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YSSP Report
Young Scientists Summer Program

IMPACTS OF GRID ELECTRICITY ACCESS ON RURAL NON-FARM ENTREPRENEURSHIP AND EMPLOYMENT IN ETHIOPIA AND NIGERIA

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Approved by

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Program: ENE/TNT
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Abstract

Rural electricity supply is broadly considered a key driver of the structural transformation away from a dependence on agricultural livelihoods. Nevertheless, the causal effect of improving electricity access on the diversification of rural livelihoods away from agricultural incomes remains poorly understood. Recent systematic syntheses of electrification impacts in literature confirm that there remains limited quasi-experimental quantitative evidence describing the effects of electrification on non-farm entrepreneurship and labor market outcomes in Sub-Saharan African countries. In this report, we investigate the causal effects of household-level electrification on household non-farm entrepreneurship and employment trends in rural Ethiopia and Nigeria, contributing to the literature in terms of the geographical region of analysis and through the application of modern quasi-experimental methods. We analyze household-level observational panel datasets collected under the World Bank's Living Standards Measurement Survey (LSMS) program, between 2010 and 2015. Our analysis indicates that rural household electrification alone was insufficient to trigger shifts in household non-farm entrepreneurship and labour market outcomes in the 2-4 years following grid connection. These findings are aligned with contemporary rural electrification impact literature urging caution in the interpretation of descriptive and potentially biased analyses that are unable to effectively disentangle the many co-determinants of non-farm entrepreneurship and labour market outcomes with respect to electrification.

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About the authors

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Introduction

Providing all populations around the world with reliable, sustainable and affordable access to electricity is a key component of the Sustainable Development Goals set for the year 2030 (UN, 2015). The development effects of this goal have been discussed at length in literature, ranging from improvements to economic development and education to gender equality and healthcare (McCollum et al., 2018).

Although one of the broader development effects of improved electricity supply is considered to be the structural transformation of the economy away from a dependence on agricultural livelihoods. Their remains little robust evidence describing the causal effect of improving electricity access on the diversification of rural livelihoods away from agricultural incomes in regions with developing infrastructure, such as Sub-Saharan Africa. While there is no doubt that access to electricity unlocks energy services such as lighting, cooling and reduces mechanical drudgery – arguably all prerequisites for economic growth – the effects of this service provision on rural non-farm entrepreneurship and household non-farm employment are contested.

In this report, we contribute to the sparse literature through analysis of the causal effects of household-level electrification on household non-farm entrepreneurship and employment trends in rural Ethiopia and Nigeria using household-level observational panel datasets collected between 2010 and 2015. We provide new evidence in regions with limited electrification impact analysis and demonstrate the use of robust identification strategies in delineating the causal effects of electrification from a myriad of co-determinants and confounding factors.

Background

Robust causal inference requires disentangling the effects of electrification from other determinants of non-farm entrepreneurship and employment, such as access to roads and finance, the effects of which are heterogenous and unclear themselves. For example, access to credit was found to be a robust determinant of non-farm entrepreneurship in just two of the six countries across Sub-Saharan Africa (including Ethiopia but not Nigeria) for which nationally representative panel data was available (Owoo and Naudé, 2016; Nagler and Naudé, 2017). Similarly, while a robust relationship with the distance to roads or markets was not able to be identified in any of African literature (Owoo and Naudé, 2016; Davis et al., 2017; Broeck and Kilic, 2019), looking beyond Sub-Saharan Africa, positive relationships between distance to road infrastructure and non-farm entrepreneurship were found in both rural Indonesia (Gibson and Olivia, 2010) and rural India (Rao, 2013).

In the few studies investigating the effects of electricity access on rural household non-farm entrepreneurship, literature finding positive associations, for example with non-farm entrepreneurship incidence in Indonesia and Nigeria (Gibson and Olivia, 2010; Tagliapietra et al., 2020), and non-farm incomes in India (Rao, 2013) has been recently debated on the grounds of their reliance on relatively strong methodological assumptions and a concern of endogeneity between household electrification and household-level non-farm enterprise outcomes (Lee et al., 2020). This recent critique is discussed in the context of a randomized controlled trial finding limited evidence of broad socioeconomic outcomes (including non-farm entrepreneurship) following electrification in rural Kenya, with positive effects restricted to those few households with a high willingness to pay for a grid connection (Lee et al., 2020). Notwithstanding the fact that work to find sound identification strategies is clearly still evolving, the lack of consensus is also likely to be in part due to differences in contexts, cultures and social norms regarding entrepreneurship and differences between short-term and long-term outcomes.

Looking beyond household-level entrepreneurship, the literature describing broader labor market effects of rural electrification is both less optimistic and less contentious, perhaps due to the likely exogeneity between household member employment changes and a household's decision to connect to the national grid. That is to say, trends in household member employment outside the home are linked to broader shifts in the local economy (i.e. the creation of new jobs in the local area following electrification) that have little to do with an individual household's decision to connect to the national grid, easing the identification challenges described above. Not surprisingly, aside from the recent work of Tagliapietra et al. (2020), which found a positive effect on non-farm employment in Nigeria, and the much debated seminal work by Dinkelman (2011), which found a strong benefit on women's labor market participation in South Africa, all of the literature investigating the effects of rural electrification on non-farm employment in both Sub-Saharan Africa and in Asia fails to identify a robust causal relationship between household electrification and employment outcomes (Walle et al., 2015; Burlig and Preonas, 2016; Salmon and Tanguy, 2016; Samad and Zhang, 2017; Lee et al., 2020). The broader conclusion we can draw here is not that electrification is unrelated to labor market outcomes, but rather, that further analysis of differences in short-term and long-term trends following electrification is necessary, alongside continued work on robust identification methods.

Overall, our brief review of the literature indicates that although newer studies are trying to distinguish between short-term and longer-terms effects of electrification on non-farm entrepreneurship and employment outcomes, further efforts are needed to fill in the geographic and methodological gaps. Recent systematic syntheses of electrification impact literature confirms that there remains limited quasi-experimental quantitative evidence describing the effects of electrification on non-farm entrepreneurship and labor market outcomes in Sub-Saharan African countries (Bayer et al., 2019; Hamburger et al., 2019). This motivates our selection of our case study countries, Nigeria and Ethiopia, discussed in the following section.

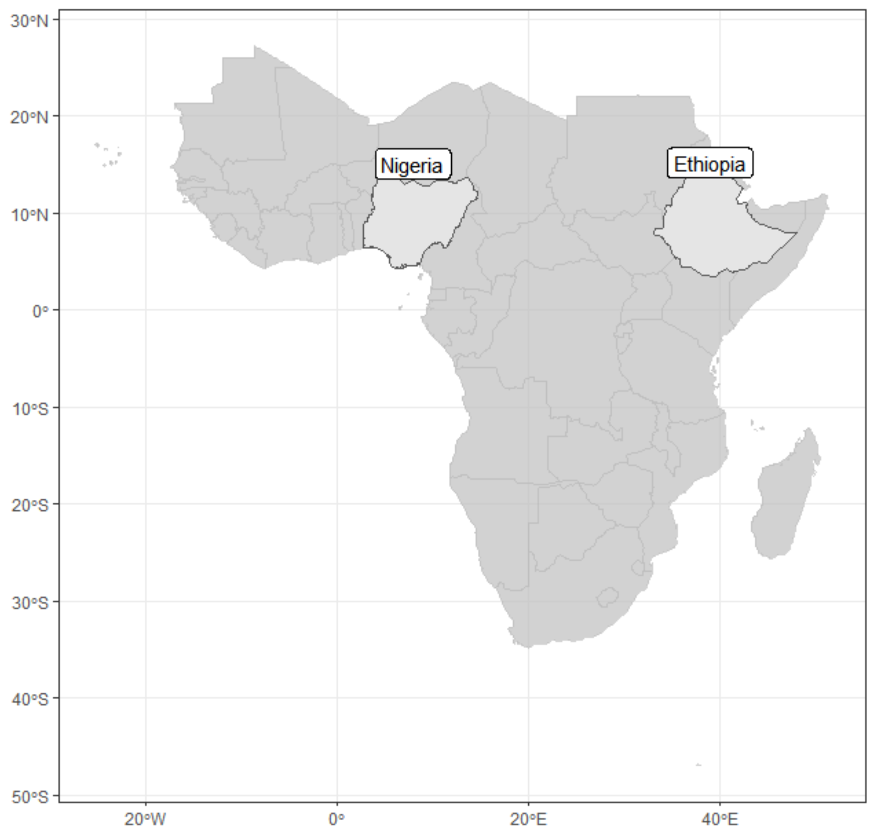

Figure 1 Map of Sub-Saharan Africa, showing the two case study countries.

Case study countries

In this project, we select rural Nigeria and Ethiopia as two very different country contexts in terms of economic power, rural development and rural electricity access baselines. These two countries also feature representative household survey panel datasets collected through the World Bank's Living Standards Measurement Survey program, covering a timespan of five years between 2010 and 2015.

Nigeria, located in the west, boasts the largest economy in Sub-Saharan Africa, whereas Ethiopia, located in the east, remains largely agrarian, with over two-thirds of the population reliant on agricultural incomes (see Figure 2). In terms of economic development, Nigeria reported over three times the GDP per capita relative to Ethiopia in 2016, however life expectancies were higher in Ethiopia (65 years versus 53 years in 2015)[1].

Baseline rural electricity access rates in Nigeria and Ethiopia also depict two differing starting points. Although both countries reported an urban electrification rate of around 85% in 2016, 41% of the rural population in Nigeria reported having access to the national grid in 2016, whereas, only 26% of the population in rural Ethiopia reported having access to the national grid in the same year (see Figure 3).

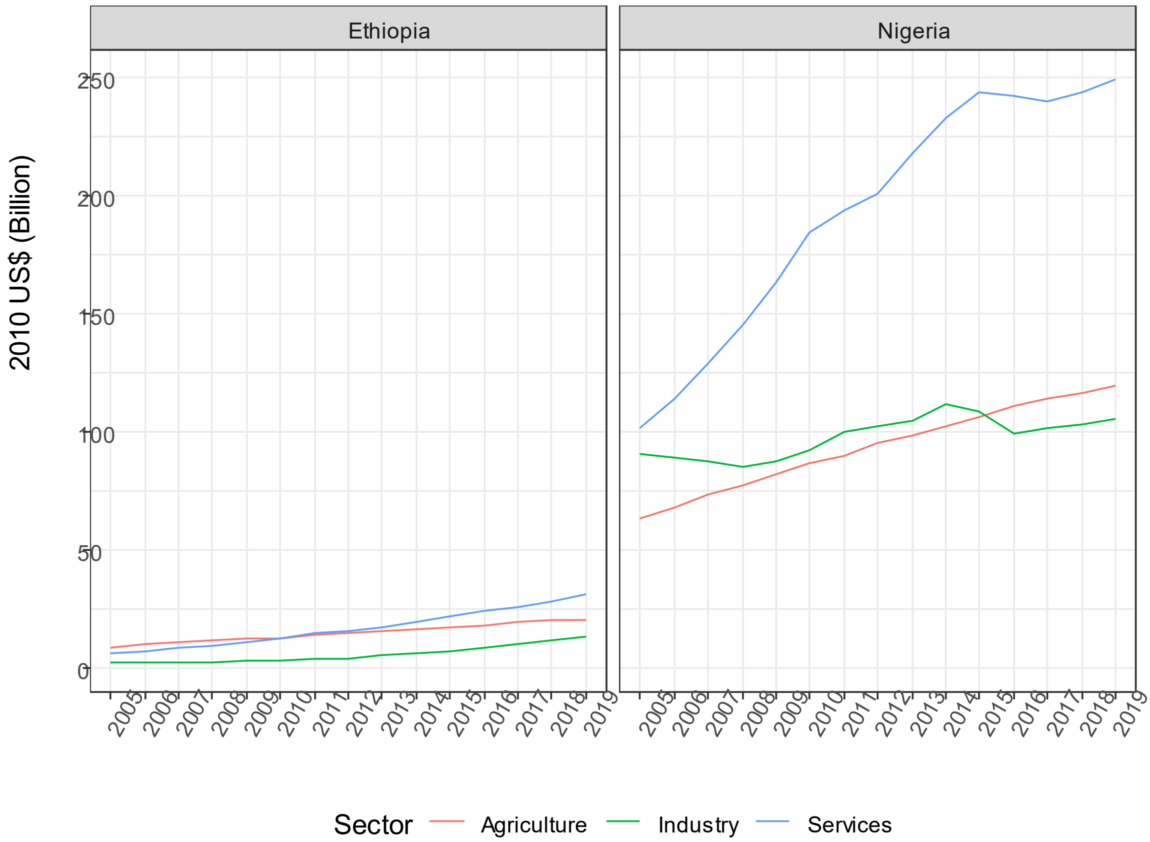

Figure 2 Structure of economic output (GDP) in Ethiopia and Nigeria[1].

Overall, Nigeria and Ethiopia represent two very different country contexts and are thus ideal to study the causal effects of electrification on household non-farm entrepreneurship and employment outcomes with different starting points, contributing to the sparse literature in terms of the geographical region of analysis and through the application of modern quasi-experimental methods described in the following section.

[1] World Development Indicators, The World Bank

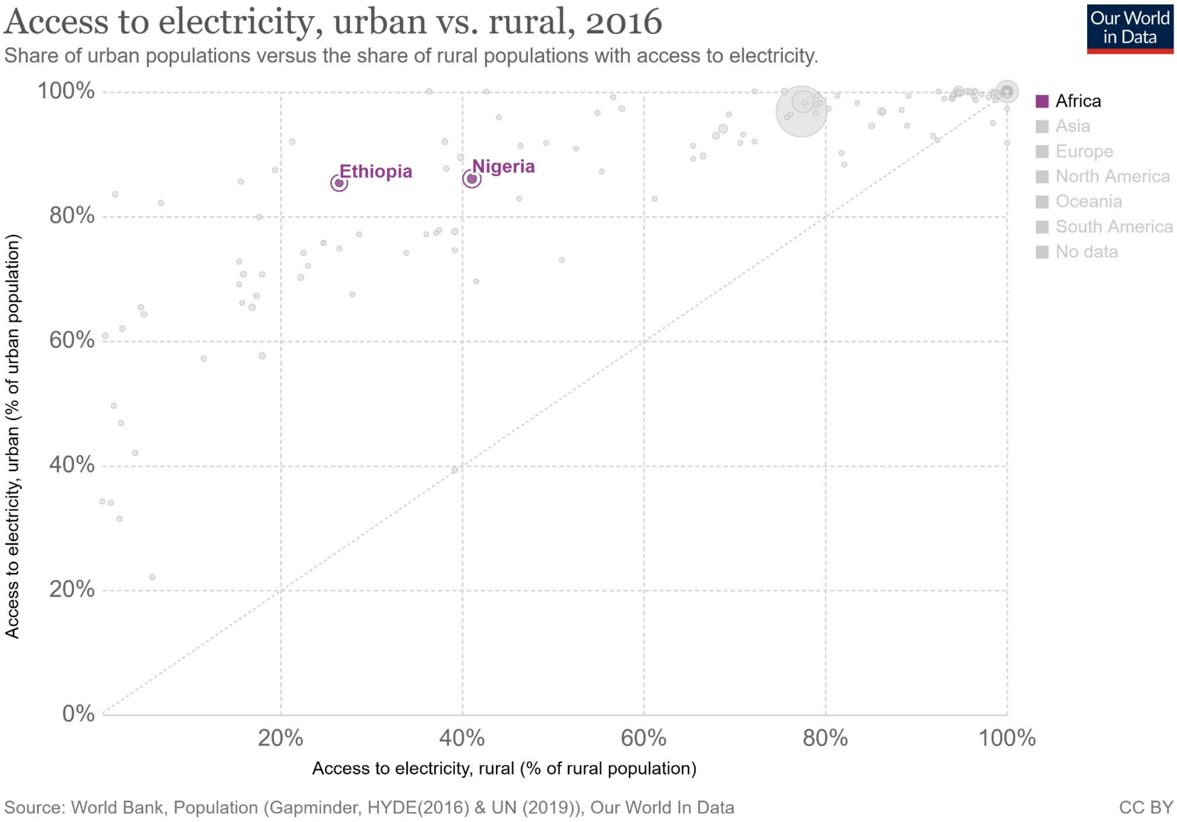

Figure 3 Rural and urban access to electricity in Ethiopia and Nigeria.

Research Design

In this work, we analyse the Nigerian and Ethiopian Living Standards and Measurement Survey (LSMS) surveys collected by the World Bank in collaboration with national statistics agencies between 2010 and 2016. The surveys consist of individual, household and community surveys conducted with tracked households and individuals over three waves across both urban and rural areas of the country.

We restrict our analysis to rural areas of both countries as defined by the LSMS rural-urban indicator and compare differences in outcomes between the baseline year (2010 in Nigeria; 2011 in Ethiopia) and the end year (2015 in both Nigeria and Ethiopia). Extensive data cleaning and processing was necessary to enable this analysis. R programming language scripts to process raw LSMS survey data in a transparent and reproducible manner can be found in the appendices.

Estimation

The methodological challenges posed by unmeasured confounding variables motivates our usage of a robust difference-in-differences (DiD) estimator developed by Sant'Anna and Zhao (2020) to identify the causal effect of household electrification on several outcomes relating to a transition away from agricultural livelihoods.

The intuition behind this methodological approach is to remove, as far as possible, the influence of unmeasurable confounders as well as endogeneity concerns by i) creating a robust counterfactual (i.e. as good as identical and thus having the same likelihood to be treated, in aggregate terms) from the treatment group, conditional on a set of covariates and ii) comparing the difference in outcomes between baseline and end years across the groups, thus removing the absolute differences in outcomes between the groups at baseline.

Our reasoning for using this approach rather than traditional DiD estimation is that the latter relies on a relatively strong "parallel trends" assumption which is often challenging to justify. That is, practitioners must assume that the two groups, treatment and control, are almost identical and trend in parallel prior to the treatment taking effect, as shown in Figure 3. As we do not have data on outcomes prior to the baseline year, we are unable to robustly defend such an assumption.

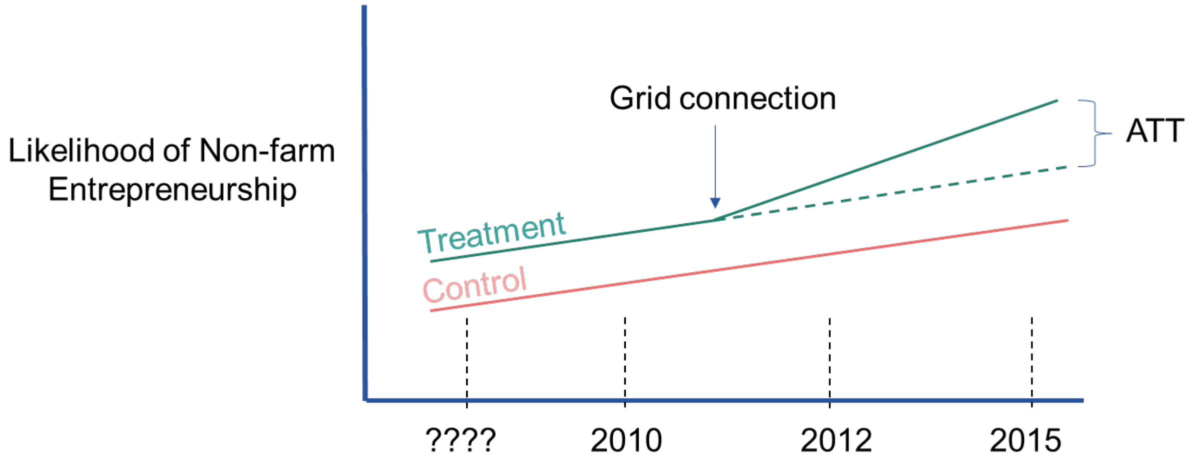

Figure 4 Parallel trends assumption necessary for estimation of average treatment effect on the treated (ATT).

The estimation method we apply can be broken down into three steps. First, we identify consistent treatment and control groups of households, to distinguish between those that gained connection to electricity from those that did not. This is necessary to compare aggregate changes across these groups over time.

Then, we weight households in the control group by their similarity to those in the treatment group using a collection of village- and household-level covariates in the baseline year. This is done through a logistic propensity score model that predicts the likelihood of a control household being in the treatment group, conditional on a set of covariates in the baseline year. This weighting approach theoretically ensures, in aggregate terms, that the control group represents the counterfactual for the treatment group. Finally, we effectively compare the weighted average differences in outcomes over time between the two groups (through regression analysis), giving us the average treatment effect on the treated or the ATT (i.e. the treatment effect for households in the treatment group).

Formal definition of the causal model used to estimate the ATT is provided in Equation 3.1 of Sant'Anna and Zhao (2020), alongside proofs and a Monte Carlo simulation demonstrating the bias reduction achieved[2].

Treatment designation

To enable a comparison of differences in outcomes for consistent groups, we retain only those households present in both survey waves and that did not move house. This leaves a total of 2971 households in Ethiopia (of the original 3170 rural households surveyed in 2011) and 2630 households in Nigeria (of the original 3103 rural households surveyed in 2010).

[2] Open source R software for applying this approach for policy evaluation is provided here: https://pedrohcgs.github.io/DRDID/reference/drdid.html.

We define the treatment group as those that gained connection to the national grid between baseline and end years, and the control group as those households that never received a grid connection. Households that either always had a grid connection, or gained and lost this between the baseline and end years are removed from our analysis.

Figure 1 and Figure 2 describes both treatment and control group assignment as well as whether households had a grid connection in each survey wave.

Ethiopia	Description	Households
Treatment Group	Get grid connection	173
Control Group	Never grid connected	2,499

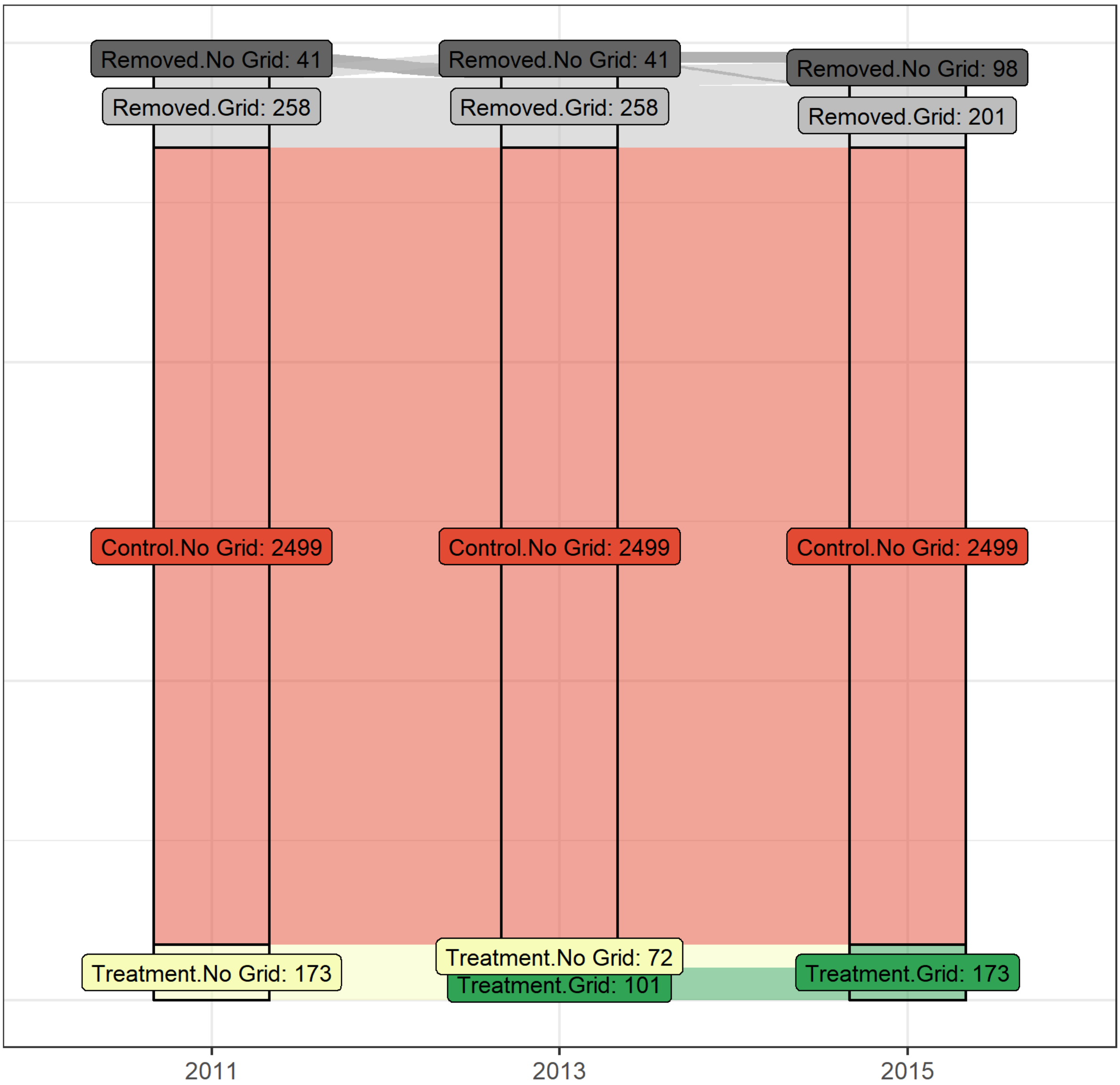

Figure 5 Treatment assignment diagram (Ethiopia)

Nigeria	Description	Households
Treatment Group	Get grid connection	345
Control Group	Never grid connected	1,401

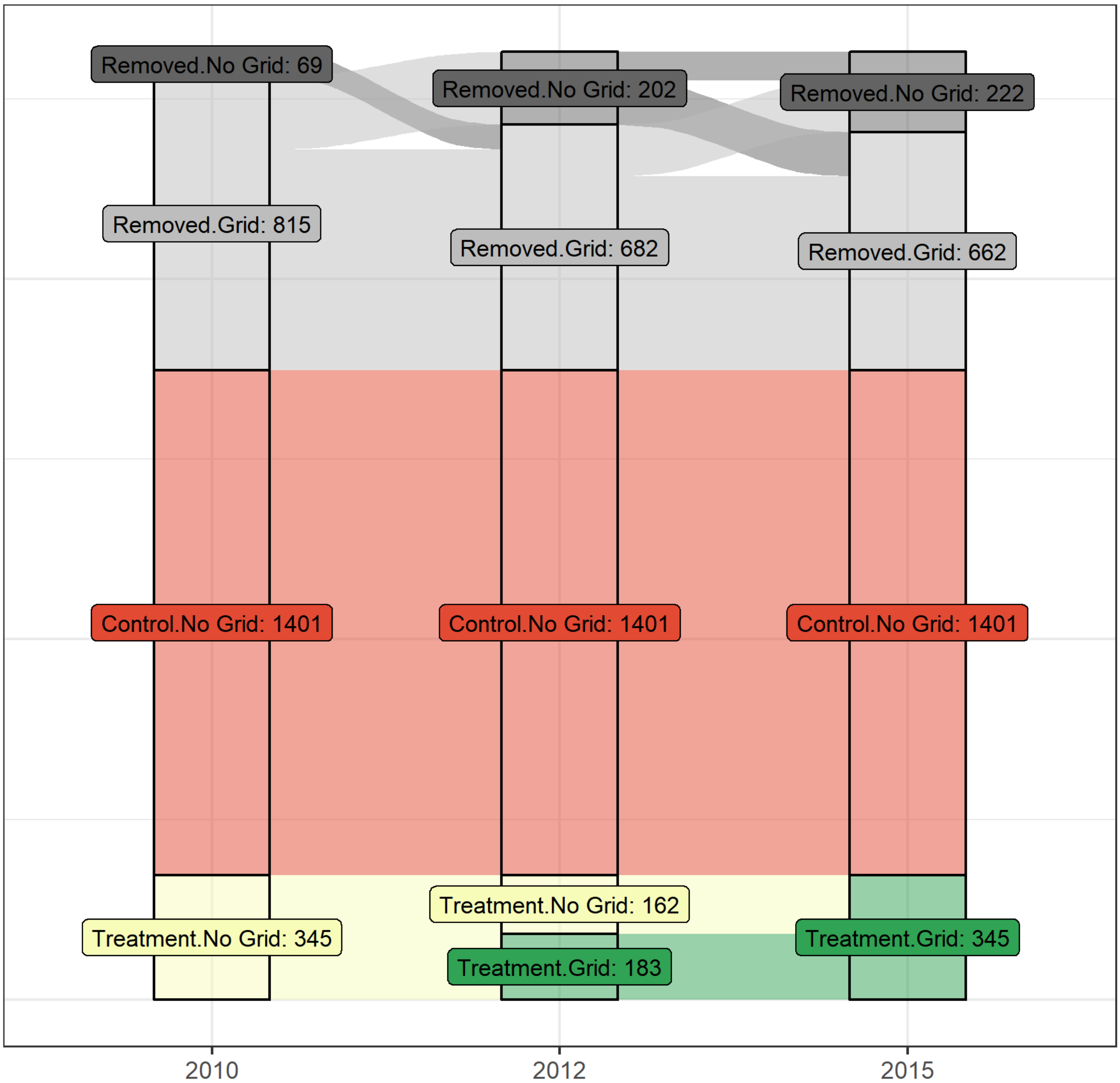

Figure 6 Treatment assignment diagram (Nigeria)

Matching variables

Literature indicates that household wealth, education and demography, as well as distance to complementary infrastructure and services are possibly drivers of the outcomes and the treatment designation, and are therefore selected to match the treatment and control groups in the baseline year. A full definition of the selected variables is provided in Table 1 and the differences between the groups across these variables in the baseline year are described in Table 2 and Table 3. All of the variables are taken directly from the survey datasets except the *Asset index*, which reflects an index derived through a principle component analysis of dummy variables reflecting household ownership of a series of non-energy related assets (Mattress, Sofa, Bicycle, Motorbike, Car).

Table 1 Description of variables used to match control and treatment groups

Variable	Description
Household size	The number of adults and children permanently residing in the home
Avg. age of adults	The average age of all household members over the age of 15 years
Proportion of males	The proportion of male household members over the age of 15 years
Household head married	A binary variable, indicating whether the household head is married (= 1)
Years of education	The total estimated years of education earned by the household head
Rooms in home	The total number of rooms excluding kitchen, toilet and bathroom
Distance to MFI	The distance in KM to the nearest microfinance institution (village survey)
Distance to road	The distance in KM to the nearest major road
Distance to market	The distance in KM to the nearest market
Distance to town	The distance in KM to the nearest town with a population > 20,000
Distance to capital	The distance in KM to the nearest zonal capital
Perc agr. 1km buffer	Percent agricultural landuse within approximately 1 km buffer
Asset index	PCA index reducing dimensionality of non-electrical asset ownership (1-5)

Table 2 Covariate balance prior to matching in the baseline year (Ethiopia)

	Control (N=2499)		Treatment (N=173)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Household size	2.5	1.2	2.4	1.2	-0.1	0.1
Avg. age of adults	36.6	12.0	35.6	13.0	-1.0	1.0
Proportion of males	0.5	0.2	0.5	0.3	0.0	0.0
Household head married	0.8	0.4	0.7	0.4	-0.0	0.0
Years of education	3.8	3.4	6.2	4.3	2.4	0.3
Rooms in home	1.6	0.9	1.8	1.0	0.2	0.1
Distance to MFI	15.5	16.7	12.2	14.7	-3.2	1.2
Distance to road	17.9	23.6	12.0	13.6	-5.9	1.1
Distance to market	71.1	52.3	49.5	37.5	-21.6	3.0
Distance to town	41.1	33.3	37.1	31.2	-4.0	2.5
Distance to capital	168.3	116.6	146.4	111.3	-21.9	8.8
Perc agr. 1km buffer	31.8	20.1	37.3	22.7	5.5	1.8
Asset index	1.1	0.4	1.1	0.5	0.0	0.0

Table 3 Covariate balance prior to matching in the baseline year (Nigeria)

	Control (N=1399)		Treatment (N=345)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Household size	3.1	1.5	3.2	1.7	0.2	0.1
Avg. age of adults	38.6	11.8	38.3	10.9	-0.3	0.7
Proportion of males	0.5	0.2	0.5	0.2	-0.0	0.0
Household head married	0.9	0.3	0.8	0.4	-0.0	0.0
Years of education	5.1	4.9	8.4	5.1	3.3	0.3
Rooms in home	3.8	2.4	4.0	2.1	0.3	0.1
Distance to MFI	6.5	9.0	2.4	5.8	-4.2	0.4
Distance to road	21.9	19.0	14.8	18.2	-7.1	1.1
Distance to market	80.6	38.8	65.0	32.7	-15.7	2.0
Distance to town	31.9	22.1	18.4	16.8	-13.5	1.1
Distance to capital	92.5	57.3	61.2	52.1	-31.3	3.2
Perc agr. 1km buffer	37.8	29.6	33.0	24.6	-4.7	1.5
Asset index	1.3	0.7	1.6	1.1	0.3	0.1

The summary statistics presented in Table 2 and Table 3 indicate that the treatment and control groups are indeed somewhat different in the baseline year, both in terms of household-level and village-level factors. Treatment group households are more likely to be led by a household head with 2-3 years more education, though the demographic composition of the households is quite similar. In Nigeria, treatment households have a higher Asset Index, indicating that they are more likely to own expensive assets, hinting towards higher wealth at baseline, though the same trend is not seen in Ethiopia. Across both countries, treatment households live in villages that are closer to MFIs, roads, markets, towns and regional capitals.

These baseline differences underline the challenges of causal inference using observational data in the context of household-level electrification impact analysis, as discussed in our literature review. While we could potentially control for these factors in an outcomes regression analysis, such as a two-way fixed-effects analysis with time and treatment interactions, we are unable to exclude the possibility that our model omits unmeasured confounders that will bias our estimates, most likely in the positive direction given the direction of the observable bias. This motivates our use of modern identification strategies that can address, or at least minimise, this uncertainty.

Outcome variables

We select five outcome variables relating to household non-farm entrepreneurship (Outcomes 1 and 2) and non-farm employment (Outcomes 3 – 5), as shown in Table 4.

Table 4 Description of outcome variables relating to non-farm livelihoods.

ID	Outcome	Description
1	NFE activity	Household has at least one non-farm enterprise (Binary)
2	NFE revenues	Monthly non-farm enterprise revenues (Continuous, zero if no NFE)
3	Non-farm employment	At least one member employed in the non-farm sector (Binary)
4	Farm employment	At least one member is employed in the farm sector (Binary)
5	Any employment	At least one member is employed in any sector (Binary)

Outcome 1 reflects the extensive margin of household non-farm entrepreneurship, that is the rate at which households engage in non-farm entrepreneurship, and is further split into retail, manufacturing and any non-farm enterprises based on the International Standard Industrial Classification of All Economic Activities (ISIC) codes.

Outcome 2 reflects the intensive margin of household non-farm entrepreneurship, or the intensity with which one or more non-farm enterprises are operated as reflected in the total average monthly revenues they generate at household level.

Outcomes 3 – 5 describe the extensive margin of non-casual wage employment between men and women at household level, which is captured as the share of households with at least one (male and female) household member employed in the non-farm, farm or any sector (farm + non-farm). We consider gendered differences across all of the outcome variables.

For Outcomes 1 and 2, this is reflected in separately estimating effects on non-farm enterprises co-owned by household members of any gender, and those enterprises co-owned by at least one female household member. For Outcomes 3 – 5 this is reflected in separately estimating effects on employment for men and women. Furthermore, for Outcomes 3 – 5 we separately consider so called *decent employment*, reflecting non-casual wage employment for greater or equal to 20 hours per week on average, and *employment*, reflecting non-casual wage employment for any hours per week.

Results

Descriptive analysis

We begin with descriptively visualizing the change in non-farm entrepreneurship and non-farm enterprise revenues for households across the three survey waves in Figure 6 and Figure 7. The left panels indicate the change in the proportion of households with at least one non-farm enterprise while the right panels describe the total average monthly household income derived from all household non-farm enterprises, which is zero for households without any non-farm enterprises. The upper charts include all non-farm enterprises co-owned by household members of any gender, while the lower charts describe those enterprises co-owned by at least one female household member.

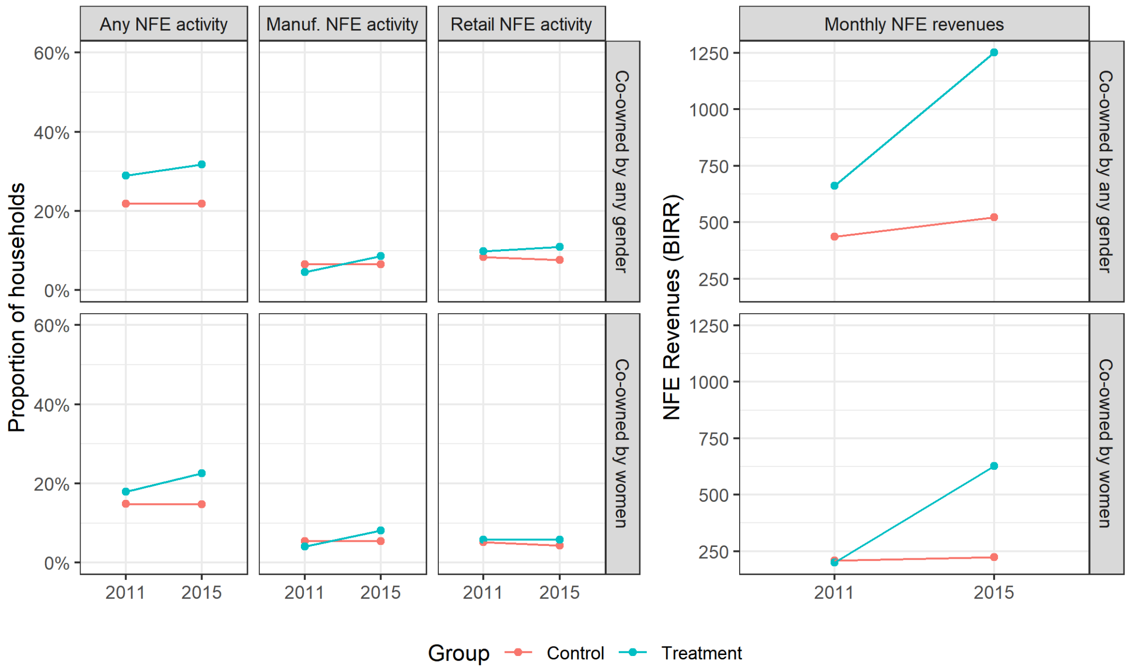

Figure 7 Descriptive trends in Ethiopia: Non-farm enterprise activity (= 1 if household has a NFE) and monthly revenues from household non-farm enterprises.

The majority of household non-farm enterprises in our Nigerian sample can be classed as retail or manufacturing firms, with the former being far more common. This is less clear cut in the Ethiopian sample where local manufacturing (such as carpentry or tailoring) is as equally prevalent as retail, and the two combined reflect approximately half to two-thirds of all non-farm enterprises. We also note the difference in starting points between the two countries in terms of household non-farm enterprise activities, with an approximately 20%-point higher rate of any non-farm entrepreneurship in Nigeria relative to Ethiopia.

Interestingly, trends in manufacturing non-farm enterprise rates diverge between the two countries. It is evident that there are other factors at play that must be disentangled in order to draw out the relationship between household-level electrification and this outcome.

Overall, this descriptive visualization indicates the presence of selection bias among the treatment group as shown by the generally higher outcomes at the baseline year. Nevertheless, despite evidence of selection bias and country-level differences in starting points, the differences in trends indeed indicate a weak treatment effect in terms of non-farm enterprises co-owned by women, and a relatively strong treatment effect with respect to overall household non-farm enterprise revenues.

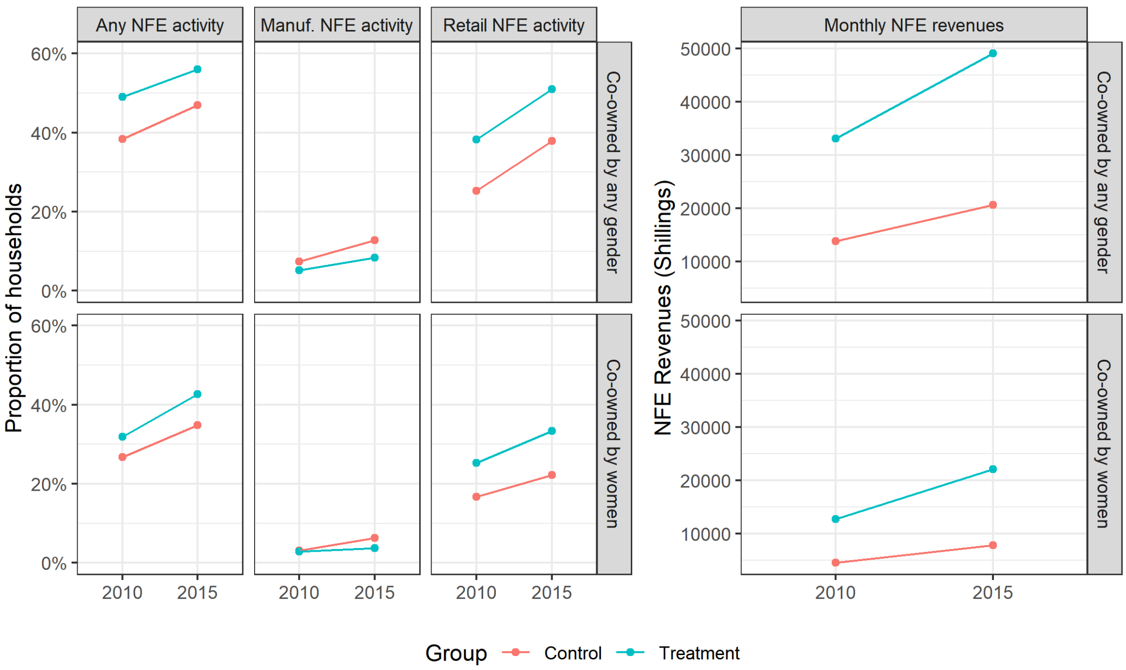

Figure 8 Descriptive trends in Nigeria: Non-farm enterprise activity (= 1 if household has a NFE) and monthly revenues from household non-farm enterprises.

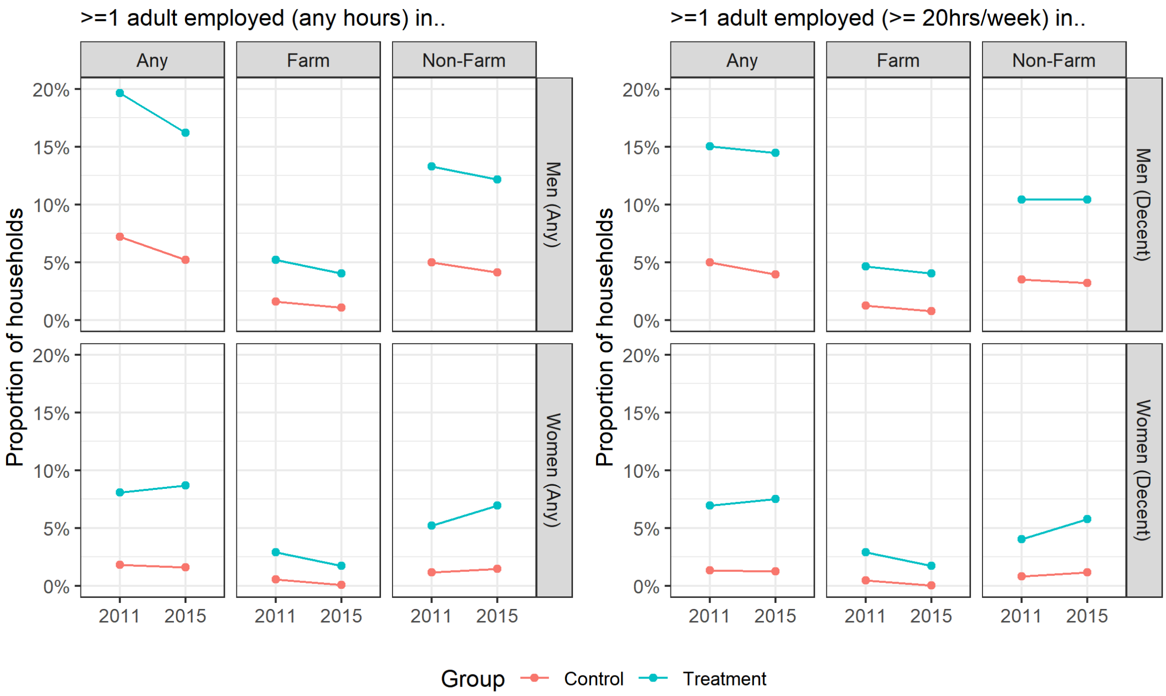

Figure 9 Descriptive trends in Ethiopia: Binary variables indicating that at least one household member (male, female) was employed in either non-farm, farm or any (farm + non-farm) employment for i) any hours and for ii) at least 20 hours per week over the last 12 months.

Figure 8 and Figure 9 visualize household employment trends (Outcomes 3 – 5). We see very strong indicators of selection bias within the treatment group as shown in the baseline year differences, however the difference in starting points across countries is less evident. This is an interesting observation in itself, given the stark difference in non-farm entrepreneurship between the two (far more rural households in our sample have a NFE in Nigeria than in Ethiopia).

A descriptive difference in trends between the treatment and control groups is not clearly visible, suggesting that adults (household members over the age of 15) in treatment group households show mixed responses to household-level electrification relative to the control group across outcomes and genders in both countries.

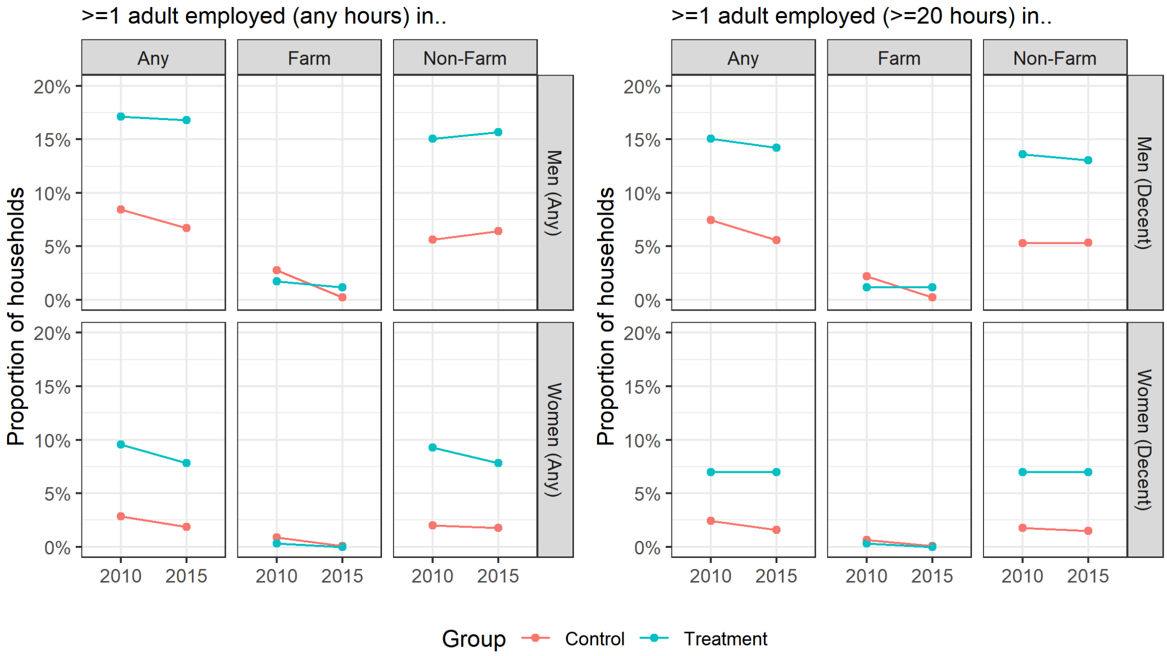

Figure 10 Descriptive trends in Nigeria: Binary variables indicating that at least one household member (male, female) was employed in either non-farm, farm or any (farm + non-farm) employment for i) any hours and for ii) at least 20 hours per week over the last 12 months.

Causal inference

We now move on to the results of our main analysis, describing the average treatment effect on the treated group of households in the 2-4 years following their decision to connect to the national grid.

We begin with the effects of a household decision to connect to the national grid on the extensive and intensive margins of household non-farm entrepreneurship (Outcomes 1 and 2). The evidence presented in Figure 10 and Figure 11 indicates that no broad causal relationship between household decision to connect to the national grid and household non-farm entrepreneurship and household non-farm revenues (whether owned by any gender, or co-owned by women) can be identified. This suggests that the descriptive trends observed are more likely to be an artefact of factors endogenous to a household decision to connect to the national grid, rather than an effect of electrification, at least in the short-term.

Looking more closely at the individual outcomes, we note that rural small scale manufacturing non-farm enterprise activity (such as carpentry and tailoring) in Ethiopia is indeed positively influenced by a household decision to grid-connect. While the absolute treatment effect is quite small (~4 percentage points), this result suggests that short-term household-level electrification effects are heterogenous across sectors and motivates further research into these distributional effects. At the same time, the stark lack of agreement across countries in terms of this outcome cautions against assuming external validity of the Ethiopian result.

Finally, we must be cautious in our interpretation of the effect of household electrification on household non-farm revenues from enterprises co-owned by women. Here, although we see quite large and positive point estimates, the confidence intervals are equally wide and require cautious interpretation. Rather than explicitly stating that we find no statistically significant effect, we would argue that it is at least quite muddled and requires further investigation.

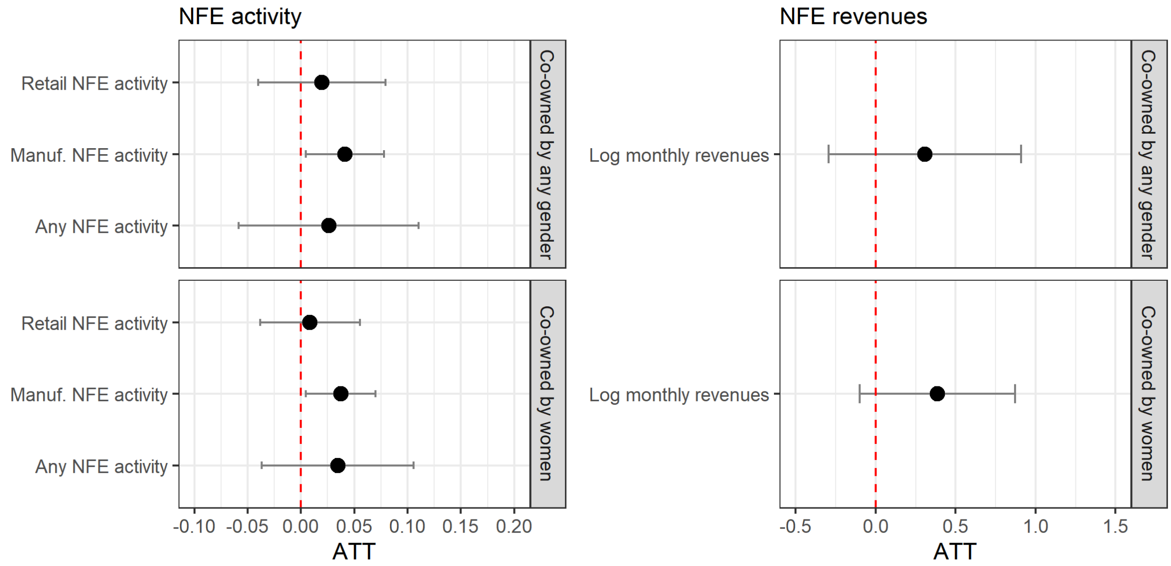

Figure 11 Ethiopia: The DiD Average Treatment Effect on the Treated (ATT) estimator describing the causal effect of grid connection on non-farm enterprise startup likelihood (ATT x 100 percentage points) and monthly NFE revenues (ATT x 100 percentage of revenues). 95% confidence intervals derived from bootstrapped standard errors clustered at household level are shown as error bars.

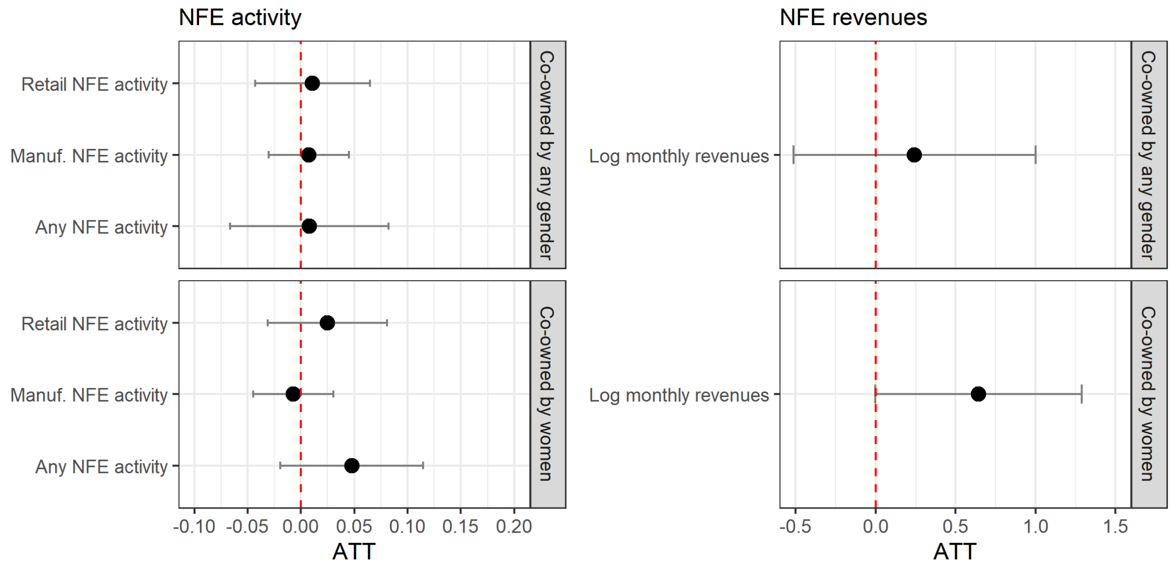

Figure 12 Nigeria: The DiD Average Treatment Effect on the Treated (ATT) estimator describing the causal effect of grid connection on non-farm enterprise startup likelihood (ATT x 100 percentage points) and monthly NFE revenues (ATT x 100 percentage of revenues). 95% confidence intervals derived from bootstrapped standard errors clustered at household level are shown as error bars.

Next, we present the effects of a household decision to connect to the national grid on household employment outcomes in Figure 12 and Figure 13. The evidence indicates that we are once again unable to plausibly reject the null hypothesis and thus do not identify a robust causal relationship between household decision to grid connect and household-level employment outcomes in the 2-4 years following household grid connection. This conclusion holds for both female and male members of the household, as well as for both decent employment (>= 20 hours per week) and other employment (any hours per week). Unlike the uncertainty in our previous estimates, we can quite conclusively argue that, at least in the short-term, household-level employment trends in the treatment group in our sample were not statistically different to those in the control group.

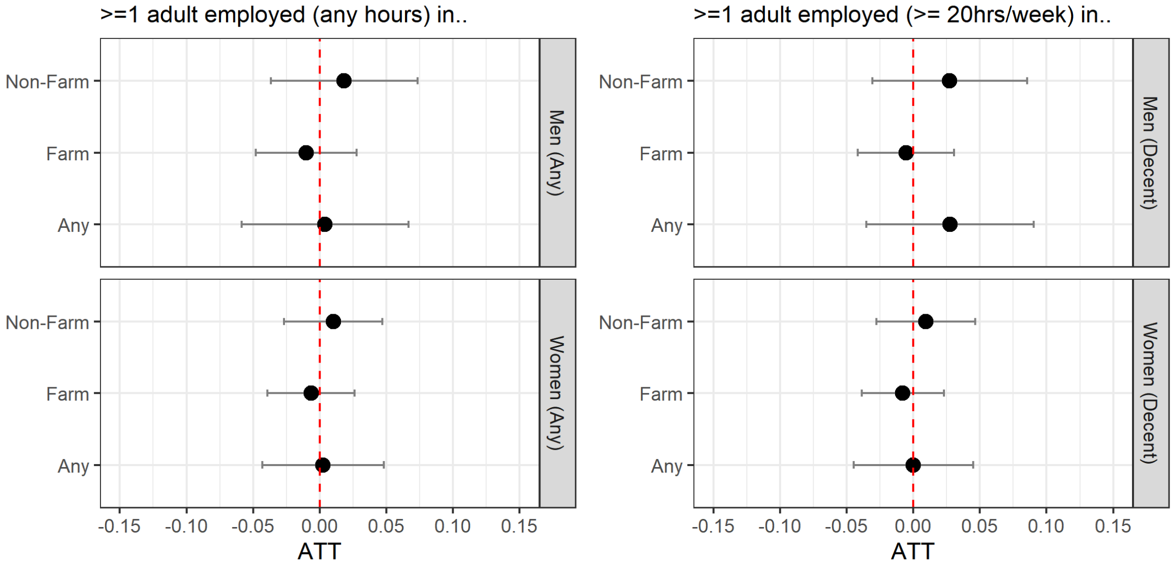

Figure 13 Ethiopia: The DiD Average Treatment Effect on the Treated (ATT) estimator describing the causal effect of household grid connection on household employment outcomes (ATT x 100 percentage points). 95% confidence intervals derived from bootstrapped standard errors clustered at household level are shown as error bars.

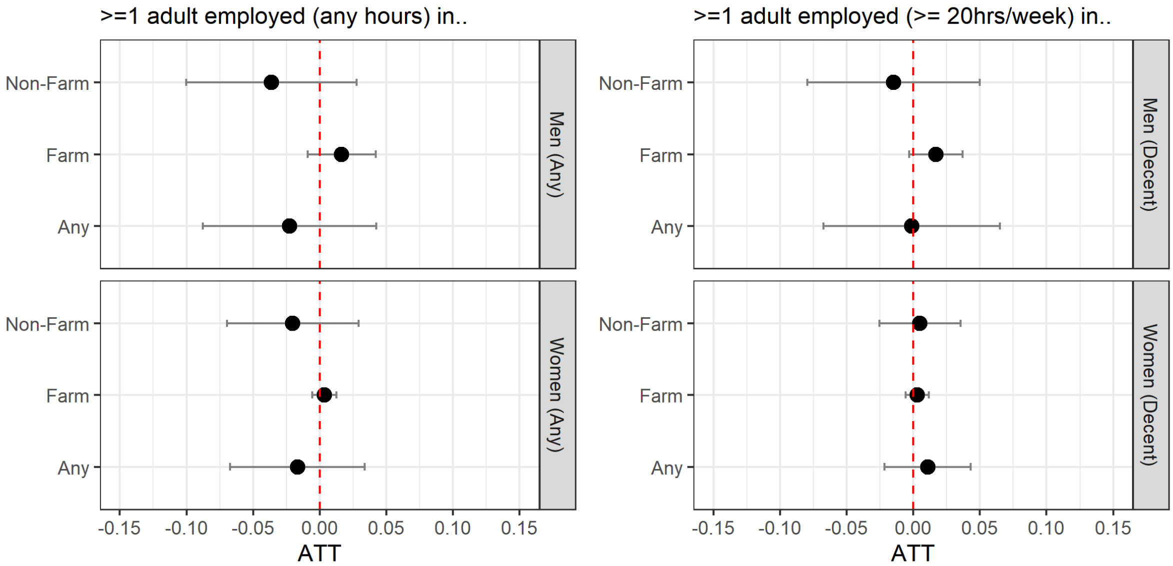

Figure 14 Nigeria: The DiD Average Treatment Effect on the Treated (ATT) estimator describing the causal effect of household grid connection on household employment outcomes (ATT x 100 percentage points). 95% confidence intervals derived from bootstrapped standard errors clustered at household level are shown as error bars.

Discussion and Policy Implications

The results of our descriptive and causal analysis in the two very different contexts of rural Ethiopia and Nigeria indicate that household electrification alone was insufficient to trigger shifts in non-farm entrepreneurship and labour market outcomes 2-4 years following grid connection.

Notably, our focus on the rural sample within Nigeria rebuts recent work using the same dataset which indeed identified a positive association between electrification and labour market outcomes, combining rural and urban samples using regression and matching analyses (see Tagliapietra et al. (2020)). We argue that while descriptive evidence in rural and urban areas is crucial to the development of a broader understanding, causal analysis should not combine rural and urban samples due to the stark differences in unmeasurable confounders between these two groups, which may not be solved through the doubly robust DiD method we have applied. Moreover, our work highlights several challenges with establishing robust associations between household-level electrification and a range of outcomes relating to the transition away from agricultural livelihoods, using observational data.

The first challenge is the identification of sufficiently large and consistent treatment and control groups in contexts where electrification has improved quite slowly, or in some regions, not at all. Without variation in electrification status, this form of inference is naturally not possible. This constraint is evident in the size of our treatment group relative to the control group, which it could be argued is perhaps simply too small to provide the sufficient power to our estimates, resulting in wide confidence intervals. Our transparent and clear determination of treatment and control households, along with the year of treatment, reflects best-practice in terms of gaining confidence in any following regression analyses.

The second challenge is the short-term nature of available observational data. Most, if not all household level panel surveys in the public domain, extend at most 5 to 10 years into the past, which may not be long enough to recover slower but nevertheless causal shifts in labour market outcomes following electrification. The evidence for longer-term effects of electrification on employment outcomes remains sparse, however this is developing through analysis of governmental administrative census data (see Chhay and Yamazaki (2021)).

The third challenge is the inherent endogeneity between household-level electrification and household non-farm entrepreneurship. The challenge here is that household-level electrification remains the decision of the household, conditional on the availability of a connection in the village. While the doubly robust DiD approach helps reduce the effects of this bias, recent analysis emphasises the role of household wealth and willingness to pay for a grid connection on the short-term socioeconomic outcomes (see Lee et al. (2020)).

Figure 15 and Figure 16 describe our initial attempts to address these challenges through the definition of treatment as a function of grid-extension in the local area determined through an analysis of night-time lights data. This would theoretically enable the expansion of the treatment group to include those households that do not explicitly choose to be grid connected, but benefit from the effects of local electrification nonetheless. While we will continue to work on this aspect of the research project in the following months, to date, the definition of treatment as a function of night-time light irradiance as well as the short-term nature of the analysis, such that there was little variation in the treatment group, lead to inconclusive results.

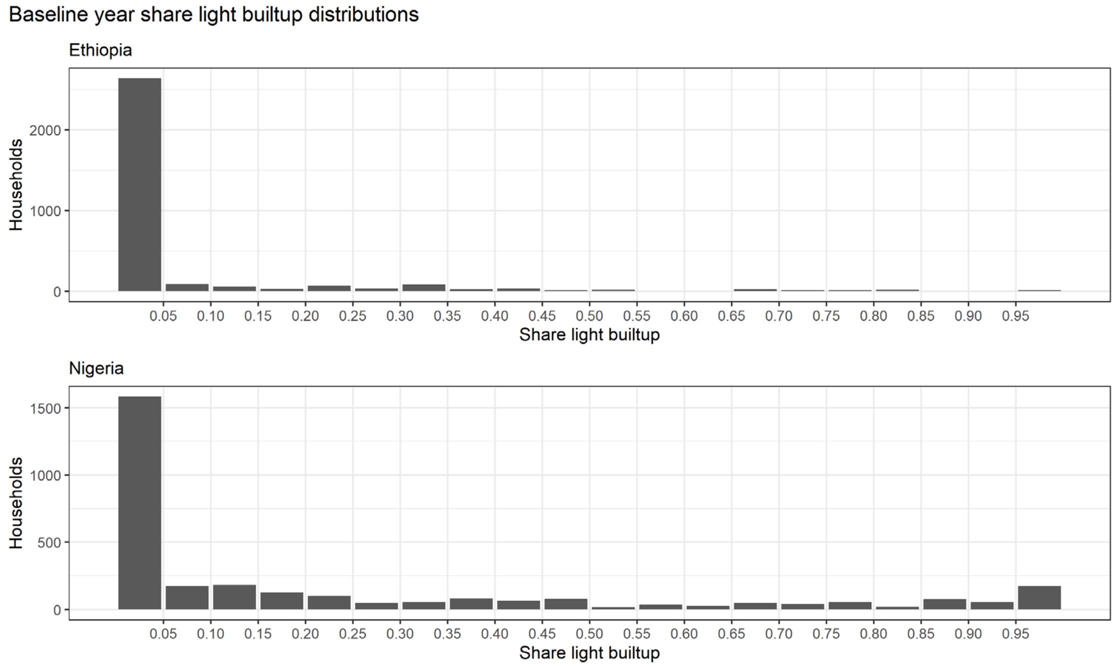

Figure 15 Histogram of households in bins reflecting the share of built-up area “lit” in a 10km radius around surveyed villages based on VIIRS nighttime lights data in the baseline year.

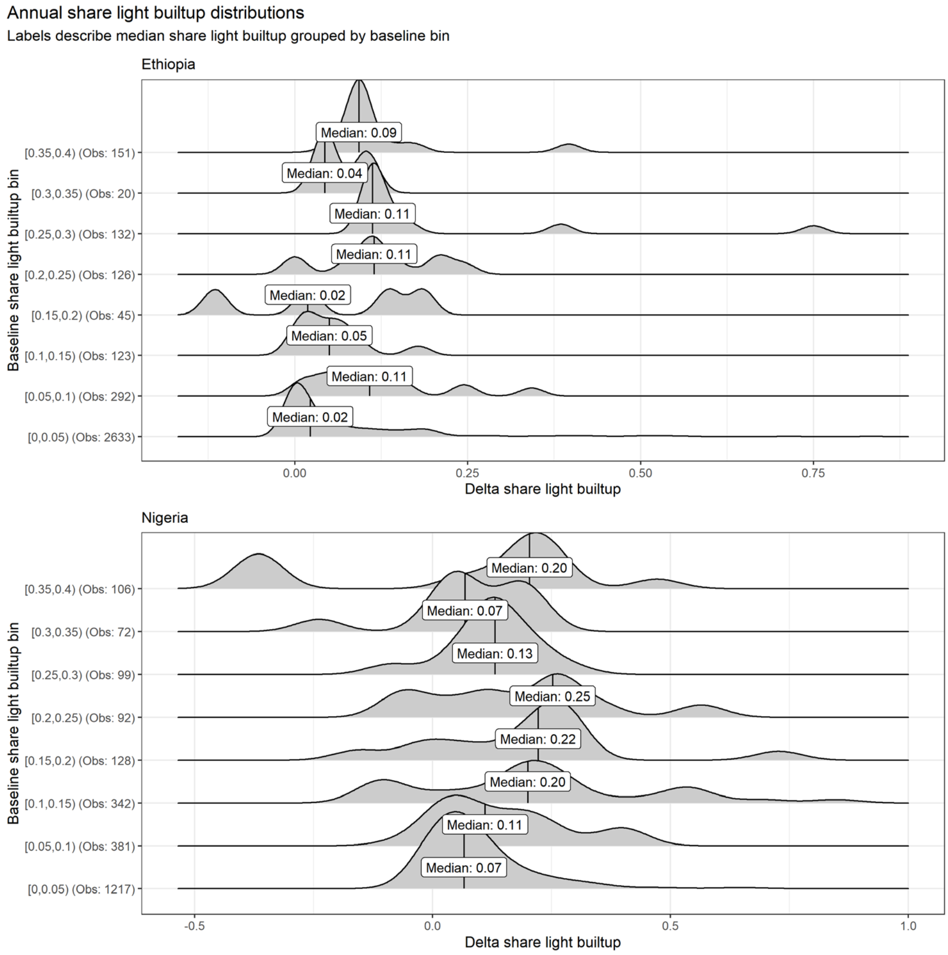

Figure 16 Density plots of households describing the change in the share of built-up area “lit” within a 10km radius of surveyed villages between baseline and end years, grouped in bins corresponding to Figure 15.

Notwithstanding the challenges and limitations we have described above, the overarching policy implications of our work are limited to the provision of robust evidence of limited short-term economic development outcomes following electrification in Ethiopia and Nigeria, and methodological advancement in the context of electrification impact analysis. While we have not yet explored the role of complementary infrastructure as modifiers, we speculate that rural household electrification efforts must be accompanied with expansion of complementary infrastructure and market integration to create the necessary pull effects which been shown in the literature to trigger rapid economic development following electrification (see Fetter and Usmani (2020)).

Conclusion

In this report we contribute to the sparse literature on household-level electrification and transitions away from agricultural livelihoods in Sub-Saharan Africa. Our results indicate that no broad robust causal relationship between household-level electrification and transitions away from agricultural livelihoods could be established in the 2-4 years (between 2010 – 2015) following grid connection in our panel dataset of households from rural Ethiopia and Nigeria, two very different country contexts.

Looking closer at the distinct outcomes we study, we can nevertheless speculate that for those households already engaged in non-farm entrepreneurship, a connection to the grid may help increase income/revenues even in a rather short-term. However, for employment patterns to change wider structural changes and infrastructure provision are likely necessary.

These findings are aligned with contemporary rural electrification impact literature urging caution in the interpretation of descriptive and potentially biased analyses that are unable to effectively disentangle the many co-determinants of non-farm entrepreneurship and labour market outcomes with respect to electrification. At the same time, we note several methodological challenges in establishing sufficient sample sizes when reliant on observational survey data conducted over short periods of time.

Our work joins a growing chorus of research urging caution as to the shorter-term economic development effects of grid connection in rural areas. However, there remain many unanswered questions in the context of economic development outcomes in Sub-Saharan Africa, a region with rapidly developing grid and off-grid electrification infrastructure. Future scholarship should look beyond household-level electrification survey data to recover variation in local electrification infrastructure improvement, such as through administrative records or remotely sensed night-time lights datasets, and over longer periods of time, in order to improve identification of the causal effects of access to this service.

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