09)
Slope of the household		− 0.01 (0.02)	− 0.01 (0.02)					− 0.01 (0.02)	− 0.01 (0.02)
ρ (Rho)	− 0.63** (0.22)	− 0.62** (0.29)	− 0.66*** (0.23)				− 0.72*** (0.14)	− 0.87*** (0.16)	− 0.63*** (0.16)
Number of obs.	11991	7999	7909	11990	7999	7909	11991	7999	7909

The dependent variables are overall employment in columns 1, 2 and 3; agricultural employment in columns 4, 5 and 6; non-agricultural employment in columns 7, 8 and 9. Lagged values of access to electricity (columns 2, 3, 5, 6, 8 and 9) and employment (3, 6 and) as well as a dummy for full connection to the grid in the Local Government Authority (LGA) are included; Rho shows the correlation between the estimated residuals from the first and second stage regression (Wald test of exogeneity); Standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

Table 8 Average marginal effects of access to electricity, labour allocation at t + 1 (upper part), alternative access definition (lower part)

	(1) Overall	(2) Male	(3) Female
Employment at T+1			
Employment	0.05	0.07**	0.02
Agri employment	− 0.07***	− 0.12***	− 0.06***
Non-agri employment	0.15***	0.19***	0.06***
Access to Electricity, alternative definition			
Employment	− 0.03**	− 0.05**	0.02
Agri employment	− 0.08***	− 0.12***	− 0.06***
Non-agri employment	0.14***	0.15***	0.05***

Average marginal effects of access to electricity on overall, agricultural and non-agricultural household employment outcomes, both without and with gender differentiation from biprobit and probit regressions at t + 1 in the upper part of the table and with alternative definition of access in the lower part of the table; *p < 0.1, **p < 0.05, ***p < 0.01. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

values allows us to determine if access to electricity is still a significant predictor of employment shares once we control for the history of labour supply within the household. In almost all cases the coefficients on the lagged variables are significant and with the expected sign, while the effect of electricity access remains significant and with similar magnitude to the previous regressions. However, the average marginal effect on overall employment becomes insignificant in the specification where only lagged electricity access is included, suggesting that the biggest reorganisation of household labour allocation plays out soon after acquiring access.

It is also of interest to try and assess if electricity access still has an effect on household labour allocation in the longer term. To do so, we switch our dependent variables from labour allocation in the current period to labour allocation in the following one, while keeping electricity access at current period. As our dataset only contains three waves, we can only explore changes in the medium term, and furthermore, as biprobit estimation does not allow for panel components, the analysis is not dynamic in nature. Still, if we found that electricity access has a significant impact on future household labour allocation, it would add weight to the stability of the changes brought about by the access. Results are presented in the higher part of Table 8, which only reports the marginal effect for ease of exposition.[8] As it can be seen, all the marginal effects remain significant, with coherent sign and similar magnitude to those obtained when the depended variable is current period. It appears then that the effect of access to electricity remains stable over time, and that households do not revert back to previous labour allocation structure over the medium term.

[8] Full regression results available upon request.

Table 9 Average marginal effects of access to electricity, urban and rural households (upper part), female and male headed households (lower part)

Access to Electricity	(1) Overall	(2) Male	(3) Female
Urban			
Employment	0.07	-0.02	− 0.01
Agri employment	− 0.06***	− 0.07***	− 0.05***
Non-agri employment	0.09*	0.01	0.00
Rural			
Employment	0.00	0.01	0.02
Agri employment	− 0.08***	− 0.09***	− 0.07***
Non-agri employment	0.11***	0.11***	0.07***
Female Headed			
Employment	0.19***	− 0.03	0.14
Agri employment	− 0.10***	− 0.04	− 0.09***
Non-agri employment	0.04*	0.06	0.04*
Male Headed			
Employment	0.01	0.02	− 0.06*
Agri employment	− 0.13***	− 0.14***	− 0.13***
Non-agri employment	0.15***	0.17***	0.16***

Average marginal effects of access to electricity on overall, agricultural and non-agricultural household employment outcomes, both without and with gender differentiation from biprobit and probit regressions on urban and rural households in the upper part of the table and in female and male headed households in the lower part of the table; *p < 0.1, **p < 0.05, ***p < 0.01. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

The lower part of Table 8 presents instead the results when we change our definition of electricity access to household who received at least an hour of electricity per day as opposed to one hour per week. This has a relevant impact on the proportion of households now qualifying, as 24.7% of connected households do not pass this threshold. All marginal effects reported in the table are broadly in line with those obtained using our original definition, with a reduction in agricultural labour and an increase in non-agricultural one. The main difference is represented by the impact on the overall proportion of working household member, which now seems to be slightly lower.

As expansion of our main analysis, we also explore the potential heterogeneity of effects over two different axes, namely the urban and rural households firstly and female and male headed households secondly. In both cases we obtain these estimates by dividing the sample over these two categories, as including interaction terms between our electricity access variable and the relevant dummy would automatically imply including a second endogenous regressor. While this would not be an issue from an identification point of view—we always include more than one instrument—current routines for biprobit estimation only allow for a single endogenous regressor. Even in this case we only report average marginal effects for both these sets of robustness checks for ease of exposition.[9]

We present the results for the regression where the sample has been split between rural and urban households in Table 9. Prior to the analysis of the marginal effects, it must be noted that this division greatly decreases the incidence of endogeneity in the relationship between electricity access and labour allocation, as we only find evidence to support the application of biprobit estimation for urban overall and non-agricultural employment (column 1 in the top part of the table) and for rural male agricultural and non-agricultural employment (column 2 in the upper-medium part of the table). This implies that there might be relevantly different channels in which access to electricity and labour allocation interact across the urban and rural divide. With regard to the marginal effects, it can be noted that for urban households only the decrease in agricultural employment remains strongly significant, while there is only scant evidence of an effect on non-agricultural labour allocation, and only when the gender divide is ignored. On the other hand, for rural households both effects remain significant, but very close in magnitude, so that there is no perceivable effect on overall labour allocation.[10]

The lower part of Table 9 reports the average marginal effect of electricity access for all the different types of employment considered across female and male headed household. To start with, we find less evidence of an endogenous relationship between access to electricity and household labour allocation for female headed household than for male headed ones. For the former, only overall and female labour allocation show signs of endogeneity (first line of columns 1 and 3, lower-medium part of the table), while for the latter only overall and male labour allocation do not (first line of columns 1 and 2, lower part of the table). This suggests that gender power-dynamics play a role in shaping both the decision to acquire an electricity connection and intra-household labour allocation. This could also be observed by the fact that we find no significant effect on male labour allocation in female headed households, while for male headed ones all marginal effects are of greater magnitude and that of overall female labour allocation has a negative sign, although only significant at the 10% level.[11]

[9] Full regression results available upon request.

[10] As the timing of grid expansion is also likely to have been different between urban and rural areas, we also tried including lagged access to electricity in both urban rural split samples to see if this significantly impacts the results, which remain largely consistent. Results are available upon request.

[11] The discrepancy between the magnitude of female overall employment and those where the type of employment is divided arises from the fact that while the first is obtained via biprobit estimation, the latter are both obtained via probit estimation. While we find some evidence of endogeneity in the relationship between non-agricultural labour allocation and access to electricity for female headed household, none of our usual instrument is significant, so we prefer the marginal effect obtained through the probit estimation. However, the latter might suffer from under-estimation.

7.2 Propensity score matching analysis

We now move to the analysis of the results obtained through PSM analysis, which we performed both through nearest neighbour and through Kernel matching algorithms, in both cases imposing a restriction so to consider only observations which fall within the common support. Regarding the set of covariates used to calculate the propensity score (PS), we first considered using exactly the same variables included in the baseline probit or biprobit analysis, but then opted for a reduction in the number of covariates so as to achieve a better overall balance. However, to ensure that households in both the treated and the untreated groups are comparable, we also include both instruments used in most biprobit estimations, namely the slope of the household site and distance to the grid. Both in the case of nearest neighbour and Kernel matching, Rubin's B and R fall within the acceptable threshold and the matching achieves a very significant reduction in covariates imbalance between the two groups, so that no covariate is flagged as being of concern after matching. Average treatment effects are also widely comparable in the two cases.

Table 10 above presents the results of the logistic regression from which the PS of the chosen specification were obtained, together with a series of measures of the balancing of covariates achieved by the matching. As it can be seen from the table, with the exclusion of age of the household head and of the distribution of the third wealth quintile, all other covariates experience a significant reduction in bias after matching (94.1% on average). While those two variables experience an increase in imbalance after matching—and a fairly noticeable one in the case of the third wealth quintile—their Rubin's ratio of the variance of residuals, reported in the last column, is still within the acceptable boundaries (above 0.8 and below 1.25) to conclude that such imbalance is not cause of concern (Rubin 2001). As a consequence, both Rubin's R and B—reported in the lower part of the table—are well within the thresholds required to consider the distribution of covariates across the two groups as balanced (an R between 0.5 and 2 and a B lower than 25, Rubin 2001).

Table 11 presents then the average treatment effect on the treated, along with the Abadie and Imbens (2006) standard errors and the correspondent t-statistic. The resulting picture is somewhat similar from that emerging from the probit and biprobit analysis, with a reduction in the proportion of household members employed in agricultural activities twice the size of the increase of those employed in non-agricultural ones. However, there does not seem to be any significant effect on overall employment.. The exact same picture emerges with regard to male employment, while a significant reduction in agricultural female employment is not matched by any increase in the non-agricultural one—with a nonetheless insignificant effect on overall employment.

In Tables 12 and 13 Kernel matching has been used instead of nearest neighbour. The overall balance is very close to that achieved by the previous technique, with now only the third wealth quintile experiencing an increase in imbalance after matching but with an average reduction in imbalance for the remaining covariates somewhat smaller than with nearest neighbour matching (82.4%). The picture emerging from the average treatment effect is also very close to that of the previous case, with the only difference being that now the increase in non-agricultural

Table 10 Logistic regression of access to electricity on factors affecting household employment outcomes as basis for Propensity Score Matching using nearest neighbour algorithm

Variable	PS Logit		Matched	Mean		Bias		Equality of means		Rubin ratio of residuals Var
	Coeff.	Std. Err.		Treated	Control	Std. Bias	Bias Red. (%)	t	p > t	
Household head gender	− 0.216***	(0.062)	Before	0.80942	0.86368	− 14.7	95.4	− 8.32	0	1.34*
			After	0.81708	0.81459	0.7		0.35	0.725	1
Household head age	0.003**	(0.002)	Before	51.516	50.964	3.8	− 51.2	2.13	0.033	0.97
			After	51.444	52.278	− 5.7		− 3.23	0.001	1.11
Maximum education	0.057***	(0.005)	Before	11.285	7.5825	79.3	97.9	44.49	0	0.72*
			After	11.239	11.318	− 1.7		− 1.05	0.293	1.02
Household size	− 0.028***	(0.008)	Before	5.5676	6.1583	− 18.7	84.1	− 10.55	0	0.91
			After	5.5871	5.4934	3		1.71	0.087	1.16
Second wealth quintile	0.914***	(0.085)	Before	0.098	0.29401	− 51	98.6	− 28.48	0	0.34**
			After	0.099	0.09619	0.7		0.52	0.602	1.04
Third wealth quintile	1.683***	(0.083)	Before	0.20141	0.20268	− 0.3	− 1484.2	− 0.18	0.859	0.99
			After	0.20348	0.22355	− 5		− 2.69	0.007	0.97
Fourth wealth quintile	2.438***	(0.088)	Before	0.30433	0.11345	48.3	95.7	27.44	0	2.72**
			After	0.30746	0.29934	2.1		0.97	0.332	1.02
Fifth wealth quintile	3.051***	(0.099)	Before	0.359	0.05357	81.5	98.4	46.6	0	3.51**
			After	0.3524	0.34743	1.3		0.57	0.567	1.01
Slope	− 0.054***	(0.009)	Before	2.8022	2.9146	− 4.3	79.1	− 2.4	0.017	0.74*
			After	2.8163	2.7928	0.9		0.56	0.578	1.23
Distance to the grid	− 1.69***	0.111	Before	0.12438	0.26956	− 65.1	98.9	− 36.45	0	0.50**
			After	0.12552	0.12705	− 0.7		− 0.49	0.624	1.24
Urban area	1.294***	(0.052)	Before	0.52626	0.11135	99.4	99.2	56.59	0	1.81*
			After	0.52139	0.51824	0.8		0.35	0.729	0.99

Table 10 (continued)

Variable	PS Logit		Matched	Mean		Bias		Equality of means		Rubin ratio of residuals Var
	Coeff.	Std. Err.		Treated	Control	Std. Bias	Bias Red. (%)	t	p > t	
Sample Statistics	Ps R2	LR chi2	p > chi2	Mean bias	Median bias	b	r			
	0.002	35.39	0	2.4	1.3	11.3	0.99			

The columns include (1) Propensity Score (PS) Logit, Standard errors are in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$, Likelihood Ratio (LR) chi-squared test; (2) Mean values of the regressors among households with (Treated) and without (Control) access to electricity before and after matching and chi-squared test; standardized bias and percent of bias reduced including Rubin's R and B; equality of means t-statistic and p-value; Rubin's ratios comparing the variance of continuous covariates between treated and untreated before and after matching, * of concern, ** problematic. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

Table 11 Average treatment effect on the treated of access to electricity on employment outcomes based on Propensity Score Matching using nearest neighbour algorithm

Access to Electricity	ATT	Std. Err.	T-stat
Employment	− 0.009	0.012	− 0.8
Agri employment	− 0.103	0.014	− 7.4
Non-agri employment	0.063	0.128	4.92
Male employment	− 0.002	0.014	− 0.16
Male agri amployment	− 0.104	0.016	− 6.48
Male non-Agri employment	0.068	0.015	5.07
Female employment	0.027	0.014	− 1.92
Female agri employment	− 0.1	0.016	− 6.46
Female non-agri employment	0.023	0.015	1.49

The columns include the estimated average treatment effect of the treated (ATT), standard errors and t-statistics for overall employment, agricultural (agri) employment and non-agricultural (non-agri) employment. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

female employment is also significant, but with a still insignificant impact on overall employment.

As in the case of the probit and biprobit analysis, we also assess the extent of the heterogeneity between the average effects for urban and rural households by recalculating the propensity score for these two groups separately. Table 14 presents the average treatment on the treated for urban and rural households when matching is performed through the nearest neighbour algorithm.[12] In this case, the results are very similar to those of the probit and biprobit analysis. For urban households, there is a negative and significant effect on agricultural labour allocation but not any perceivable one on non-agricultural labour. On the other hand, for rural households the reduction in agricultural labour is matched by an increase in non-agricultural one, with the former being somewhat bigger in magnitude than the latter.

7.3 Discussion

As we have seen in the previous sections, applying techniques which are based on different sets of assumptions lead to results which are logically only broadly comparable. As previously stated, PSM assumes that observable characteristics are sufficient to establish treatment and comparison groups and that unobservable characteristics are ignorable, while biprobit analysis assumes that the latter are present and that will directly impact both selection within the treatment group and the outcome of interest. In the absence of unobserved confounding factors, estimates from the

[12] For ease of exposition we do not report the ATT when Kernel matching is employed instead. These results, as well as all tables for the calculation of the new propensity scores and for covariate imbalance testing are available upon request.

Table 12 Summary statistics for Propensity Score Matching using Kernel Matching algorithm

Variable	Matching	Mean		Bias		Equality of means		Ratio of var residuals
		Treated	Control	Std. Bias	Bias Red. (%)	t	p >t	
Household head gender	Before	0.80942	0.86368	− 14.7	96.2	− 8.32	0	1.34*
	After	0.81708	0.81499	0.6		0.3	0.767	1
Household head age	Before	51.516	50.964	3.8	21.1	2.13	0.033	0.97
	After	51.444	51.879	− 3		− 1.68	0.093	1.08
Maximum education	Before	11.285	7.5825	79.3	97.2	44.49	0	0.72*
	After	11.239	11.135	2.2		1.39	0.165	1
Household size	Before	5.5676	6.1583	− 18.7	91.7	− 10.55	0	0.91
	After	5.5871	5.6361	− 1.6		− 0.9	0.369	1.11
Second wealth quintile	Before	0.098	0.29401	− 51	99.8	− 28.48	0	0.34**
	After	0.099	0.09863	0.1		0.07	0.945	1
Third wealth quintile	Before	0.20141	0.20268	− 0.3	-699.2	− 0.18	0.859	0.99
	After	0.20348	0.21361	− 2.5		− 1.37	0.171	0.97
Fourth wealth quintile	Before	0.30433	0.11345	48.3	90.9	27.44	0	2.72**
	After	0.30746	0.32477	− 4.4		− 2.04	0.041	0.98
Fifth wealth quintile	Before	0.359	0.05357	81.5	91.5	46.6	0	3.51**
	After	0.3524	0.32646	6.9		3.01	0.003	1.06
Slope	Before	2.8022	2.9146	− 4.3	42.5	− 2.4	0.017	0.74*
	After	2.8163	2.881	− 2.5		− 1.51	0.131	1.11
Distance to the grid	Before	0.12438	0.26956	− 65.1	94.3	− 36.45	0	0.50**
	After	0.12552	0.13374	-3.7		-2.6	0.009	1.11
Urban area	Before	0.52626	0.11135	99.4	99.3	56.59	0	1.81*
	After	0.52139	0.51842	0.7		0.33	0.744	0.99
Sample Statistics		Ps R2	LR chi2	p > chi2	Mean bias	Median bias	B	R
		0.001	22.39	0.022	2.6	2.5	8.6	1.18

The columns include (1) Likelihood Ratio (LR) chi-squared test; (2) Mean values of the regressors among households with (Treated) and without (Control) access to electricity before and after matching and chi-squared test; standardized bias and percent of bias reduced including Rubin's R and B; equality of means t-statistic and p-value; Rubin's ratios comparing the variance of continuous covariates between treated and untreated before and after matching, * of concern, ** problematic. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

two methods should be fairly close to each other, while if unobservable characteristics are indeed present then the estimates should differ more substantially.

This is indeed the case, as a comparison between PSM and biprobit estimates for overall and non-agricultural employment clearly points out (see Fig. 9). When the presence of confounding factors is ignored, the coefficients are downwardly biased, leading to an under-estimation of the impact of electrification on non-agricultural labour participation and subsequently to an under-estimation of the

Table 13 Average treatment effect on the treated of access to electricity on employment outcomes based on propensity score matching using Kernel matching

Access to Electricity	ATT	Std. Err.	z	P > z
Employment	− 0.007	0.008	− 0.86	0.39
Agri employment	− 0.093	0.011	− 8.43	0.00
Non-agri employment	0.055	0.011	5.09	0.00
Male employment	0.002	0.010	0.16	0.88
Male agri amployment	− 0.099	0.013	− 7.93	0.00
Male non-Agri employment	0.072	0.011	6.63	0.00
Female employment	− 0.016	0.011	− 1.47	0.14
Female agri Employment	− 0.086	0.011	− 7.86	0.00
Female non-agri employment	0.035	0.012	2.89	0.00

The columns include the estimated average treatment effect of the treated (ATT), standard errors and t-statistics for overall employment, agricultural (agri) employment and non-agricultural (non-agri) employment. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16]

Table 14 Average treatment effect on the treated of access to electricity on employment outcomes based on propensity score matching using nearest neighbour matching for urban and rural households

Access to Electricity	Urban			Rural		
	ATT	Std. Err.	T-stat	ATT	Std. Err.	T-stat
Employment	− 0.008	0.020	− 0.38	− 0.009	0.010	− 0.82
Agri employment	− 0.092	0.022	− 4.13	− 0.1	0.016	− 6.4
Non-agri employment	0.026	0.020	1.3	0.087	0.015	5.9
Male employment	− 0.004	0.024	− 0.16	− 0.004	0.011	− 0.37
Male agri amployment	− 0.078	0.025	− 3.07	− 0.125	0.019	− 6.49
Male non-Agri employment	0.028	0.023	1.21	0.1	0.019	5.31
Female employment	− 0.034	0.023	− 1.47	− 0.015	0.014	− 1.03
Female agri Employment	− 0.114	0.025	− 6.46	− 0.08	0.018	− 4.36
Female non-agri employment	− 0.012	0.025	− 0.49	0.059	0.018	3.25

The columns include the estimated average treatment effect of the treated (ATT), standard errors and t-statistics for overall employment, agricultural (agri) employment and non-agricultural (non-agri) employment. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

overall effects on labour allocation within the household. On the other hand, for agricultural employment (and to some extent for female non-agricultural employment), where the data rejects the presence of unobserved confounding factors, estimates from the two methods are very similar. A similar point can also be made for the similarity of the results between the two techniques when the sample is divided across rural and urban households, as this further differentiation should also reduce the impact of confounding factors.

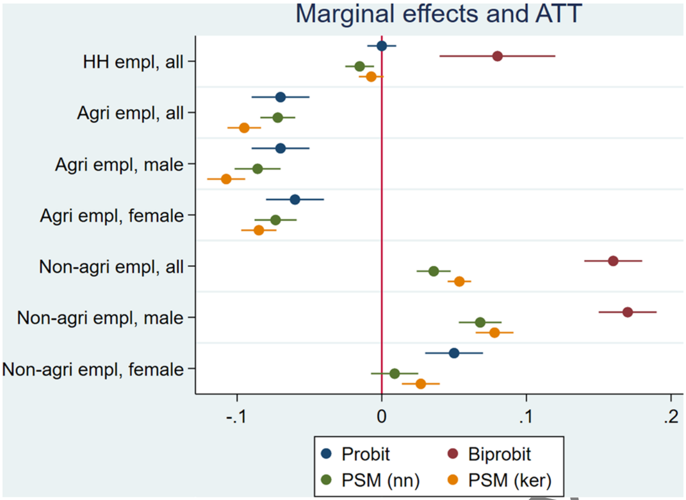

Fig. 9 Marginal effects and ATT of access to electricity on household employment outcomes. Note: the chart shows marginal effects (for probit and biprobit models) and ATT (for PSM models), with the respective 95% confidence interval. ATT = Average Treament effect on the Treated; PSM = Propensity Score Matching; nn = Nearest Neighbour; ker = Kernel matching. Source: Authors' estimation using data from the Nigerian General Household Survey 2010/11, 2012/13 and 2015/16

It is then of crucial importance to evaluate the appropriateness of different assumptions on a case by case basis, and the application of diverse techniques can help to decide when the evidence points towards one outcome or another.

8 Conclusion and policy implications

This article aims to provide a better understanding of the effects of electricity access on labour market outcomes in Nigeria. We assess, through a rigorous econometric analysis carried out employing diverse techniques, the impact on the proportion of employed working-age household components, decomposed between female and male employment, and agricultural and non-agricultural employment.

Our results show that the presence of endogeneity in the relationships under investigation must be taken into account but should not simply be assumed. We found evidence of its relevance for overall and non-agricultural employment but not for agricultural employment, possibly due to the relevance of village level connection for that outcome. Different patterns also emerge when the analysis is differentiated between urban and rural households—with much more evidence of an endogenous relationship between investment in acquiring a connection to electricity and labour allocation choices for the latter than for the former. Results when we look separately at male and female headed households are less conclusive.

Once all of these aspects have been considered, we show that the overall proportion of employed household members in working age increases on average by a little more than 8%. This change is brought about by a shift out of agricultural employment of around 7% and into non-agricultural employment of about 15%. While the effects do not differ particularly for male and female employment in agricultural activities, the effects for male employment in non-agricultural activities appear to be thrice as strong as those for female employment. These results are robust to the inclusion of other variables such as the electricity connection at village level, former connection status of the household, or former employment level in different sectors. While the divergence between biprobit and PSM estimates confirms that the presence of unobserved confounding factors is relevant for overall and non-agricultural employment, the convergence between probit and PSM estimates indicates that this is not the case for agricultural employment. Furthermore, there is evidence that the effect on non-agricultural employment is mainly driven by rural households, while the shift out of agricultural employment is relevant for both rural and urban ones.

These findings have important policy implications as they illustrate that the expansion of electricity access to households which are not yet connected to the grid could play a relevant role in both increasing labour market participation and in helping the transformation of the Nigerian economy away from agricultural activities. Similarly to previous literature, our results show that in Nigeria this effect is stronger for wealthier households and in urban areas. Importantly, however, positive effects are still significant also for poorer households and in rural areas. Indeed, an average household from the lowest wealth quintile living in a rural area will experience an increase in the proportion of employed household members of 3.6%, and a significant reallocation of employment towards non-agricultural activities (+9.6%).

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