World Development Perspectives 29 (2023) 100473

Contents lists available at ScienceDirect

World Development Perspectives

journal homepage: www.sciencedirect.com/journal/world-development-perspectives

Short-run effects of grid electricity access on rural non-farm entrepreneurship and employment in Ethiopia and Nigeria

Setu Pelz [a,*], Shonali Pachauri [a], Giacomo Falchetta [a,b]

[a] International Institute for Applied Systems Analysis, Vienna, Austria
[b] CMCC and Universitá Ca'Foscari, Venice, Italy

A R T I C L E I N F O

Keywords:
Electrification
Productive electricity use
Non-farm transitions
Household surveys
Nigeria
Ethiopia

A B S T R A C T

Empirical evaluation of the household-level economic effects of electricity access in rural regions has challenged researchers due to data scarcity issues and identification challenges. Previous studies provide mixed evidence depending on the context and the empirical approach adopted. Continued efforts towards a robust understanding of this linkage are necessary for guiding the design of rural electricity access and economic development policies. Here we carry out a difference-in-differences analysis with staggered treatment timing, revisiting prior work reporting short-run effects of rural electrification on household non-farm entrepreneurship and employment trends in Ethiopia and Nigeria between 2010–2015. Our results indicate that rural electrification considered alone was insufficient to trigger shifts in non-farm entrepreneurship and non-farm household employment outcomes in the 2–4 years following grid connection in either country. We do find some evidence in Nigeria of farm employment intensification over this short-term. Our work contributes to improving the understanding of the causal pathway in question while also highlighting the limitations of short-term survey datasets in pursuing this goal.

1. Introduction

Providing universal, reliable, sustainable and affordable access to electricity falls under goal 7.1 of the Sustainable Development Goals (SDGs) set for the year 2030 (UN, 2015). The development interlinkages of this goal have been discussed at length in literature, ranging from broad economic growth to other SDGs including education, gender equality and healthcare (McCollum et al., 2018; Nerini et al., 2018). One often discussed positive linkage of SDG 7.1 is the productive use of electricity and corresponding transitions away from agricultural livelihoods in rural regions (Kuete, Yselle, & Asongu, 2022; Perez-Sebastian, Steinbuks, Feres, & Trotter, 2020). While there is no doubt that access to reliable, affordable and sustainable electricity is a necessary condition to enable essential modern services such as lighting or cooling, and powers equipment that reduces physical drudgery or enables digital services provision - arguably all prerequisites for economic development - the causal effects of rural electrification on household entrepreneurship and employment are contested.

Recent summaries of the literature describe geographic and methodological differences in the empirical evidence asserting short-run shifts in labour market outcomes following rural electrification specifically in regions with developing infrastructure, such as in rural Sub-Saharan Africa (see Bayer et al., 2019; Hamburger et al., 2019; Mori, 2020; Jeuland et al., 2021; Muchapondwa, 2021 for systematic reviews and meta analyses). Several contemporary articles highlight the extent of the replication problems in this literature relevant to our work. For example Bensch et al. (2020) and Bensch et al. (2021) revisit the seminal publications of Dinkelman (2011) and Lipscomb et al. (2013), finding methodological vulnerabilities in the original conclusions which linked electrification and household economic development outcomes in rural South Africa and Brazil. Muchapondwa (2021) synthesize this literature, discussing the specific limitations in causal interpretation of rural electrification effects to date. The authors build on the work of Lee et al. (2020) who provided the first critical review and also describe a recent randomised controlled trial of household electrification in rural Kenya, finding no significant short-run shifts in household economic outcomes.

In the context of a contested literature, our article provides new evidence in regions with limited electrification impact analysis and demonstrates the use of a contemporary identification strategy in delineating the causal effects of electrification from a myriad of confounding factors. The contribution of this paper is therefore twofold: (i)

* Corresponding author.
E-mail address: pelz@iiasa.ac.at (S. Pelz).

https://doi.org/10.1016/j.wdp.2022.100473
Received 5 May 2022; Received in revised form 23 September 2022; Accepted 23 November 2022
Available online 2 December 2022

firstly, we apply a doubly robust differences-in-differences econometric approach with staggered treatment timing to identify the short-run effects of household- and community-level electrification on household non-farm entrepreneurship and employment (NFE). Here NFE describes non-farm enterprises such as retail and manufacturing activities operated by or employing members of the household. (ii) Secondly, we provide novel empirical estimates for rural Ethiopia and Nigeria. Whilst significantly different in geographic and socio-economic terms, these two countries represent major hotspots of energy poverty, hosting 58 and 90 million people without access to electricity, respectively (IEA, 2021). Together, they sum to almost 20% of the global total electricity access gap. Although previous studies - albeit with different identification strategies and estimation techniques - have been carried out for Nigeria, the empirical analysis we conduct for Ethiopia has not yet appeared in the literature.

Our analysis is conducted using nationally representative household-level observational panel survey datasets collected in three survey waves between 2010 and 2015 in the two countries. Overall, we find limited evidence of shifts towards non-farm entrepreneurship and employment following rural electrification in either Nigeria or Ethiopia. Rather, our work suggests that agricultural employment intensified among the electrified households in the short run in rural Nigeria, contrasting with prior work using the same dataset.

2. Background

2.1. Country contexts

Nigeria and Ethiopia represent two very different country contexts in terms of the sizes of their economies and rate of rural electricity access, as detailed in the indicators plotted in Fig. 1. 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. In terms of economic development, Nigeria reported over three times the GDP per capita relative to Ethiopia in 2015, however life expectancies were higher in Ethiopia (65 years versus 53 years in 2015). In addition, baseline rural electricity access rates in Nigeria and Ethiopia also depict two differing starting points. 36% of the rural population in Nigeria reported having access to the national grid in 2015, whereas, only 8% of the population in rural Ethiopia reported having access to the national grid in the same year.

While most indicators in Fig. 1 show that the observed structural socio-economic differences between Ethiopia and Nigeria are long-standing, there are a number of convergent and divergent dynamics worth discussing. One of the most striking examples concerns female farm employment: while in Ethiopia it remained rather stable during the 2006–2015 period under analysis, in Nigeria it decreased rapidly as women transitioned to non-farm employment. On the other hand, male employment underwent more gradual change in the two countries, albeit with a more pronounced farm to non-farm transition in Ethiopia than in Nigeria.

Another important aspect concerns demographic and urbanisation trends: while Nigeria and Ethiopia are already the first and second countries of Africa by population, respectively, their populations are still growing quickly. Yet, contrary to anecdotal evidence where population growth is generally inversely proportional to economic development levels, the fertility rate in Ethiopia has been declining significantly faster than in Nigeria, where as of 2015 rural women had on average more than six children each. Finally, urbanisation rates are diverging in the two countries: while Nigeria was already largely more urban than Ethiopia in 2006, its urbanisation rate has since climbed by nearly ten percentage points in a decade, while this has mostly stagnated in Ethiopia.

Overall, Nigeria and Ethiopia represent two distinct country contexts and are thus ideal for a comparative study of the causal effects of electrification on household non-farm entrepreneurship and employment outcomes. With respect to regulatory indicators relevant to rural electrification, according to the *Regulatory Indicators for Sustainable Energy* database produced by the World Bank and ESMAP - both countries have fairly developed frameworks for electrification planning, including scientifically sound and regularly updated electrification plans, suggesting comparability despite differences in overall access rates (Banerjee et al., 2017).

2.2. Literature

We first reflect on literature describing the path from improvements in rural electrification to increased ‘non-farm’ entrepreneurship. This reflects the shift from subsistence farming and agricultural household enterprises towards non-agricultural household enterprises[1]. Here, the recent literature generally describes positive short-run effects. Gibson and Olivia (2010) conduct a cross-sectional fixed-effects analysis of household surveys from rural Indonesia, finding that improvements to road infrastructure and electricity access were positively associated with rural non-farm entreneurship. Rao (2013) applies fixed-effects, instrumental variables (instrumenting with village electrification rate) and propensity score matching to a cross-sectional dataset from India, finding a positive association between electricity access and state road density with non-farm enterprise incomes. Khurana and Tanvi (2022) apply fixed-effects and a Heckman two-stage selection model (using access to farm land) to panel data from India, finding positive effects between electrification and household non-farm entrepreneurship/ non-farm enterprise incomes. Although this literature is optimistic, recent advances in methods in this context indicate that the possible endogeneity between grid connection and household non-farm entrepreneurship may not have been adequately adressed (Lee et al., 2020; Bensch et al., 2020; Bensch et al., 2021)[2]. The main criticisms stem from the selection of an endogenous instrumental variable and the inadequacy of (panel) fixed-effects in providing an unbiased estimate of the desired causal estimand. Further discussion of these limitations are provided by Mori (2020) and Muchapondwa (2021).

Next we turn to literature describing the path from rural electrification to shifts in the labour market towards increased non-farm employment. Most of the work investigating short-run effects in both Sub-Saharan Africa and in Asia does not identify a robust causal relationship in this direction, though literature considering longer-term administrative datasets report positive outcomes. Burlig et al. (2022) use regression discontinuity and difference-in-differences designs in the context of a large national electrification program in India, failing to find meaningful short-run labour market shifts towards non-farm employment. Salmon and Claire (2016) analyse cross-sectional data from Nigeria in 2010–11 using an instrumental variable strategy, reporting mixed labour market shifts. In contrast, Tagliapietra et al. (2020) apply a battery of econometric approaches including fixed effects, instrumental variables (following Dinkelman, 2011) and propensity score matching on panel data in Nigeria (the same as is used in our work), finding a positive relationship between household electricity access and a shift towards non-agricultural employment in both urban and rural regions.

[1] Examples of such non-farm enterprises commonly referred to in the productive electricity use literature include handicrafts, tailoring, carpentry, metalworking and retail.

[2] This is distinct from the problem that recovering the causal effect of rural electrification on household non-farm entrepreneurship requires disentangling the effects of electrification from other potential determinants such as the construction of roads and the availability of finance. Interestingly, literature describing linkages between access to finance or roads and household economic outcomes is itself quite mixed, see Owoo and Naudé, 2016; Nagler and Naude, 2017; Davis et al., 2017; den and Goedele Broeck, 2019; Gibson and Olivia, 2010 and Rao, 2013.

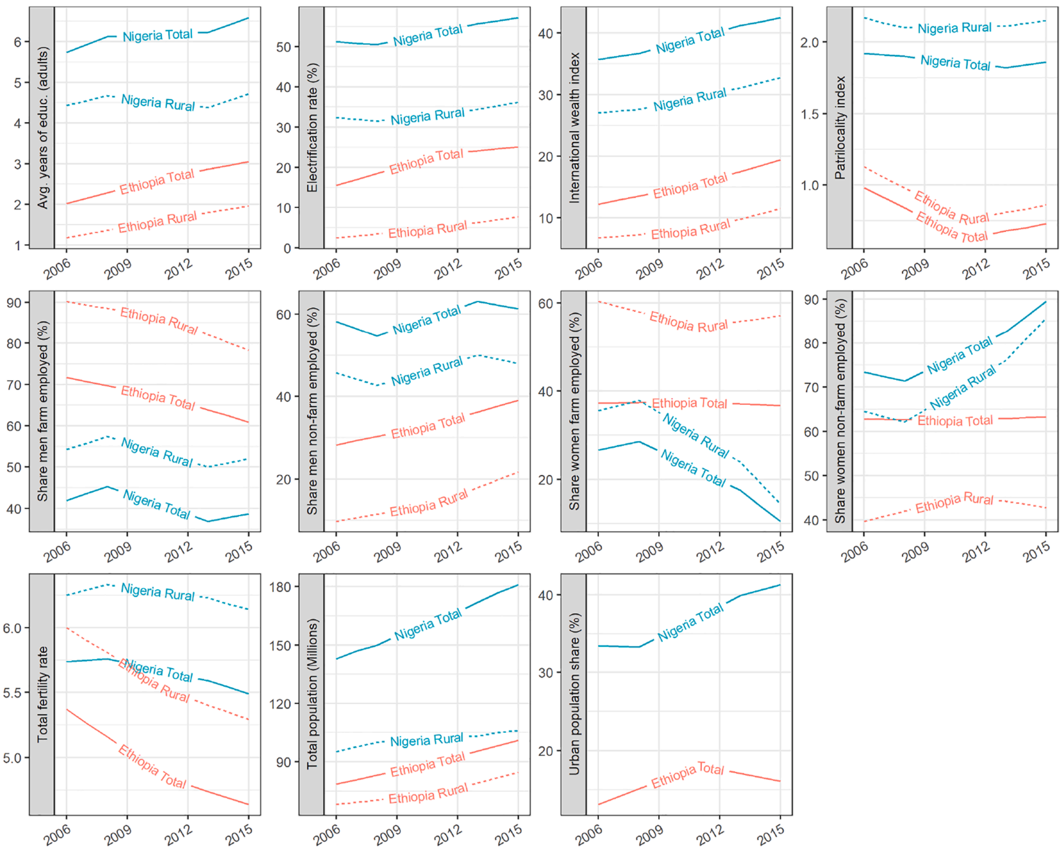

Fig. 1. Time-series comparison of global development indicators by total and urban population. Source: Global Data Lab, https://globaldatalab.org/areadata/.

Samad et al. (2017) evaluate the effects of the quality and length of electricity supply using an instrumental variable and propensity-score-weighed fixed-effects model applied to panel data in Bangladesh, finding that labour market shifts accrue only over the long run. Lee et al. (2020) use experimental data from a randomised control trial in Kenya to show that the household willingness to pay for electricity (and thus a set of complementary conditions) is a crucial determinant of whether electrification leads to labour market shifts. Chhay and Panharoth (2021) apply both inverse probability weighted fixed-effects regression analysis and a combination of this with a difference-in-differences specification to pooled longitudinal data from Cambodia, identifying non-negligible shifts in the labour market towards non-farm sectors over a period of 10 years. van de Walle et al. (2015) apply conditional difference-in-difference and instrumental variable (instrumenting with long lags of distance to primary power generators) specifications on longitudinal data from India, finding that rural electrification increased non-farm employment, but only among males, over a period of 17 years. Relative to the non-farm entrepreneurship literature, literature describing non-farm shifts in the labour market is generally less optimistic over the short-term, pointing towards longer lags in the expected development outcomes. The same empirical limitations as those discussed earlier also apply to some of the work described here.

Overall, the work of Lee et al. (2020), Mori (2020) and Muchapondwa (2021) summarizes the ongoing debate and limitations of the literature across both of these facets, discussing publication bias and the identification strategies employed. Notwithstanding the fact that work to find sound identification strategies is clearly still evolving, the lack of agreement is certainly attributable in part due to differences in contexts, cultures and social norms regarding entrepreneurship and differences between short-term and long-term outcomes. The broader conclusion we can draw here is therefore not that electrification is unlikely to be a driver of household shifts towards non-farm livelihoods, but rather, that further analysis of differences in short-term and long-term trends following electrification across different contexts is necessary, alongside continued work on robust identification methods.

3. Research Design

3.1. Data

We analyse the Nigerian and Ethiopian Living Standards and Measurement Survey (LSMS) surveys collected by the World Bank in collaboration with national statistics agencies across three survey waves between 2010 and 2015. This consists 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 across the three survey waves; the baseline (2010 in Nigeria; 2011 in Ethiopia), mid (2012 in Nigeria, 2013 in Ethiopia) and the end (2015 in both Nigeria and Ethiopia). R programming language scripts to process raw LSMS survey data in a transparent and reproducible manner can be found in the replication archive.

We retain only those households present in all three survey waves and those that did not move house, removing those that were always electrified and those with mixed electrification (i.e., gained and lost). As will be explained in the following subsection, our empirical approach relies on clearly defining treatment cohorts of households by the year of treatment (i.e. connection to the national grid). In Nigeria, we define treatment separately as (i) household connection to the national grid, and (ii) community connection to the national grid. In Ethiopia, we define treatment only as household connection to the national grid due to limitations in the survey data. Our analysis subset is shown in Table 1. We retain a total of 2,594 households in Ethiopia (of the original 3,466

Table 1
Counts of the rural household analysis subsets in Nigeria and Ethiopia.

(a) Nigeria

Treatment	Never Treated (Control)	Treated by 2012	Treated by 2015
Household	1583	191	146
Community	1369	152	129

(b) Ethiopia

Treatment	Never Treated (Control)	Treated by 2013	Treated by 2015
Household	2444	82	68

rural households surveyed in 2011) and 1,920 households (household-treatment) or 1,650 (community-treatment) in Nigeria (of the original 3,356 rural households surveyed in 2010). These households are separated into three groups, including one control group (never treated) and two treatment cohorts (treated by mid and treated by end).

3.2. Empirical approach

We are interested in inferring the effect of rural grid electrification on household non-farm entrepreneurship and employment outcomes. We do this using panel survey data capturing variation in electrification, household economic outcomes and a set of relevant covariates. Panel data reflects repeated observations of the same unit (household) over time. The methodological challenges posed by possible endogeneity between rural electrification and household economic outcomes discussed in the literature review motivates our usage of the doubly robust difference-in-differences approach (DRDiD) proposed by Sant'Anna and Zhao (2020) and further developed by Callaway and Brantly (2021b). Briefly, in our context, such endogeneity can stem from (i) *village-level selection bias* - where the placement of village electrical infrastructure and electrification planning more broadly is endogenous to socio-economic and political factors that drive household economic outcomes, (ii) *household-level selection bias* - where household uptake of electricity (i.e. decision to connect to available village infrastructure) is linked with household economic outcomes, and (iii) *other omitted variable bias* - which reflects the omission of variables which affect both electrification and household economic outcomes, such as complementary road infrastructure.

The intuition behind this empirical approach is to address endogeneity concerns by (i) creating a counterfactual group for the treatment group conditional on a set of baseline covariates using both inverse probability weighting (IPW) and outcome regression (OR), and (ii) comparing the difference in outcomes over time and across the treatment and counterfactual groups (the difference-in-differences). The parallel trends assumptions implicit in the application of a DiD estimator is relaxed conditional on correctly specifying covariates in either or both of these two stages. The practical implementation can be broadly simplified into three steps. First, we identify consistent control and treatment groups to distinguish between those that gained connection to electricity (treatment) from those that did not (control). Then, we both 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 (IPW) and impute a counterfactual for the treatment group using these same covariates (OR). Finally, we effectively compare the conditional differences in outcomes over time between the treatment and imputed counterfactual groups, recovering an estimated average treatment effect on the treated or the ATT (i.e. the treatment effect for households in the treatment group). This approach generally has three requirements: (i) we have access to panel (or repeated cross-sectional) data, (ii) we can assume parallel trends conditional on a set of baseline covariates X and (iii) we have common support (at least a small fraction of control observations) for every possible treatment group value of the covariates X.

Table 2
Describing village-level and household-level covariates in the baseline year across control and treatment cohorts.

(a) Nigeria 2010, Household treatment

	Never Treated		Treated by 2015		Treated by 2012	
	Mean	SD	Mean	SD	Mean	SD
Distance to road	2215	21.17	14.35	20.80	13.92	14.99
Distance to market	81.51	38.76	63.42	35.43	60.65	32.76
Distance to admin. centre	92.59	56.86	64.44	55.23	59.55	53.58
Percent agricultural	37.10	29.16	31.72	24.91	32.46	24.68
Household size	3.08	1.54	3.10	1.73	3.23	1.79
Adult age	38.39	11.79	39.50	12.60	39.01	12.15
Adult males	0.47	0.20	0.44	0.22	0.47	0.22
Head married	0.87	0.33	0.81	0.39	0.79	0.40
Education years	5.12	4.92	8.18	4.89	7.64	5.35
Asset index	2.45	1.04	2.71	1.17	2.80	1.10

(b) Nigeria 2010, Community treatment

	Never Treated		Treated by 2015		Treated by 2012	
	Mean	SD	Mean	SD	Mean	SD
Distance to road	23.57	21.78	14.22	23.53	15.03	10.04
Distance to market	84.86	38.67	61.36	35.80	67.52	32.14
Distance to admin. centre	96.66	55.59	57.72	53.07	66.06	57.36
Percent agricultural	37.92	29.74	33.69	21.93	31.60	18.48
Household size	3.13	1.55	2.96	1.52	3.11	1.66
Adult age	37.52	11.07	39.72	11.86	40.51	14.28
Adult males	0.48	0.18	0.45	0.22	0.46	0.24
Head married	0.90	0.30	0.82	0.38	0.77	0.42
Education years	5.00	4.93	7.13	4.76	6.83	5.64
Asset index	2.45	1.03	2.78	1.22	2.74	1.18

(c) Ethiopia 2011, Household treatment

	Never Treated		Treated by 2015		Treated by 2013	
	Mean	SD	Mean	SD	Mean	SD
Distance to road	17.85	23.36	11.78	9.92	10.78	13.36
Distance to market	71.24	51.68	50.21	28.21	49.53	32.58
Distance to admin. centre	174.00	122.22	133.72	86.18	189.46	112.64
Percent agricultural	32.16	19.94	38.60	23.10	35.98	20.75
Household size	2.47	1.17	2.46	0.89	2.39	1.35
Adult age	36.87	12.16	35.55	10.83	36.88	15.51
Adult males	0.45	0.22	0.49	0.20	0.44	0.27
Head married	0.78	0.41	0.78	0.42	0.73	0.45
Education years	3.83	3.44	5.16	3.51	5.54	3.77
Asset index	1.06	0.41	1.12	0.53	1.11	0.39

As we have three survey waves in total, and two separate treatment cohorts, we also have the special case of staggered treatment timing. Thus we take advantage of recent developments in staggered treatment timing treatment effect estimation with a difference-in-differences approach, describing the effects both in terms of treatment cohort (grouped by year of treatment) and average effects across both cohorts. This relies on the extension of the DRDiD approach for staggered treatment timing as proposed by Callaway and Brantly (2021b) and implemented in the R package *did* (Callaway et al., 2021a). Formal definition of the staggered treatment DRDiD ATT estimation is taken directly from Eq. 2.4 in Callaway and Brantly (2021b), and provided in Eq. 1:

$$ATT_{DR}(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}\left[G_g\right]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)\left(Y_t - Y_{g-1} - m_{g,t}(X)\right)\right], \tag{1}$$

where g indexes the treatment cohort (e.g. 2012 and 2015 in Nigeria). t indexes the year (e.g. 2010, 2012 and 2015 in Nigeria). G is a dummy variable indicating whether the observation is in treatment cohort g - this fraction weights treatment cohort observations by the share of treated units in cohort g relative to the total observations for that time period t. $p_g(X)$ is the propensity score reflecting the likelihood that the observation would be in treatment cohort g conditional on a set of covariates X - this fraction weights control group observations by their propensity to be treated. C is a dummy variable indicating whether the observation is in the control (never treated) group - this effectively nullifies the IPW weights if the observation is in the treatment group. Y_t reflects the outcome at time t. Y_{g-1} reflects the outcome at baseline (pre-treatment) for group g. $m_{g,t}(X)$ reflects the OR modeled counterfactual change in the outcome for the treatment group, conditional on covariates X.

Intuition underlying this estimator can be gained through a brief revision of the two-period difference-in-differences estimator with the potential outcomes notation. This is provided in Eq. 2 which describes an *unobservable* aggregate calculated using only the treated group where the term $Y_{\text{post}}^{\text{untreated}}$, or the counterfactual outcome had the treated group not been treated in the post period, is unable to be observed by definition:

$$\text{ATT} = \mathbb{E}\left[\left(Y_{\text{post}}^{\text{treated}} - Y_{\text{pre}}\right) - \left(Y_{\text{post}}^{\text{untreated}} - Y_{\text{pre}}\right)\right], \tag{2}$$

Under the strict parallel trends assumption, trends in the observed control group pre and post ($Y_{\text{control,post}}^{\text{untreated}} - Y_{\text{control,pre}}^{\text{untreated}}$) are used as an estimate of the treated group counterfactual trends. As we have already noted, this is not able to be defended in our case for several reasons. Thus we must impute a counterfactual group conditional on a set of covariates X. The DRDiD approach does this for each treatment cohort g using both IPW and OR, such that if either of these are correctly specified we will recover the true ATT. Conditional on correct specification, Eq. 2 is thus estimated, with the unobserved counterfactual difference in the second set of brackets imputed using the control group and a set of covariates X in the baseline period. Detailed proofs for this approach are provided by Sant'Anna and Zhao (2020) and Callaway and Brantly (2021b). Further helpful discussion of the intuition underlying this approach is provided by Cunningham (2021).

3.2.1. Baseline covariates

In the context of our empirical strategy, it is important to correctly specify covariates for performing the inverse probability weighting (IPW) or the outcome regression (OR) operations. Previous literature contributions indicate that household wealth, education and demography, as well as distance to complementary infrastructure and services are potential important determinants of the entrepreneurship and employment outcomes assessed in this study.

Baseline level of household wealth is likely related to the capital expenditure capacity, which in turns translates to the likelihood of purchasing and operating electric appliances which are required for non-farm entrepreneurship (Tesfamichael et al., 2020; Taneja, 2018a), as well as employing personnel and covering operational costs. Similar considerations hold for education and demography, with areas with *ceteris paribus* more educated and younger population both being likely positively associated with entrepreneurial activity (Quatraro and Vivarelli, 2015). Finally, ancillary services such as the presence of roads and telecommunications (Ajide, 2020) have also been shown to be crucial enablers of entrepreneurship in developing countries of Africa.

We can evaluate the differences between each selected covariate conditional on the treatment status in Table 2, which reports the mean and standard deviation of selected covariates in the baseline year for each treatment category. 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 (*Nigeria*: Mat, Chairs, Tables, Bed, Mattress, Sofa, Bicycle, Motorbike, Car; *Ethiopia*: Mattress, Sofa, Bicycle, Motorbike, Car).

The summary statistics indicate that reasonably large differences exist in the covariates conditional on the group. Reflecting on the differences in these baseline covariates between treatment and control groups, we would need to be very confident that these differences would ahve had no dynamic effects on treatment outcomes if we were taking the alternative 'simple' two-way fixed-effects empirical approach. Indeed we know from the literature that access to household assets and complementary infrastructure have at least an uncertain effect on the outcomes we are interested in. The DRDiD approach we take allows us to use these baseline differences to create a counterfactual for the treatment group and thus requires both different and fewer assumptions as noted above.

3.2.2. Outcome variables

We define two categories of outcome variables that are further disaggregated by gender and other factors. These are non-farm entrepreneurship (NFE) and household employment (Employment), as shown in Table 3 below. The first category reflects the number of non-farm enterprises operated by the household, and is split into those owned by any gender, or those co-owned by a women, as well as those categorised as retail, manufacturing and any non-farm enterprises based on the International Standard Industrial Classification of All Economic Activities (ISIC) codes. The second category reflects the share of wage-employed adults within the household, and is split by gender as well as non-farm, farm and any employment. Table 4 compares the outcome variable group means between treatment (combining mid and end cohorts)

Table 3
Overview of outcome variables by category and group.

Category	Description (aggregated to household level)	Group	Variable
NFE	Total number of NFEs by group	All household	NFE All
		All household	NFE Retail
		All household	NFE Manuf.
		Co-owned by females	NFE All (Wmn)
		Co-owned by females	NFE Retail (Wmn)
		Co-owned by females	NFE Manuf. (Wmn)
Employment	Number of adults employed by group	All household	Emp. All
		Household males	Emp. All (Men)
		Household females	Emp. All (Wmn)
	Number of adults non-farm employed by group	All household	Emp. Non-farm
		Household males	Emp. Non-farm (Men)
		Household females	Emp. Non-farm (Wmn)
	Number of adults farm employed by group	All household	Emp. Farm
		Household males	Emp. Farm (Men)
		Household females	Emp. Farm (Wmn)

Table 4
Group means of selected outcome variables across control and treatment groups and over the three survey waves.

(a) Nigeria 2010–2015, Household treatment

	Never Treated			Treated by 2015			Treated by 2012		
	2010	2012	2015	2010	2012	2015	2010	2012	2015
NFE All	0.64	0.82	0.80	0.68	0.79	0.75	0.67	0.92	0.91
NFE Retail	0.26	0.35	0.38	0.40	0.43	0.42	0.36	0.50	0.54
NFE Manuf.	0.07	0.12	0.13	0.05	0.05	0.07	0.06	0.09	0.12
Emp. All	1.99	2.00	1.92	2.08	1.99	2.11	1.87	1.85	1.95
Emp. Non-farm	0.60	0.59	0.57	0.68	0.81	0.67	0.91	0.91	0.84
Emp. Farm	1.37	1.41	1.35	1.39	1.18	1.44	0.93	0.95	1.12

(b) Nigeria 2010–2015, Community treatment

	Never Treated			Treated by 2015			Treated by 2012		
	2010	2012	2015	2010	2012	2015	2010	2012	2015
NFE All	0.65	0.84	0.81	0.58	0.76	0.72	0.79	0.92	0.90
NFE Retail	0.26	0.34	0.38	0.27	0.35	0.36	0.37	0.49	0.51
NFE Manuf.	0.07	0.12	0.13	0.07	0.04	0.04	0.05	0.08	0.10
Emp. All	1.99	2.04	1.96	2.19	1.98	2.09	2.09	2.09	2.09
Emp. Non-farm	0.58	0.58	0.58	0.73	0.76	0.64	0.82	0.78	0.73
Emp. Farm	1.38	1.46	1.38	1.46	1.22	1.46	1.26	1.30	1.36

(c) Ethiopia 2011–2015, Household treatment

	Never Treated			Treated by 2015			Treated by 2013		
	2011	2013	2015	2011	2013	2015	2011	2013	2015
NFE All	0.27	0.28	0.27	0.32	0.29	0.31	0.44	0.59	0.45
NFE Retail	0.08	0.08	0.10	0.09	0.13	0.15	0.12	0.23	0.20
NFE Manuf.	0.06	0.06	0.08	0.06	0.01	0.09	0.06	0.04	0.13
Emp. All	4.14	3.62	3.40	3.04	2.79	2.18	3.52	2.52	2.59
Emp. Non-farm	0.84	0.37	0.35	0.72	0.79	0.63	1.51	1.04	1.00
Emp. Farm	3.21	3.23	3.05	2.18	2.00	1.54	2.00	1.47	1.59

across all survey years.

4. Results

Estimates derived from our empirical analysis are now discussed. The figures presented here show the estimated average treatment effect on the treated (the ATT), i.e. on households that received access to electricity in the periods under analysis, in units of the outcome variable. The group-level treatment cohort ATT's are aggregated for simplicity, further detail on cohort-specific ATTs are provided in the appendices. Community-level treatment in Ethiopia cannot be estimated due to lack of community-level treatment information in the survey data. We consider the community-level treatment definition in Nigeria to be the most robust to possible endogeneity as the effect of household self-selection into treatment are removed here, while the other two concerns remain present and are argued to have been addressed through our empirical approach.

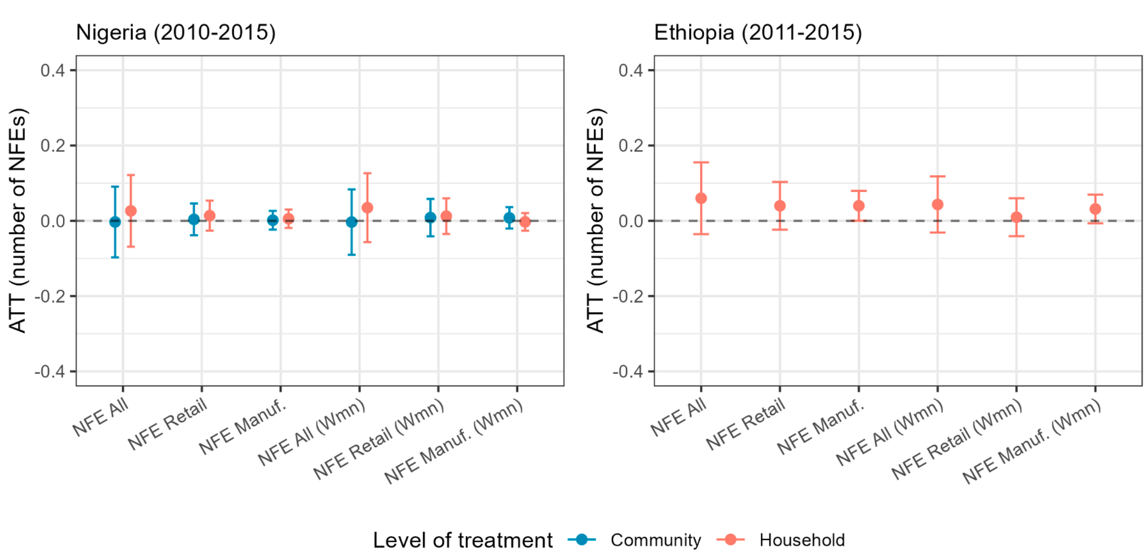

Fig. 2. Main results, estimated change in average number of NFEs per household following grid electrification. Treatment is assigned at both the household- and community-levels in Nigeria, and only at the household-level in Ethiopia. The results shown are aggregates of distinct treatment cohort ATTs which are provided separately in the appendices.

4.1. Non-farm Entrepreneurship

The results for the first category of outcome variables are presented in Fig. 2. The first three estimates describe the change in total NFEs, retail NFEs and manufacturing NFEs, while the latter three estimates restrict these to NFE's co-owned by women in the household. The results indicate that the coefficients for the average change in number of NFEs operated by households following electrification are generally not statistically significant at a 95% level of confidence. That is, we are unable to identify a treatment effect distinct from what we would expect to occur under normal sampling variation. This holds at both the household-level and at the arguably more defensible community-level of treatment in Nigeria, and similarly at the household-level of treatment in Ethiopia. Heterogeneity across different types of non-farm enterprises and those co-owned by women household members are not evident.

4.2. Employment

The results for the second category of outcome variables are presented in Fig. 3. The first three estimates describe estimated change in number of household adults employed in the farm or non-farm sector, also disaggregated by gender[3]. The second three estimates describe change in non-farm employment and the final three estimates describe change in farm employment.

We observe some heterogeneity across our two country case studies in terms of the expected shift away from farm employment towards non-farm employment. First, reflecting on overall average rate of employment among household adults, we find some evidence of a positive shift in Nigeria among both male and female household adults. This is not evident in Ethiopia, where we see much wider error bars likely attributable to high rates of farm-based self employment (see Table 4). Decomposing this effect, we reflect on the estimated change in non-farm and farm employment across both countries. The data from Nigeria appears to suggest a shift away from non-farm employment (not statistically significant), towards farm employment (statistically significant). This is once again not evident in Ethiopia, where we see no relevant shifts in employment outcomes following treatment, across either of the treatment cohorts and when disaggregating by gender.

5. Discussion

5.1. Results and policy implications

The results of our analysis in the two very different contexts of rural Ethiopia and Nigeria indicate that rural electrification considered alone was insufficient to trigger shifts towards non-farm entrepreneurship and employment in the 2–4 years following grid connection. Rather, we observe some evidence of an intensification of employment in the agricultural sector among the treatment group in rural Nigeria. We now discuss some of the potential mechanisms behind these findings.

Previous literature has discussed why the availability of electricity access is certainly an enabler and largely a necessary condition of modern energy services adoption, but likely not a sufficient one (Taneja, 2018b; Poblete and Miguel, 2021; Action, 2013; Riva et al., 2018; Muchapondwa, 2021). Availability of electrical equipment and machinery, as well as the capital (or access to capital) necessary to purchase and use these is a complementary condition, which is largely not observed in the short-term in contexts of diffused poverty such as among households and areas that only very recently received access to electricity. These constraints are associated with market inefficiencies, recently shown to trigger private sector firms targeting the gap in affordable finance of productive equipment for micro- and small-enterprises consuming off-grid electricity in similar contexts (Trotter, 2021). Moreover, entrepreneurial activities and corresponding increased employment require market access in order to sell products and services beyond the local community, a condition which requires suitable transport infrastructure that itself is still developing (Berg et al., 2018; Bryceson et al., 2008). This has been recently explored using high-resolution longitudinal electricity consumption data among micro- and small firms in Kenya, describing low levels of productive electricity utilisation in rural areas modified positively by access to road infrastructure (Muhwezi et al., 2021). Finally, although we do not discuss this in our empirical work, it is well understood that electricity access is multi-dimensional and corresponds to distinct attributes of supply. While differences in electricity supply duration may modify our findings, we are unable to directly test this as the data necessary was not collected in Ethiopia and ambiguously defined in Nigeria.

While we speculate here that rural electrification efforts must be accompanied with expansion of complementary infrastructure and market integration, Fetter et al. (2020) show that short-run effects of rural electrification are also modified by the local natural environment. Their work using a regression discontinuity design identified a strong positive effect of electrification on village economic outcomes in rural India for those villages proximate to natural Guar resources - a key input for the fracking industry in the USA. Electrification in this context was thus essential to exploit the resource effectively and resulted in heterogenous outcomes between villages similar in all other respects. Indeed there is a growing literature finding heterogeneous treatment effects with respect to specific types of firms (or household businesses) and the environment in which they operate (Mori, 2020; Muchapondwa, 2021). This leads to the intuitive and somewhat mundane hypothesis that electrification unequally modifies productive enterprise performance depending on their ability to leverage this input.

In this context, we discuss our finding of a positive effect of electrification on agricultural employment in rural Nigeria. There are several intuitive channels through which electricity access could theoretically improve the enabling environment for agricultural enterprises, such as farm mechanisation and pumped irrigation (Cabraal et al., 2005; Barnes, 2014). The corresponding increase in yield (e.g. through irrigation) and added value to raw harvests (e.g. through local processing) could be argued to lead to a net increase in labour demand in the agricultural sector as businesses expand, though this would be attenuated through corresponding higher labour productivity. A longitudinal study of the labour market effects of historical rural electrification in the U.S. identifies evidence of precisely such short-term trends in the agricultural sector, with longer-term effects identified in other sectors (Lewis and Joshua, 2020).

Why do we see evidence of this in Nigeria and not in Ethiopia? Beyond qualifying our findings with the limitations of our sample size and panel length, we can reflect on the broader differences between these two countries discussed earlier in this work. National-level data describes Nigeria as country with higher levels of wealth and education in rural areas, and Ethiopia as a country with already very high levels of farm-dependent livelihoods. The short-term shift in Nigeria towards increased agricultural employment is perhaps more likely given the capacity of the population (and firms) to take advantage of this, and more noticeable given the pre-treatment rates of farm employment in rural areas. In contrast, compositiitional changes in the type of farm employment necessary to see these shifts in Ethiopia are not measured and thus any shifts may be hidden given the level of farm employment saturation already evident. While we are only able to speculate about this in our context, the notion that agricultural enterprises may expand and drive up agricultural employment in the short-term following the availability of electricity is aligned with the literature. At the very least, this provides a pathway for further research into differences in complementary infrastructure and enabling environments in rural regions of these two countries.

[3] Households without either male or female adults were excluded from the respective analysis

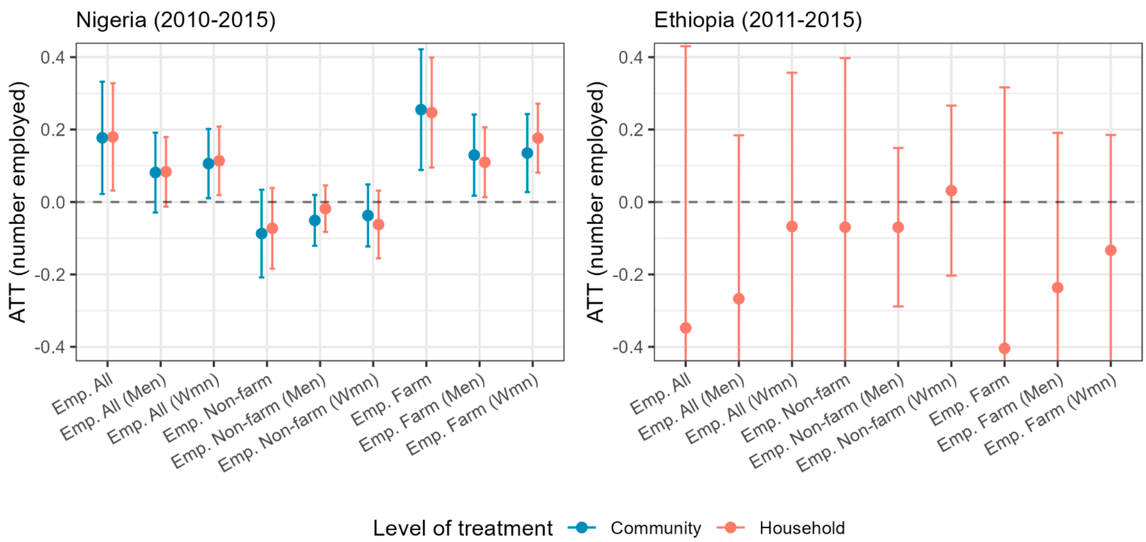

Fig. 3. Main results, estimated change in number of working age household adults employed following grid electrification. Treatment is assigned at both the household- and community-levels in Nigeria, and only at the household-level in Ethiopia. The results shown are aggregates of distinct treatment cohort ATTs which are provided separately in the appendices.

5.2. *Methodological aspects and limitations*

Our empirical approach follows recent criticisms of the literature with respect to the identification strategies employed (see Bensch et al., 2020; Bensch et al., 2021; Lee et al., 2020; Mori, 2020; Muchapondwa, 2021). Notably, our analysis of the rural sample within Nigeria provides contrary evidence to recent work using the same dataset which identified a positive association between electrification and shifts towards non-farm employment using IV regression and matching analyses (see Tagliapietra et al., 2020, though we note that our work is not a replication and was conceived independently.).

In addition, in our study we strictly separate rural and urban samples in the survey data. We argue that while descriptive evidence combining rural and urban areas is crucial to the development of a broader understanding, causal analysis with such small numbers of treated households should not combine rural and urban samples due to the stark compositional differences and unmeasured confounding factors between these two groups. The problems caused by combining rural and urban samples in this context may not be solved through the DRDiD approach we have applied, nor the approaches employed in the literature.

With respect to limitations, first, the identification of sufficiently large and consistent treatment and comparative control groups is challenging in contexts where electrification has improved quite slowly, or in some regions, not at all. Without variation in electrification status, any 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. At the same time, with such low levels of treatment, avoiding vast compositional differences such as those between rural and urban samples is even more necessary. 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 analyses.

Second, the short-term nature of available observational data limits inference and, arguably, reduces policy relevance. 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 rural 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 Panharoth, 2021).

Third, we have identified three channels of endogeneity between rural electrification and household economic outcomes that confound inference of the causal parameter. These include, (i) *village-level selection bias*, (ii) *household-level selection bias*, and (iii) *other omitted variable bias*. The DRDiD approach we employ can effectively deal with (i) and (iii) conditional on correctly specifying the vector of baseline covariates. Channel (ii) continues to be a problem given that it is arguably much harder to defend conditional parallel trends with household self-selection into treatment as this may indeed be related to a variety of unmeasured confounders that may result in time-varying heterogeneity in outcomes. For example, recent analysis emphasises the role of household willingness to pay for a grid connection on the short-term socioeconomic outcomes (see Lee et al., 2020). Our use of community-level treatment specification in Nigeria is one attempt to address this channel. This refers to the definition of the treatment group as those households that do not explicitly choose to be grid connected, but benefit from the effects of local electrification of their community. We propose that community-level treatment designation is less vulnerable to channel (ii) as the community-level confounders that are related to household economic outcomes (i.e. that reflect the selection bias) are arguably better able to be controlled for given the covariates available. At the very least, these are more straightforward than other household-level confounders such as willingness to pay or inherent entrepreneurship which may change over time and are likely to dynamically affect household economic outcomes.

Notwithstanding the challenges and limitations we have described above, the overarching policy implication of our work is evidence of limited short-term household employment outcomes following electrification in Ethiopia and Nigeria, and applied methodological advancement in the context of electrification impact analysis with sparse survey data.

5.3. *Conclusion*

In this article we analysed the effects of grid electrification on household transitions away from agricultural livelihoods in rural Sub-Saharan Africa, specifically in the cases of rural Nigeria and Ethiopia. Our results indicate that no broad causal relationship between rural 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. These findings are aligned with the contemporary rural electrification effects literature urging caution in drawing inference from potentially biased identification strategies that are unable to effectively extract a reliable estimate of the desired causal estimand. At the same time, we note several limitations 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. We speculate that structural economic impacts of electrification should likely be evaluated over longer periods of time, in order to improve identification of the causal effects of access and its relationship with necessary complementary infrastructure and capacity, which can take a substantial amount of time to be developed. In addition, we cautiously welcome complementing survey data with remotely sensed datasets. In this context, and despite presenting limitations and sources of uncertainty, an increasing number of studies have sought to proxy (part of) the variation in local infrastructure improvement through administrative records, remotely sensed datasets, or mobile phone utilisation data (Brian, 2021; Falchetta et al., 2020; Salat et al., 2020; Salat et al., 2021).

We conclude with a note of caution in the interpretation of our work. A strict economic cost-benefit analysis informed by studies such as ours may arrive at the conclusion that rural electrification efforts are not worthwhile, especially in remote and hard to reach areas. This would be a limited uni-dimensional perspective. Rather, we propose that rural electrification efforts are justified in the capabilities and freedoms that these provides rural households and businesses in the short- and long-run. While the need for appropriate cost-recovery and associated support to electricity distribution companies serving rural areas is clear, we argue that designing electrification policy based on expected short-term economic shifts will likely disappoint policy makers and may increase inequity as sub-national implementation efforts coalesce around regions (already) developing rapidly. We consider our findings to speak for more alignment between economic development and infrastructure access policies with the goal to improve the well-being of the population over the long-term. We argue that the provision of modern infrastructure should be embedded in frameworks of human well-being, such as the Decent Living Standards (Rao and Min, 2017). Under a framework such as the DLS, infrastructure provision that serves the normative purpose of improved household well-being would not be considered or justified in isolation, but rather together with the other services necessary to achieve the desired human development outcomes. The motivation for infrastructure policy development from this perspective would then be of providing all households with the necessary freedoms and capabilities to live a decent life, which is quite distinct from an economic cost-benefit motivation governed by the expected returns to a specific intervention. Such a holistic perspective would also provides a suitable foundation upon which the cross-cutting challenges and constraints posed by climate change mitigation and adaptation can be considered and addressed.

CRediT authorship contribution statement

Setu Pelz: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Validation, Visualization, Investigation, Writing - original draft, Writing - review & editing. **Shonali Pachauri:** Conceptualization, Supervision, Writing - review & editing. **Giacomo Falchetta:** Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

A complete replication archive is provided here: https://doi.org/10.7910/DVN/9ZLPFR

Acknowledgement

This work was first developed during the Young Scientists Summer Program (YSSP) at the International Institute for Applied Systems Analysis (IIASA) in 2020. We thank the organisers and participants of YSSP 2020 for their helpful advice in improving the research design. We also thank the two anonymous reviewers and editor for providing helpful criticisms in improving our manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wdp.2022.100473.

References

Action, Practical (2013). *Poor people's energy outlook 2012: Energy for earning a living.* Practical Action Publishing.

Ajide, Folorunsho M. (2020). Infrastructure and entrepreneurship: Evidence from Africa. *Journal of Developmental Entrepreneurship, 25*(03), 2050015.

Banerjee, Sudeshna Ghosh, Francisco Alejandro Moreno, Jonathan Sinton, Tanya Primiani, and Joonkyung Seong. 2017. "Regulatory indicators for sustainable energy.".

Barnes, Douglas F. (2014). *Electric Power for Rural Growth: How Electricity Affects Rural Life in Developing Countries* (1st ed.). New York: Routledge.

Bayer, Patrick, Kennedy, Ryan, Yang, Joonseok, & Urpelainen, Johannes (2019). The need for impact evaluation in electricity access research. *Energy Policy*, Article 111099.

Bensch, Gunther, and Jörg Peters. 2020. "Effects of Rural Electrification on Employment: A Comment on Dinkelman (2011).".

Bensch, Gunther, Jörg Peters, and Colin Vance. 2021. "Development Effects of Electrification in Brazil – A Comment on Lipscomb et al. (2013)." SSRN Electronic Journal.

Berg, Claudia N, Blankespoor, Brian, & Selod, Harris (2018). Roads and rural development in Sub-Saharan Africa. *The Journal of Development Studies, 54*(5), 856–874.

Bryceson, Deborah Fahy, Bradbury, Annabel, & Bradbury, Trevor (2008). Roads to poverty reduction? Exploring rural roads' impact on mobility in Africa and Asia. *Development Policy Review, 26*(4), 459–482.

Burlig, Fiona, and Lous Preonas. 2022. Out of the Darkness and Into the Light? Development Effects of Rural Electrification. Technical Report WP 268 Energy Institute at HAAS.

Cabraal, R. Anil, Barnes, Douglas F., & Agarwal, Sachin G. (2005). Productive uses of energy for rural development. *Annual Review of Environment and Resources, 30*(1), 117–144.

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021a. "did: Difference in Differences.". R package version 2.1.1.

Callaway, Brantly, & Sant'Anna, Pedro H. C. (2021b). Difference-in-Differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230.

Chhay, Panharoth, & Yamazaki, Koji (2021). Rural electrification and changes in employment structure in Cambodia. *World Development, 137*, Article 105212.

Cunningham, Scott (2021). *Causal Inference: The Mixtape*. Yale University Press.

Davis, Benjamin, Di Giuseppe, Stefania, & Zezza, Alberto (2017). Are African households (not) leaving agriculture? Patterns of households' income sources in rural Sub-Saharan Africa. *Food Policy, 67*, 153–174.

den Broeck, Goedele Van, and Talip Kilic. 2019. "Dynamics of off-farm employment in Sub-Saharan Africa: A gender perspective." World Development 119: 81–99.

Dinkelman, Taryn (2011). The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review, 101*(7), 3078–3108.

Falchetta, Giacomo, Pachauri, Shonali, Byers, Edward, Danylo, Olha, & Parkinson, Simon C (2020). Satellite observations reveal inequalities in the progress and effectiveness of recent electrification in sub-Saharan Africa. *One Earth, 2*(4), 364–379.

Fetter, T. Robert, and Faraz Usmani. 2020. Fracking, Farmers, and Rural Electrification in India. Technical report Ruhr Economic Papers 864.

Nerini, Fuso, Francesco, Julia Tomei, To, Long Seng, Bisaga, Iwona, Parikh, Priti, Black, Mairi, Borrion, Aiduan, Spataru, Catalina, Broto, Vanesa Castán, Anandarajah, Gabrial, et al. (2018). Mapping synergies and trade-offs between energy and the Sustainable Development Goals. *Nature Energy, 3*(1), 10–15.

Gibson, John, & Olivia, Susan (2010). The Effect of Infrastructure Access and Quality on Non-Farm Enterprises in Rural Indonesia. *World Development, 38*(5), 717–726.

Hamburger, David, Jaeger, Joel, Bayer, Patrick, Kennedy, Ryan, Yang, Joonseok, & Urpelainen, Johannes (2019). Shades of darkness or light? A systematic review of geographic bias in impact evaluations of electricity access. *Energy Research & Social Science, 58*, Article 101236.

IEA, IRENA, UNSD, World Bank, and WHO. 2021. "Tracking SDG 7: The Energy Progress Report.".
Jeuland, Marc, Robert Fetter, T., Li, Yating, Pattanayak, Subhrendu K., Usmani, Faraz, Bluffstone, Randall A., Chávez, Carlos, Girardeau, Hannah, Hassen, Sied, Jagger, Pamela, Jaime, Mónica M., Karumba, Mary, Köhlin, Gunnar, Lenz, Luciane, Litzow, Erin L., Masatsugu, Lauren, Naranjo, Maria Angelica, Peters, Jörg, Qin, Ping, Ruhinduka, Remidius D., Serrano-Medrano, Montserrat, Sievert, Maximiliane, Sills, Erin O., & Toman, Michael (2021). Is energy the golden thread? A systematic review of the impacts of modern and traditional energy use in low- and middle-income countries. *Renewable and Sustainable Energy Reviews, 135*, Article 110406.
Khurana, Tanvi, & Sangita, Seema (2022). Household access to electricity and non-farm business in rural India: A panel data analysis. *Energy for Sustainable Development, 67*, 125–134.
Lee, Kenneth, Miguel, Edward, & Wolfram, Catherine (2020). Does Household Electrification Supercharge Economic Development? *Journal of Economic Perspectives, 34*(1), 122–144.
Lewis, Joshua, & Severnini, Edson (2020). Short- and long-run impacts of rural electrification: Evidence from the historical rollout of the U.S. power grid. *Journal of Development Economics, 143*, Article 102412.
Lipscomb, Molly, Mushfiq Mobarak, A., & Barham, Tania (2013). Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. *American Economic Journal: Applied Economics, 5*(2), 200–231.
Kuete, Malah, Yselle, F., & Asongu, Simplice A. (2022). Infrastructure development as a prerequisite for structural change in Africa. *Journal of the Knowledge Economy*, 1–27.
McCollum, David L, Echeverri, Luis Gomez, Busch, Sebastian, Pachauri, Shonali, Parkinson, Simon, Rogelj, Joeri, Krey, Volker, Minx, Jan C., Nilsson, Måns, Stevance, Anne-Sophie, & Riahi, Keywan (2018). Connecting the sustainable development goals by their energy inter-linkages. *Environmental Research Letters, 13* (3), Article 033006.
Min, Brian. 2021. "Lighting the Way: Nighttime Lights for Electrification Planning.".
Mori, Raul Jimenez. 2020. Development Effects of Electrification: A Meta-Analysis for Income, Labor and Educational Outcomes. Technical report The Latin American and Caribbean Economic Association - LACEA.
Muchapondwa, Edwin, Marc Jeuland, and Abebe Shimeles. 2021. "Addressing the Challenges of Sustainable Electrification in Africa through Comprehensive Impact Evaluations.".
Muhwezi, Bob, Williams, Nathaniel J., & Taneja, Jay (2021). Ingredients for growth: Examining electricity consumption and complementary infrastructure for Small and Medium Enterprises in Kenya. *Development Engineering, 6*, Article 100072.
Nagler, Paula, & Naudé, Wim (2017). Non-farm entrepreneurship in rural sub-Saharan Africa: New empirical evidence. *Food Policy, 67*, 175–191.
Owoo, Nkechi S., & Naudé, Wim (2016). Spatial proximity and firm performance: evidence from non-farm rural enterprises in Ethiopia and Nigeria. *Regional Studies, 51*(5), 688–700.
Perez-Sebastian, Fidel, Steinbuks, Jevgenijs, Feres, Jose Gustavo, & Trotter, Ian Michael (2020). Electricity Access and Structural Transformation: Evidence from Brazil's Electrification. *World Bank Policy Research Working Paper, 9182*.
Poblete-Cazenave, Miguel, & Pachauri, Shonali (2021). A model of energy poverty and access: Estimating household electricity demand and appliance ownership. *Energy Economics, 98*, Article 105266.
Quatraro, Francesco, & Vivarelli, Marco (2015). Drivers of entrepreneurship and post-entry performance of newborn firms in developing countries. *The World Bank Research Observer, 30*(2), 277–305.
Rao, Narasimha D. (2013). Does (better) electricity supply increase household enterprise income in India? *Energy Policy, 57*, 532–541.
Rao, Narasimha D., & Min, Jihoon (2017). Decent Living Standards: Material Prerequisites for Human Wellbeing. *Social Indicators Research, 138*(1), 225–244.
Riva, Fabio, Ahlborg, Helene, Hartvigsson, Elias, Pachauri, Shonali, & Colombo, Emanuela (2018). Electricity access and rural development: Review of complex socio-economic dynamics and causal diagrams for more appropriate energy modelling. *Energy for Sustainable Development, 43*, 203–223.
Salat, Hadrien, Schläpfer, Markus, Smoreda, Zbigniew, & Rubrichi, Stefania (2021). Analysing the impact of electrification on rural attractiveness in Senegal with mobile phone data. *Royal Society open science, 8*(10), Article 201898.
Salat, Hadrien, Smoreda, Zbigniew, & Schläpfer, Markus (2020). A method to estimate population densities and electricity consumption from mobile phone data in developing countries. *PloS one, 15*(6), Article e0235224.
Salmon, Claire, & Tanguy, Jeremy (2016). Rural Electrification and Household Labor Supply: Evidence from Nigeria. *World Development, 82*, 48–68.
Samad, Hussain, and Fan Zhang. 2017. "Heterogeneous Effects of Rural Electrification: Evidence from Bangladesh.".
Sant'Anna, Pedro H. C., & Zhao, Jun (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics, 219*(1), 101–122.
Tagliapietra, Simone, Occhiali, Giovanni, Nano, Enrico, & Kalcik, Robert (2020). The impact of electrification on labour market outcomes in Nigeria. *Economia Politica, 37* (3), 737–779.
Taneja, Jay. 2018a. "If you build it, will they consume? Key challenges for universal, reliable, and low-cost electricity delivery in Kenya." Center for Global Development Working Paper (491).
Taneja, Jay. 2018b. "If you build it, will they consume? Key challenges for universal, reliable, and low-cost electricity delivery in Kenya." Center for Global Development Working Paper (491).
Tesfamichael, Meron, Bastille, Clifford, & Leach, Matthew (2020). Eager to connect, cautious to consume: An integrated view of the drivers and motivations for electricity consumption among rural households in Kenya. *Energy Research & Social Science, 63*, Article 101394.
Trotter, Philipp A. (2021). From silos to systems: Enabling off-grid electrification of healthcare facilities, households, and businesses in sub-Saharan Africa. *One Earth, 4* (11), 1543–1545.
UN. 2015. "Transforming Our World: The 2030 Agenda for Sustainable Development. Draft resolution referred to the United Nations summit for the adoption of the post-2015 development agenda by the General Assembly at its sixty-ninth session. UN Doc. A/70/L.1 of 18.".
van de Walle, Dominique, Ravallion, Martin, Mendiratta, Vibhuti, & Koolwal, Gayatri (2015). Long-Term Gains from Electrification in Rural India. *The World Bank Economic Review.*