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ABSTRACT

Evaluating the Impacts of Minigrid Electrification in Sub-Saharan Africa

A large share of the population of sub-Saharan Africa (SSA) lacks access to modern energy services. To bridge the electricity access gap, distributed power generation systems such as minigrids and stand-alone photovoltaic systems emerge as attractive options in the power supply solution space. In this study, we analyze the impact of minigrid electrification on household welfare and agricultural development across SSA countries. The empirical analysis makes use of a novel geocoded database covering 1,888 minigrid projects from 27 SSA countries, which is merged with various data sources including satellite-based nighttime light data, vegetation health index, and Demographic and Health Surveys. Our results indicate that minigrid electrification is positively associated with households' electricity uptake, ownership of low-power home appliances, and agricultural employment and productivity, while being effective in changing neither overall labor market outcomes nor the choice of cooking fuels.

JEL Classification: O13, J43, Q01, Q42, N57

Keywords: electricity access, minigrids, household welfare, agriculture, sub-Saharan Africa

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1. Introduction

Nearly half of the sub-Saharan African (SSA) population, namely almost 600 million people, lack access to electricity, while clean cooking solutions are only available to about one in six people in the region (IEA, 2019; World Bank, 2022b). To achieve universal electricity access in SSA, distributed power generation and supply systems such as minigrids and solar home systems are increasingly seen as attractive and financially viable solutions in the electricity access solution space (IEA, 2019; SEforAll, 2020). At present, over 1,500 minigrids are estimated to be operating across SSA, connecting around 15 million people, and at least 400 additional minigrids are planned (ESMAP, 2019). Despite the growing relevance of minigrids, a comprehensive, multi-country ex-post assessment of the socio-economic impacts of electrification through minigrids has so far been lacking in the literature.

Unlike standalone systems (e.g. solar home systems, pico-PV systems), properly sized minigrids are capable of providing sufficient energy for productive uses[1], without incurring into the high upfront costs of extending transmission lines required for grid extension (AMDA, 2020; Peters et al., 2019). Given our key interest in the productive use of energy, we limit the scope of this study to minigrid electrification, excluding stand-alone systems from the present analysis. The present analysis is built on two pillars, namely the effects of minigrid electrification on (i) household welfare and (ii) agricultural development. Concerning the first pillar, we use household-level outcome variables and incorporate the behavioral responses of households through the access to electricity, ownership of electrical appliances, choice of cooking fuel, and employment related

[1] See the appendix for power requirements of selected income-generating appliances presented in Table A.1 and the tier system for measuring energy access presented in Table A.2.

outcomes. For the second pillar, we consider community-level agricultural vegetation health status as a proxy for agricultural productivity as well as agricultural employment at household level.

It is worth noting that due to strong and multiple sources of endogeneity, substantial challenges exist in the establishment of an identification strategy capable of causally linking electrification and development outcomes, as recently noted in a set of discussion papers (Bensch et al., 2020a, 2021). Building on this literature, here we seek to evaluate the impacts of electrification through minigrids on lightening and empowering rural African communities. To the best of our knowledge, it is the first attempt to provide causal evidence on household welfare and agriculatural development effects of minigrid electrification across a broad set of SSA countries.

The lack of a structured dataset has so far been the main limitation for the empirical research in the field (Knuckles, 2019). The increasing attention on off-grid solutions has recently stimulated several data collection initiatives. One of the most comprehensive and publicly available databases on minigrids has been published by the African Association for Rural Electrification (CLUB-ER), which involves 1,888 georeferenced minigrid projects from twenty-seven SSA countries and their characteristics including the year of installation, installed capacity, technology type, operational status, and ownership structure. This study makes use of the CLUB-ER minigrid database combined with other sources of data to assess the social and economic effects of minigrid electrification. To assess household welfare outcomes, we complement the minigrid database with geo-referenced Demographic and Health Surveys (DHS) from eleven SSA countries collected by the U.S. Agency for International Development (USAID). With regards to the potential of minigrid technology for productive uses by providing sufficient power for irrigation equipment and conducing toward labor force reallocation (AMDA, 2020), we focus on the impacts on the "Enhanced Vegetation Index" (EVI) derived from MODIS satellite sensor as a proxy for agricultural productivity (MODIS, 2021). The index is averaged over country-specific dominant harvest season of maize (the most cultivated crop in SSA) to quantify the annual variation in the health of crop vegetation (IFPRI, 2020). Previous literature demostrates that the input of electricity and appliances such as pumps can have a significant impact on crop health and yields, which in turn can be estimated through remotely sensed data (Best, 2014; Burke & Lobell, 2017; Gupta, 2019).

For the main empirical analysis, we follow a difference-in-differences (DiD) strategy combined with propensity score matching to achieve identification of the average treatment effect. To construct treatment and control groups, we exploit the spatial information in the minigrid database and satellite-based nighttime light (NTL) data, which enables us to distinguish electrified minigrid sites (i.e., treatment group) from non-electrified communities outside the reach of a minigrid system (i.e., control group). The results suggest that minigrid electrification increases the probability of household electricity uptake and ownership of low-power home appliances. While we can confirm substitution effects from radio towards TV, we also find limited evidence of the uptake of medium and higher power appliances (e.g. fridges), suggesting that other factors, such as income avaiability and cultural norms, are likely at play. Concerning the potential impact of minigrid electrification on local agricultural outcomes, our results reveal evidence of a positive effect on the agricultural vegetation health measured over the cropland surrounding the community served by the mini-grid. In parallel to this evidence, we find that minigrid electrification increases the probability of working in the agricultural sector. The estimated effects on the EVI show a great heterogeneity across countries and over years. The effects become more salient after a certain lag following the installation and are by far the largest in Kenya, which is a leading market for off-grid electrification solutions in the region. Our results indicate no statistically significant association with other labor outcomes and the choice of cooking fuels.

The remainder of this paper proceeds as follows. Section 2 discusses the related literature on electrification effects. Section 3 illustrates the data along with descriptive statistics and Section 4 introduces the empirical methodology adopted. Section 4 presents the estimation results of houseold welfare and agricultural productivity, while Section 5 discusses the robustness of the results, as well as the validity of the nighttime light data for the analysis. Finally, section 6 concludes.

2. Related Literature

The present study aims at contributing to two main strands of the literature. The first strand mainly focuses on socio-economic impacts of grid electrification, most commonly evaluating specific roll-out programs in rural areas for a single country. Prominent examples from SSA include Dinkelman (2011, for South Africa), Lenz et al. (2017, for Rwanda), and Salmon & Tanguy (2016, for Nigeria). In this literature, the widely investigated outcomes include the total or gender-specific employment, sectoral shifting in labor, poverty, income, and expenditure, household asset ownership, education, and business creation. The main intuition behind the quest for causality between the provision of electricity and these development indicators is that electricity is an enabler, both direct and indirect, of structural transformations that can happen within a community (Riva et al., 2018). For instance, an important mediating factor is the availability of electricity-consuming appliances, as highlighted by recent empirical surveys' information on appliance ownership and aspirations of households at different steps of the "energy ladder" (Grimm et al., 2016; Lee et al., 2016; van der Kroon et al., 2013).

Within this set of studies, there is relatively limited evidence on the evaluation of decentralised electrification systems. The existing studies mostly rely on randmoized controlled trials (RCTs); e.g., Mahajan et al. (2020, for India); Rom & Günther (2017, for Kenya); Stojanovski et al. (2018, for Zambia). These analyses find a mixed effect of pico-solar products, with positive impact on lighting use and its related domestic activities, but lack of significant impact on educational attainments or income generation. Differently from the experimental studies, Bensch et al. (2011) assess the impacts of a Rwandan micro-hydro power project through an ex-post evaluation and find robust evidence for positive effects on lighting usage, but insignificant effects on income and children's home studying after controlling for regional differences. Combining quantitative and qualitative evidence from Kenya, Kirubi et al. (2009) explore the extent to which community-based micro-grid electrification can contribute to rural development and document that access to electricity enables the use of electric equipment by small and medium enterprises and farmers, thereby resulting in productivity gains and expanded income opportunities in rural areas.

The second strand of the literature that our study contributes to refers to the potential benefits of electrification for the agricultural sector. In low-income countries, agriculture is considered as the driver for economic development given its large employment capacity and significant contribution to the GDP (Amuakwa-Mensah & Surry, 2022; Sumberg et al., 2014). The agricultural implications of electrification are particularly relevant for the SSA context, where more than half of the population is employed in the sector (World Bank, 2022a). Rural electrification can bring about long-lasting positive effects on rural development by enabling business creation and improving village-level infrastructure, while simultaneously improving the productivity of agricultural activities (Kirubi et al., 2009; Kyriakarakos et al., 2020). The adoption of modern irrigation technology such as groundwater pumps and machinery provided by access to electricity is expected to yield an expansion in irrigation land and increase in agricultural output and productivity. The increase in productivity and production potentially stimulates employment creation in the sector (Grogan & Sadanand, 2013; Knox et al., 2013). Moreover, the extended working hours owing to electricity access enable households and farmers to expand their output and improve their storage facilities to reduce post-harvest losses (Amuakwa-Mensah & Surry, 2022; Lee et al., 2020).

The link between the energy input and community development dynamics is highly complex. One question that still remains open is whether the provision of electricity is a sufficient and/or only a necessary condition for fostering development. In fact, most empirical studies find mixed results and generally weak structural economic impacts (Bayer et al., 2020). In the case of a set of seminal research papers providing evidence of significant employment or development effects of electrification, serious methodological concerns have recently been highlighted, casting doubt on the reliability of those results (Bensch et al., 2020b, 2021). As discussed in Bayer et al. (2020), impact evaluations from observational studies tend to over-promise positive impacts and lack the external validity of the results. Compared to survey data, RCTs offer more solid results thanks to rigorous ex-ante experimental designs, however they are usually limited to a specific target group and location, and thus not easy to generalize. The present study attempts to fill the gap in the literature by providing evidence on an ex-post evaluation of a key set of decentralized electrification solutions in a broad set of African countries.

3. Data

The minigrid database used in the present study is established and published by the African Association for Rural Electrification (CLUB-ER)[2] in 2019. As part of the Green Minigrid Market Development Program (GMG MDP), CLUB-ER in partnership with CARBON TRUST develops

[2] CLUB-ER is the most appropriate for the present analysis given its content and scope, when compared to other available data sources such as African Minigrid Developers Association (AMDA), which covers only private companies. For example in Senegal, a leading example of minigrid electrification, private companies account for only 15% of the sector, while hundreds of companies are state-owned.

a map of the mini-network for 27 countries in SSA.[3] There are 1,888 minigrid projects covered in the database. Besides subnational geographical information (i.e., province, region, district, county) and geo-coordinates, the database provides information on minigrids' installed capacity in megawatt (MW), technology type (i.e., diesel, hydro, solar PV, hybrid systems), operational status (i.e., operating, non-operating, under construction, in pipeline), ownership model (i.e., private, community, public-private partnership), and the year of commission/installation that ranges between 2010 and 2019.

Minigrids are typically built in remote locations where grid extension is not economically attractive. Minigrids usually have a capacity up to 10 MW (EUEI PDF, 2014), but 75% of the minigrids have a capacity equal to or less than 1 MW. Table 1 displays minigrid projects by operational status, techngology, and ownership type. Of the 1,888 minigrid projects, about 50% are currently operational, 40% are in pipeline and the rest is either not operating or under construction.

The four common categories of the minigrid technology include diesel, hydro, solar, and renewable hybrid systems. Given that the fastest growing segment of the global minigrids market is solar hybrid technology, there is a greater emphasis on this third-generation technology in the CLUB-ER database, whereas many of the existing first and second generation (i.e., diesel- or hydro-powered) minigrids are not included (ESMAP, 2019; SEforAll, 2020). Accordingly, solar PV and solar-diesel hybrid are the most predominantly used generation technology in our sample, accounting for about half of the minigrids. Nevertheless, still 41% of the installed minigrids belong to diesel/heavy fuel oil or hydro systems. Considering the ownership structure, public and utility

[3] The SSA countries covered in the CLUB-ER dataset include Angola, Benin, Botswana, Burkina Faso, Cabo Verde, Cameroon, Cote d'Ivoire, DR Congo, Ethiopia, Gambia, Ghana, Guinea, Kenya, Liberia, Madagascar, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

ownership is the most common type, followed by public-private partnership, accounting for 53 and 32% of minigrids installed, respectively (Table 1).

Table 1. Minigrid projects by operational status, technology, and ownership type

	Obs.	Percent
Operational status:		
Operating	870	49.77
Construction	49	2.8
In pipeline	705	40.33
Not operating	124	7.09
Total	1,748	100
Technology type:		
Diesel	361	19.12
Hydro	413	21.88
Solar	519	27.49
Solar-diesel	461	24.42
Other[4]	134	7.1
Total	1,888	100
Ownership status:		
Private	142	14.98
Public	503	53.06
Partnership	303	31.96
Total	948	100

Source: CLUB-ER (2019) minigrid database.

Nighttime light data

For the impact evaluation of mini-grid electrification, we rely on a counterfactual analysis and define the treatment and control group using minigrid database combined with geospatial data and satellite-based nighttime light (NTL) data. The *treatment group* is limited to electrified communities where minigrid systems are installed, whilst the *control group* comprises non-electrified communities remote from the minigrid sites. The electrification status of the

[4] Other technology category includes biodiesel, biofuel, biogas, biomass, biomass cogeneration, biomass gasification, biomass jatropha, biomass palm oil, gas, hybrid hydro/diesel, hybrid straight vegetable oil/diesel, hybrid wind/diesel, wind, as well as other hybrid solar technologies such as hybrid solar PV/biodiesel, hybrid solar PV/biomass gasification, hybrid solar PV/hydro, hybrid solar PV/wind, hybrid solar PV/wind/diesel.

communities is determined by the NTL data; in particular, for each location in the database, the yearly median nighttlime light radiance around a 2.5 km radius buffer is extracted. Locations where no radiance is detected throughout the time span of the NTL data between 2012 and 2019 are classified as unelectrified communities. Seminal literature contributions document that NTL brightness can be used to detect electrification at different scales. Min et al. (2013) find evidence of a significant relationship between NTL measure and electrification rate in rural Senegal and Mali. Baskaran et al. (2015), Burlig & Preonas (2016), and Dugoua et al. (2018) provide supportive evidence from India and document that many NTL measures derived from satellite data are accurate for measuring rural electrification.

Following the approach described in Falchetta et al. (2019, 2020), nighttime light data are extracted from the VIIRS (Visible Infrared Imaging Radiometry Suite) stray-light corrected monthly composites for the period of 2012–2019. NTL data have a native resolution of about 500m at the equator. The data is combined with the High-Resolution Settlement Layer (HRSL) 30-m ambient population, and the Global Human Settlement Layer (GHSL)—including built-up areas and settlement type layers—used for rural and urban areas classification.[5] A noise threshold of 0.25 $\mu W \cdot cm{-}2 \cdot sr{-}1$ is used in the analysis, with the threshold being increased by +0.125 $\mu W \cdot cm{-}2 \cdot sr{-}1$ from year 2017 to cope with calibration adjustment in the data (Uprety et al., 2017). The NTL measure used in the present analysis is the local nighttime yearly median radiance extracted within a 1-km radius buffer around each minigrid site geo-coordinates.

[5] The Google Earth Engine platform is used to process spatially explicit imagery and extract data, which is used for calculating trends and running statistical analysis in the R scientific computing environment.

Household welfare

To evaluate the impact of minigrid electrification on household welfare, we complement the minigrid dataset with geo-referenced Demographic and Health Surveys (DHS) for a subset of SSA countries. The eleven countries covered in this merged dataset include Angola, Cameroon, Democratic Republic of Congo, Ethiopia, Kenya, Mali, Mauritania, Senegal, Tanzania, Togo, and Uganda. The DHS dataset is an unbalanced panel covering the period between 2005 and 2019 (DHS, 2021). Only households observed at least two times over the panel period are kept in the sample. The DHS contains information on demographic characteristics of the household head including age, gender, and educational attainment; number of household members; household's residential characteristics including rural/urban location, electricity uptake, appliance ownership (i.e., fridge, TV, radio), cooking fuel type (i.e., charcoal/firewood, kerosene, LPG, natural gas, electricity); and labor market characteristics such as employment status, earning type, and occupation. While demographics are used as control variables in the analysis, household's access to electricity, ownership of home appliances, cooking fuel type, and the respondent's labor market outcomes comprise the set of dependent variables. Labor market related questions come from individual records of the female respondents.

The direct welfare impacts of household electrification on female labor supply and cooking fuel choice are well-documented in the literature. Electrification may change work opportunities in rural areas by stimulating job creation in new firms as well as in agriculture as a result of an increase in the sectoral production (Amuakwa-Mensah & Surry, 2022; Dinkelman, 2011). Household electricity may also change the home production patterns given the reduction in time-intensive home-based activities such as firewood collection, food preparation and storage, and hence may increase labor supply for market work (Dinkelman, 2011). Rural electrification is also expected to improve people's health. As a replacement for biomass cooking fuel, modern cooking energy substantially reduces indoor air pollution and carbon emissions (Khandker et al., 2014). On the other hand, other appliance ownership enable us to assess whether households' access to information and knowledge has improved (Lenz et al., 2017).

Agricultural productivity: Enhanced vegetation index (EVI)

As a proxy for agricultural productivity, we look at agricultural vegetation health, measured by the EVI. Several literature contributions show that the EVI is strongly correlated with local cropland productivity, namely yield (Burke & Lobell, 2017; Son et al., 2014). The index derived from MODIS satellite sensor is extracted over cropland area using the GFSAD1000 layer as a cropland mask for the period 2010-2019 (MODIS, 2021; Thenkabail et al., 2013). The index indicates the density of greenness of the cropland, ranging from -1, the most arid to 1, the greenest cropland. For the analysis, the index is temporally averaged over country-specific harvest season of maize (the most widely cultivated crop in SSA). Also in this case, the median EVI value is extracted within a 5-km buffer around each mini-grid site geo-coordinates for all pixels classified as cropland.

Sample selection

The main identification strategy makes use of a DiD-type counterfactual analysis based on a matched sample, which will be described in detail in the following section. The analysis sample is restricted to minigrids installed from 2010 onwards, accounting for 77% of 1,888 minigrid projects. The selection is based on the mini-grid markets report (SEforAll, 2020) indicating early 2010s as the deployment year of the minigrid installation particularly for solar and hybrid minigrid systems. This sample selection is overlapping with the time span of the nighttime light data (2012-2019) and vegetation index (2010-2019). The treatment group comprises communities covered in the minigrid dataset, while the control group is constructed using spatial data to detect communities where no minigrid is installed. To exclude on-grid electrification from the control group, the control group is further restricted to communities where zero NTL measure is detected. A randomly drawn 20% of non-treated communities are used for matching, comprising 13,923 observations, whereas the treatment group has 1,369 observations. The resulting sample hence includes 15,292 observations in total, corresponding to 12,970 individuals belonging to 8,726 households located in 52 minigrid sites. DHS surveys are spatially joined with the minigrid database using a search radius of 5 km.

4. Empirical method

To estimate the impact of minigrid installation on agricultural productivity and household welfare, we follow a standard difference-in-differences (DiD) strategy such that:

$$Y_{it} = \beta_0 + \beta_1 Dtime_t + \beta_2 Dtreat_i + \beta_3 Dtreat_i * Dtime_t + X_{it}{}'\Omega + \delta + \mathrm{v}_{it} \qquad (1)$$

where Y_{it} represents two sets of outcome variables at community or household level *i* for time *t*, including: *(i)* enhanced vegetation index on a scale of [-1,1]; *(ii)* a continuous measure of nighttime light radiance ranging between [0, +∞); and *(iii)* binary indicators for electricity uptake, appliance ownership (i.e., fridge, TV, and radio), and employment outcomes (i.e., being employed, earning cash, employed all along the year, employed in agricultural sector). While the EVI and NTL are measured at community level, the second set of outcome variables are measured at household level. The treatment group indicator $Dtreat_i$ takes the value of 1 for electrified communities with minigrids, and 0 for non-electrified communities (i.e., zero NTL measure) without a minigrid system. The treatment time indicator $Dtime_t$ capturing the post-installation years is coded 1 for survey years (coming from DHS) after 2010, and 0 for the pre-installation years (i.e., survey years before 2011). The vector X_{it} in Eq. (1) includes household level control variables such as demographic characteristics of the household head (i.e., age, gender, education), the number of household members and urban/rural location of the household. We finally add country dummies (δ) to account for country-specific factors that are invariant over time.

The coefficient β_3 on the interaction term captures the treatment effect. In this case, the treatment effect measures the change in the outcome variable in minigrid sites following the years after the minigrid was installed, compared to non-electrified communities outside the reach of a minigrid system in pre-installation years. A potential threat to the identification of the treatment effect is the violation of the identifying assumption of the DiD method, namely the common trend assumption. Because DHS is an unbalanced panel and in most country cases, only one or two years are observable for the pre-installation period, we cannot check whether the outcome variables of the treatment and control groups follow a parallel trend over several years before the treatment. Alternatively, we construct a matched sample to make the treatment and control communities comparably similar. To this end, we follow the method of propensity score matching and first estimate a probit model for the probability of receiving the treatment, which is minigrid installation in the present context.

Propensity score matching

The propensity scores estimated in this stage are used for the selection of the control group as similar as the treatment group based on pre-determined characteristics, such as population density, urban-rural location dummy, distance to the central grid system (km), travel time to the nearest city center (minutes), the number of a health centers, and share of cropland area. These matching covariates are selected following the studies by Lenz et al. (2017) and Saing (2018), who use the DiD method combined with propensity score matching to evaluate the impacts of rural electrification on household consumption patterns (amongst others) in Rwanda and Cambodia, respectively. The travel time to the city center is calculated in minutes using a cumulative cost algorithm based on the World Cities database (Simplemaps, 2021) and the friction surface layer from Weiss et al. (2020). In addition, a spatial intersection algorithm is used to calculate the count of healthcare facilities within a 2.5 km radius buffer around the installed minigrid (data from Maina et al. (2019), while a GIS distance algorithm is adopted to calculate the distance to the MV electricity grid in kilometers (data from Arderne et al. (2020)). The share of land area inside the minigrid buffer that is covered by cropland is estimated based on the GFSAD1000 layer (Thenkabail et al., 2013)[6]. The population density is measured as the sum of population (based on the the EC-JRC GHS-POP layer by European Commission (2019)) within a 2.5 km radius buffer around the installed minigrid divided by the area of the buffer in km^2. The variables population density, distance to the grid (in km), and travel time to the city center (in minutes) are scaled by 1/100 in the present analysis.

Descriptive statistics

Table 2 presents summary statistics by treatment and control group for household-level dependent variables and community-level characteristics that are used for matching. Minigrid characteristics are only available for the treated communities and hence are excluded from the counterfactual analysis, as well as from the table. Household welfare measures including electricity uptake and the ownership of fridge and TV are remarkably larger among treated-community residents. On the other hand, the radio ownership is comparable between the two groups, as it is mostly affordable by poorer rural households and does not depend on electricity access. While half of the treated communities are located in urban areas, it is less than 1% among the control communities. The remarkable difference in the urban share between the two groups is

[6] Note that in some instances this share is greater than 1 (see Table 2) for reasons linked to the GIS algorithms used to calculate the variable. Namely, while a vector area algorithm estimates the mini-grid buffer area ($2.5^2 * \pi$), the cropland area is defined as the sum of the area of the raster pixels where cropland density >50%. The latter may include the portion of the raster pixels that falls outside the mini-grid buffer area.

likely due to the construction of the control group that consists of communities without a grid system and nighttime luminosity. As a result, more densely populated, urban areas, closer to the city center are disproportionately largely represented in the treatment group. Similarly, the distance to the grid system in the control communities is about six times the treated ones. On the other hand, an average treated community has almost five health care centers, while there is hardly one health center in a control community.

Table 2. Summary statiscs by control and treatment group

	Treated communities					Control communities				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variables:										
Electricity uptake	1,368	0.60	0.49	0	1	13,904	0.11	0.31	0	1
Fridge ownership	1,368	0.18	0.38	0	1	13,913	0.03	0.16	0	1
TV ownership	1,365	0.54	0.50	0	1	13,914	0.12	0.32	0	1
Radio ownership	1,368	0.66	0.47	0	1	13,913	0.59	0.49	0	1
Cash job	693	0.84	0.37	0	1	9,662	0.57	0.50	0	1
Employed all year	693	0.71	0.45	0	1	9,668	0.45	0.50	0	1
Employed	1,368	0.46	0.50	0	1	13,888	0.62	0.48	0	1
Employed in agriculture	970	0.23	0.42	0	1	11,881	0.70	0.46	0	1
Vegetation index	709	0.24	0.08	0.05	0.41	9,263	0.23	0.08	-0.01	0.43
Matching covariates:										
Population density	1,369	53.11	68.32	0.04	381.33	13,923	1.21	2.99	0	68.88
Travel time to city (min)	1,369	0.91	3.32	0	43.70	13,923	4.86	4.84	0	72.96
Health care center	1,369	4.49	10.38	0	136	13,923	0.33	0.72	0	15
Distance to grid (km)	1,369	0.18	0.46	0	3.83	13,923	0.94	1.14	0	7.19
Urban	1,369	0.50	0.50	0	1	13,923	0.002	0.04	0	1
Cropland share	1,369	1.01	0.32	0.01	1.22	13,923	0.98	0.37	0	1.26
Demographics:										
Household size	1,369	9.04	5.71	1	36	13,923	7.83	5.07	1	59
Head: Female	1,368	0.26	0.44	0	1	13,916	0.18	0.39	0	1
Head: Age	1,368	47.88	13.78	18	93	13,906	45.94	14.52	15	99
Head: Education (years)	1,367	5.29	4.17	0	18	13,915	2.51	3.72	0	19

Notes: Statistics are computed using the merged minigrid-DHS-EVI dataset. While demographic characteristics and dependent variables (except for vegetation index) are at household level, the matching covariates and the vegetation index are at community level. The variables population density, distance to the grid (in km), and travel time to the city center (in minutes) are scaled by 1/100.

Table 2 further presents demographics used as control variables in regression analyses. Female heads are relatively more represented among households residing in the treated communities. On average, household heads are about 2 years older and better educated than households living in the control communities. Among female respondents, who are the interviewees of the labor market module in the DHS, the employment rate is about 60% in the control communities, which is larger than the rate in the treatment group. Unsurprisingly, it is due to the agricultural sector being the major employer in rural areas, employing 70% of the female population in the control communities. In contrast, the share of population employed all the year and having a cash job is higher in the treated communities.

Table 3 presents the mean differences between treatment and control groups before and after matching. The statistics shown for unmatched treated sample keeps the second column of Table 2 in Table 3 (column 5) for the sake of comparison. Although the balancing property is hardly satisfied, the mean difference between the control and treatment group is substantially reduced after matching irrespective of the algorithm in use. Table 3 shows the statistics based on Kernel matching algorithm which is used as the main specification, although the results are also produced by using radius matching method and the corresponding results are presented in the appendix as a robustness check. The weights obtained from the mathing estimation are then used to estimate Eq.(1) based on the matched sample.

The mean difference between the treatment and control group is statistically significant for each covariate at 1% level confidence interval. The difference substantially reduces after matching, although it is still statistically significant and the balancing property is hardly satisfied when all six covariates are used for matching. An alternative approach would entail reducing the set of covariates so as to satisfy the balancing property. Nonetheless, this would negatively affect the matching quality, increasing the chance of an omitted variable bias. Considering such trade-off, our main identification relies on a larger set of matching covariates and we present the results from the alternative specification, fully satisfying the balancing property, in the appendix.

Table 3. Mean differences between treatment and control group for the matched and unmatched sample

	Matched Sample				Unmatched Sample			
	Mean Treated	Mean Control	Diff.	t-test	Mean Treated	Mean Control	Diff.	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:								
Electricity uptake	0.632	0.173	0.459	12.5	0.603	0.106	0.497	53.5
Fridge ownership	0.168	0.110	0.058	2.8	0.175	0.025	0.150	28.3
TV ownership	0.551	0.201	0.350	9.2	0.543	0.117	0.426	44.1
Radio ownership	0.642	0.673	-0.031	-0.6	0.660	0.590	0.070	5.1
Cash job	0.823	0.729	0.094	1.0	0.841	0.565	0.276	14.4
Stable job	0.714	0.635	0.079	0.8	0.711	0.453	0.259	13.3
Employed	0.454	0.612	-0.157	-2.9	0.459	0.625	-0.166	-12.0
Agricultural emp.	0.299	0.687	-0.388	-7.1	0.226	0.704	-0.478	-31.5
Vegetation index	0.235	0.225	0.009	0.9	0.237	0.226	0.012	3.8
Matching covariates:								
Population density	18.610	24.608	-5.998	-4.7	53.110	1.212	51.898	88.8
Travel time to city	1.807	4.160	-2.352	-6.8	0.910	4.856	-3.946	-29.5
Health care center	2.840	3.291	-0.451	-1.6	4.495	0.325	4.169	46.3
Distance to grid	0.219	0.822	-0.604	-11.7	0.183	0.942	-0.759	-24.4
Urban	0.175	0.096	0.079	3.5	0.505	0.002	0.503	110.0
Cropland share	0.899	1.057	-0.158	-7.1	1.013	0.985	0.028	2.7

Notes: Test results rely on kernel matching with common support option. As for the test results of the matched sample, Stata *pstest* command is used following the *psmatch2* program, in which electricity uptake is used as a dependent variable.

5. Results

The results section is organized in three subsections. We first discuss the DiD estimation results evaluating the impacts of minigrid electrification on household welfare. In the subsequent subsection we provide the DiD results for agricultural productivity, in which we also shed light on the channels explaining the link from electrification to agricultural productivity through minigrid and community characteristics. To this end, we carry out an OLS estimation on the sample of minigrid communities (namely, the treated group), where the key regressor refers to a binary indicator for the period after the minigrid was installed. Although this exercise does not claim a formal causal relationship, it enables us to uncover the association between the vegetation index and minigrid and community characteristics. To control for minigrid-level time-invariant heterogeneity we also present fixed effects results, which help to benchmark the OLS results. This exercise also allows us to perform an event study-type analysis where we explore heterogeneous across years and across countries. Finally, in the third subsection, we examine the relationship between minigrid electrification and the choice of cooking fuels through a multinomial logit model.

5.1. Impacts of minigrid electrification on household welfare

To estimate the impacts of minigrid electrification on household welfare, we consider the electricity uptake; the ownership of household appliances including refrigerator, TV, and radio; and labor market outcomes including being employed, having a cash-paid job, working along the entire year, and working in the agricultural sector. The estimation relies on a DiD specification described in Eq. (1) based on a matched sample constructed by using the propensity score matching. The results presented in Table 4 (and, in particular, the DiD estimator coefficient Dtime*Dtreat) show that the probability of electricity uptake increases by 0.5 for households living in the minigrid sites after 2010, compared to counterfactual households living in non-electrified communities in pre-installation years (column 1). Similarly, minigrid electrification increases the probability of owning a television by 0.15, albeit its statistical significance at the borderline. The positive association with the TV ownership accompanies a decline in the probability of a radio ownership (although statistical insignificant), which implies a substitution effect between communication channels. On the other hand, we find no impact on the ownership of higher power appliances such as refrigerator, suggesting that other factors such as income avaiability and cultural norms, are likely at play. The results in Table 4 relying on a matched sample using weights from Kernel method are similar to those based on radius matching method that are presented in Table A.3 in the appendix.

Electricity connection can have countervailing effects on employment outcomes. On one hand, electrification could result in less labor intensive production due to an efficiency gain in agriculture. On the other hand, the increase in agricultural productivity could yield a larger amount of harvest and hence increase the labor demand. In parallel, thanks to electricity access, labor supply freeing up from collecting firewood, particularly of women might canalize to the (formal) labor market. Our results suggest that minigrid electrification increases the probability of working in the agricultural sector and holding a job along the whole year. However, the employment effect seems to be limited to the agricultural activities, as minigrid electrification is neither associated with the probability of being employed in general nor with the earning type.

Table 4. Effects of minigrid electrification on household welfare and agricultural productivity
DiD results based on a matched sample using weights from kernel matching

	(1) Electricity uptake	(2) Fridge ownership	(3) TV ownership	(4) Radio ownership	(5) Cash job	(6) Employed all year	(7) Employed	(8) Employed agriculture	(9) Vegetation index
Dtime	-0.094	0.072	0.132	-0.048	0.207***	0.030	0.282***	-0.218***	-0.037***
	(0.082)	(0.083)	(0.080)	(0.077)	(0.080)	(0.079)	(0.090)	(0.085)	(0.014)
Dtreat	0.161***	0.043	0.172***	0.070	0.156**	0.025	-0.106	-0.343***	-0.010
	(0.056)	(0.034)	(0.053)	(0.065)	(0.074)	(0.055)	(0.069)	(0.070)	(0.012)
Dtime*Dtreat	0.505***	0.030	0.146*	-0.035	-0.058	0.179**	-0.086	0.173**	0.045***
	(0.079)	(0.076)	(0.079)	(0.073)	(0.089)	(0.087)	(0.091)	(0.082)	(0.016)
Household size	0.003	0.006	0.002	0.013***	0.003	-0.004	-0.001	-0.005	
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	
Head: Female	-0.018	-0.051*	-0.152***	-0.134**	-0.027	0.001	0.031	0.040	
	(0.043)	(0.026)	(0.030)	(0.055)	(0.041)	(0.063)	(0.041)	(0.066)	
Head: Age	0.000	0.000	-0.001	0.002	-0.002	-0.004**	-0.002	0.005***	
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Head: Education	0.013**	0.022***	0.025***	0.018***	-0.000	0.008	-0.005	-0.037***	
	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	
Constant	0.207*	-0.139*	0.111	0.416***	0.490***	0.530***	0.586***	0.845***	0.232***
	(0.121)	(0.080)	(0.117)	(0.122)	(0.140)	(0.106)	(0.122)	(0.125)	(0.012)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,807	14,816	14,817	14,816	10,080	10,086	14,783	12,472	9,714

Notes: Estimation is retstricted to a matched sample, using weights obtained from Kernel matching method based on covariates including population density, urban dummy, distance to the grid, travel time to city, cropland share, the number of healthcare centers. While Dtime and Dtreat refer to dummy variables for time and group indicators, Dtime*Dtreat is the interaction term between the two variables. The covariates population density, distance to the grid, and travel time to city are scaled by 1/100. While the household level dependent variables presented in columns (1) to (8) are dummy variables, the community level dependent variable in column (9), the enhanced vegation index ranges within a scale of [-1, 1]. Robust standard errors clustered at community level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2. *Impacts of minigrid electrification on agricultural productivity*

In this section, we discuss results from the estimation of impacts of minigrid electrification on agricultural productivity measured by the enhanced vegetation index. As described earlier, the EVI ranges from -1, the most arid cropland to 1, the greenest. The DiD results presented in column (9) of Table 4 suggest that minigrid electrification leads to an increase of 0.045 percentage points in the index. Given the unconditional mean of the EVI of about 0.24 (Table 3), the estimated effect would translate into about 19% increase in the mean. While this finding does not directly indicate the channels behind this association, we suggest that this vegetation health improvement as a result of electrification might be associated with increased production in agriculture (e.g. due to water pumping and irrigation), and hence more labor demand, which is supported by the finding on the positive association with the agricultural employment (Table 4, columns 8-9).

Because the community level covariates are used for matching, the DiD specification does not control for additional variables, except for country dummies. Besides, the minigrid characteristics that are only available for the treated communities are naturally dropped from the DiD analysis. To evaluate the impacts of those community as well as minigrid characteristics on agricultural productivity, we furthermore estimate an OLS regression. In this analysis, we rely on the merged minigrid-EVI dataset[7] and define the key regressor as a binary indicator for the post-installation period that is extracted from the information on the year of installation/commissioning of minigrids. This dummy variable constitutes the time treatment indicator, coded 1 for all years following the years minigrid was installed, and 0 otherwise.

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[7] While the OLS regression relies on the merged minigrid-EVI dataset, the DiD analysis combines it with the DHS data. As a result, the size of the estimation sample differ, as presented in Table 4 and Table 5.

Table 5. Effects of minigrid installation on agricultural productivity and nighttime brightness

	Enhanced Vegetation Index				Log of Nighttime Light			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	FE	OLS	OLS	OLS	FE
Post-installation	0.013***	0.006**	0.004**	0.000	0.283***	0.290***	0.382***	0.233***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.044)	(0.046)	(0.051)	(0.033)
Baseline: Not operating								
Operating	0.016***	0.012***	-0.007**		0.132***	0.218***	0.218***	
	(0.003)	(0.004)	(0.003)		(0.047)	(0.044)	(0.052)	
In pipeline	0.029***	0.024***	0.010*		-0.116	-0.029	-0.128	
	(0.005)	(0.005)	(0.006)		(0.074)	(0.073)	(0.097)	
Construction	0.018***	0.025***	-0.040***		0.035	0.075	0.347***	
	(0.006)	(0.006)	(0.006)		(0.060)	(0.061)	(0.078)	
Baseline: Partnership								
Public	-0.039***	-0.034***	0.017***		0.689***	0.663***	0.528***	
	(0.003)	(0.003)	(0.003)		(0.043)	(0.044)	(0.050)	
Private	-0.059***	-0.059***	0.023***		0.158***	0.171***	-0.025	
	(0.004)	(0.004)	(0.005)		(0.045)	(0.046)	(0.071)	
Baseline: Diesel								
Hydro	-0.011***	-0.020***	0.006*		-0.208***	-0.194***	-0.464***	
	(0.003)	(0.003)	(0.003)		(0.046)	(0.050)	(0.060)	
Solar	-0.022***	-0.033***	-0.033***		-0.452***	-0.476***	-0.628***	
	(0.004)	(0.004)	(0.003)		(0.052)	(0.057)	(0.057)	
Solar-diesel	-0.057***	-0.065***	-0.052***		0.394***	0.353***	0.263***	
	(0.004)	(0.004)	(0.005)		(0.069)	(0.072)	(0.101)	
Other	-0.001	-0.005	-0.005		-0.278***	-0.268***	-0.274***	
	(0.004)	(0.004)	(0.004)		(0.049)	(0.050)	(0.053)	
Installed capacity (MW)	-0.003***	-0.004***	-0.002***		0.290***	0.278***	0.255***	
	(0.001)	(0.001)	(0.001)		(0.015)	(0.016)	(0.015)	
Community characteristics:								
Population density		0.000	0.000			-0.002***	-0.002***	
		(0.000)	(0.000)			(0.000)	(0.000)	
Travel time to city		0.000	-0.000			-0.006***	-0.005*	
		(0.000)	(0.000)			(0.002)	(0.002)	
Cropland (km^2)		0.001***	0.000***			0.005**	0.002	
		(0.000)	(0.000)			(0.002)	(0.002)	
Constant	0.286***	0.281***	0.243***	0.265***	-0.129**	-0.181***	0.259**	0.592***
	(0.004)	(0.005)	(0.008)	(0.001)	(0.055)	(0.064)	(0.131)	(0.025)
Country dummies	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,530	4,180	4,180	4,180	4,484	4,191	4,191	4,191
Number of id				425				526

Notes: Estimation is based on the minigrid data combined with satellite based community characteristics (bottom panel), enhanced vegetation index (left panel) and nighttime light data (right panel). While the dependent variables range over the period of 2010 and 2019, the covariates are observed one point in time. The variable *Post-installation* is a time treatment binary indicator for years following the year of commission of the minigrid. The base line categories for operational status, technology type and ownership status are not-operating, diesel technology, and public-private partnership, respectively. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The left panel of Table 5 presents the OLS results in columns (1) to (3), while column (4) shows results from the estimator of a fixed effects (FE) model at minigrid site (i.e., community) level. Columns (2) and (3) of Table 5 compares OLS results without and with country dummies, respectively, to show the importance of the country-specific unobserved heterogeneity. The results suggest that the minigrid installation is associated with an increase of up to 0.013 percentage points in the EVI, after controlling for minigrid characteristics (column 1). The coefficient estimate drops to one half once we control for community characteristics (column 2) and declines to 0.004 after adding the country dummies (column 3). The unobserved heterogeneity at minigrid level explains this variation to a large extent. In fact, the fixed effects estimation cancels out the coefficient estimate on the post-installation variable (column 4).

In line with expectations, operating minigrids are associated with a larger increase in the vegetation index, when compared to non-operating minigrid sites. Interestingly, the estimated association is by far the greatest for minigrids in pipeline, among other operational status (column 3). This might be an indicative for the non-random allocation of minigrids towards more productive agricultural areas. We have addressed this potential endogenity concern through a matching estimator, as discussed earlier. Ownership status also matters; the projects owned by private actors are the most effective in increasing agriculture productivity (column 3). As for the technology type, minigrids powered by solar and solar-diesel are negatively correlated with agricultural vegetation health, when compared to diesel-type minigrids, possibly highlighting energy storage-related limitations. Hydro systems are comparable to, even slightly better performing than the diesel technology in improving agricultural vegetation health. We also find that the larger the cropland, the higher the agricultural vegetation health is (columns 2&3). On the other hand, the negative association between the installed capacity and the vegetation index could be explain by the fact that *ceteris paribus* smaller mini-grid systems are allocated to communities dominated by agricultural activities, while larger systems might be associated with higher shares of non-farm entrepreneurial activities (column 3).

Next, we check the heterogeneity in the agricultural productivity effects across countries and years. The left panel of Figure 1 displays the estimation results for a selected group of countries, where more than a hundred minigrids are installed. The results rely on the specification indicated in the third column of Table 5. Despite a substantial heterogeneity across countries in the estimated effect, it is found to be statistically significant only in Kenya, a well-known example for an outstanding performance in the off-grid market in the SSA region (Moner-Girona et al., 2019).

Furthermore, we carry out a duration analysis and check how the average effect presented in Table 5 (column 3) varies across time before and after the installation year. To explore the heterogeneity in the operational duration of the minigrid system, we test the hypothesis whether the effectiveness of minigrids increases as the operational time passes. The duration measure is generated based on the difference between the survey year (i.e., when the EVI was measured) and the commission year of the minigrid. The duration measure is coded zero if the survey year overlaps with the year of commission, coded 1 for one year after the minigrid installation; coded 2 for two years after the installation; and so on. Minigrids running for more than 6 years are subsumed in the maximum duration value of 6. Analogously, we create the pre-installation duration ranging from -1 to -5. Minigrids commissioned 6 years ago or older are subsumed in the value of -5.

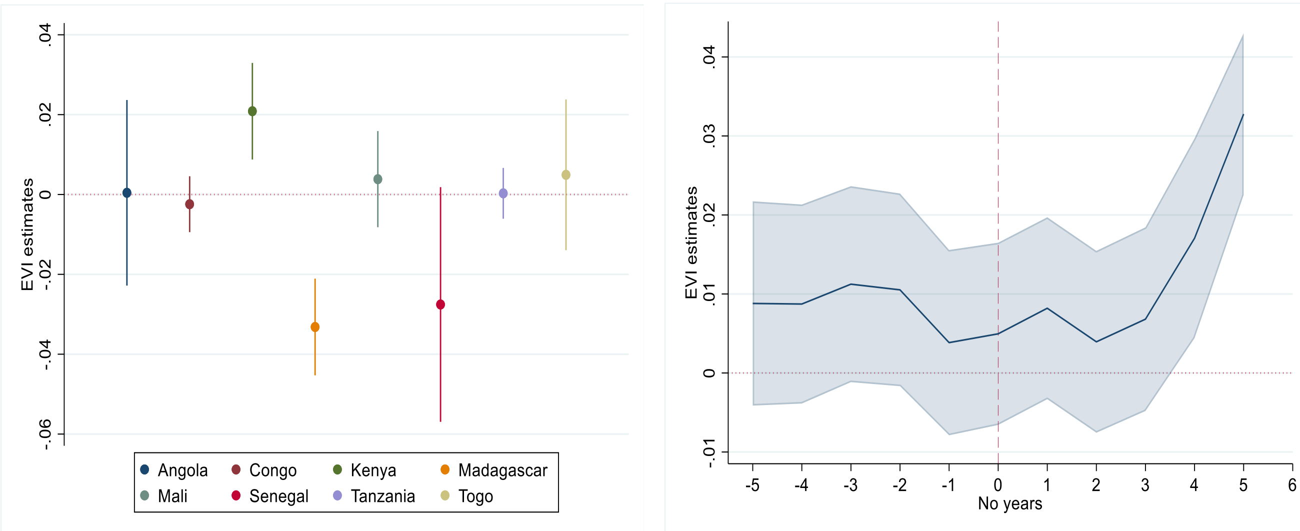

Figure 1. Effects of minigrid electrification on the agricultural productivity across countries and over time

Notes: Estimation is based on an OLS regression controlling for minigrid and community characteristics, as well as country dummies. The key regressor is *post-installation*, which is a time treatment binary indicator for years following the year of commission of the minigrid. The graph on the left hand side displays point estimates on the post-installation variable per country for a selected sample of countries, where more than a hundred minigrids are installed. The graph on the right hand side displays the results of the duration analysis for the entire set of 27 countries. The x-axis of the right panel shows the year difference between when the EVI was measured and when the minigrid was installed. While zero indicates that the EVI was measured in the year when minigrid was installed, a positive (negative) number refers to how many years after (before) the minigrid installation the EVI was measured.

The heterogeneous effects across years are displayed in the right panel of Figure 1. The estimated effect becomes statistically significant after three years following the installation and continues to increase sharply onwards. It is reasonable to find such a long lag given the time required to adopt electrical equipment for irrigation and/or to relocate labor freeing up from housework or firewood collection to agricultural activities (Dinkelman, 2011; Tagliapietra et al., 2020).

5.3. Impacts of minigrids on the choice of cooking fuels

Based on our results we argue that the installation of mini-grids can generally lead to some positive development outcomes. This is true both for electrification (and to some extent related benefits, such as appliance ownership) as well as for improvements in the agricultural sector. Yet, we find important differences depending on the design of the mini-grid. Important differences appear regarding the main fuel as well as the capacity of the grid. Solar-based mini grids seem to be less effective in providing positive effects on agricultural productivity. As we also find that with increasing capacity of the grids the effect on agricultural health increases, we hypothesize that those effects might be interrelated. That is, for larger grids that also have a positive effect on agriculture some form of backup capacity provided e.g. by diesel generators seems to be desirable. On the other hand, solar based mini grids seem to effectively deliver on electrification outcomes based on NTL data.

In addition to the effects on electrification effects, appliance uptake and agricultural productivity, from a development perspective it is also an interesting question whether minigrid electrification has any impact on the choice of cooking fuel. Given the potential health impacts of cooking with firewood or charcoal (Pratiti et al., 2020), it is interesting to check whether we can see any substitution effect from biomass stoves towards cooking with cleaner fuels or electricity. As the outcome variable is categorical, consisting of electricity, fossil fuel (i.e., kerosene, LPG, natural gas), biomass (i.e., charcoal and firewood), and other traditional biomass (i.e., agricultural by-products and dung), we estimate a multinomial logit model, where other biomass is used as a baseline category. The conditional marginal effects are, however, statistically insignificant (see Figure 6). This finding is in line with the existing evidence from lower income countries that the fuel use behavior is likely linked to lifestyle and cultural factors that determine cooking habits (Muller & Yan, 2018).

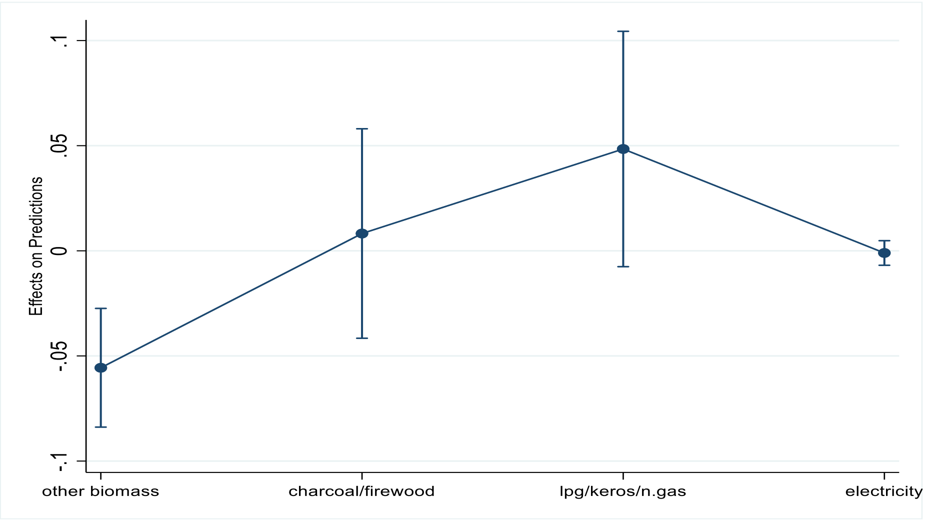

Figure 5. Conditional marginal effects of minigrid electrification on the choice of cooking fuel

Notes: The figure displays the marginal effects from the estimation of a multinomial logit model, where the outcome variable is composed of the categories of electricity, fossil fuel (i.e., kerosene, LPG, natural gas), biomass (i.e., charcoal and firewood), and other traditional biomass (i.e., agricultural by-products and dung). The other traditional biomass constitutes the baseline category.

6. Additional analyses and robustness checks

In this section, we first validate whether NTL data are able to capture minigrid electrification outcomes and then evaluate the effectiveness of minigrids in increasing nighttime light luminosity. Similar to the analysis for agricultural productivity (see Figure 1), we also examine whether the impacts on nighttime brightness show heterogeneity across countries and years. Second, we check whether the DiD estimation results are robust to the selection of a different set of matching covariates satisfying the balancing property, a different matching algorithm, and different comparison periods.

6.1. Nighttime light data: appropriateness and effectiveness

Whether mini-grids determine the emission of a sufficient level of visible light such that it can be captured by satellites is an important concern in our analysis. We check the appropriateness of the NTL data by calculating the share of electrification occurring through the installation of minigrid systems, which is detected by the satellite-based NTL data. We consider minigrid sites as satellite-detected if the NTL measure[8] is strictly greater than zero in the surroundings of the minigrid coordinates, and 0 otherwise. Figure 2 displays the maximum share of operating minigrids detected by the NTL data for each country. Tuning country-specific noise floor value and buffer areas[9], approximately 70% of minigrids are captured by the NTL data in the entire sample. There is, however, quite a large heterogeneity across countries. While Botswana, Ghana and Tanzania rank among the highest with a 100% detection rate, Ethiopia, Mozambique and Zimbabwe rank the lowest with a rate below 20%. The reason for the low rate of detection might be due to the dominance of sparsely populated rural areas in those countries, the scarce nighttime illumination due to economic, geographical, and behavioral factors, or limited energy storage capacity.

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[8] NTL measure is properly corrected with a noise threshold as described in the data section, testing for different noise floor values and buffer areas around the minigrid coordinates.

[9] We consider noise floor values in [0.15, 0.2, 0.21, 0.22, 0.25, 0.3], at which 0.125 $\mu W \cdot cm{-}2 \cdot sr{-}1$ is added starting from 2017 to account for the increased noisiness in the data as discussed in Section 2, and buffer area radius values (in meters) in [100, 1500, 2500].

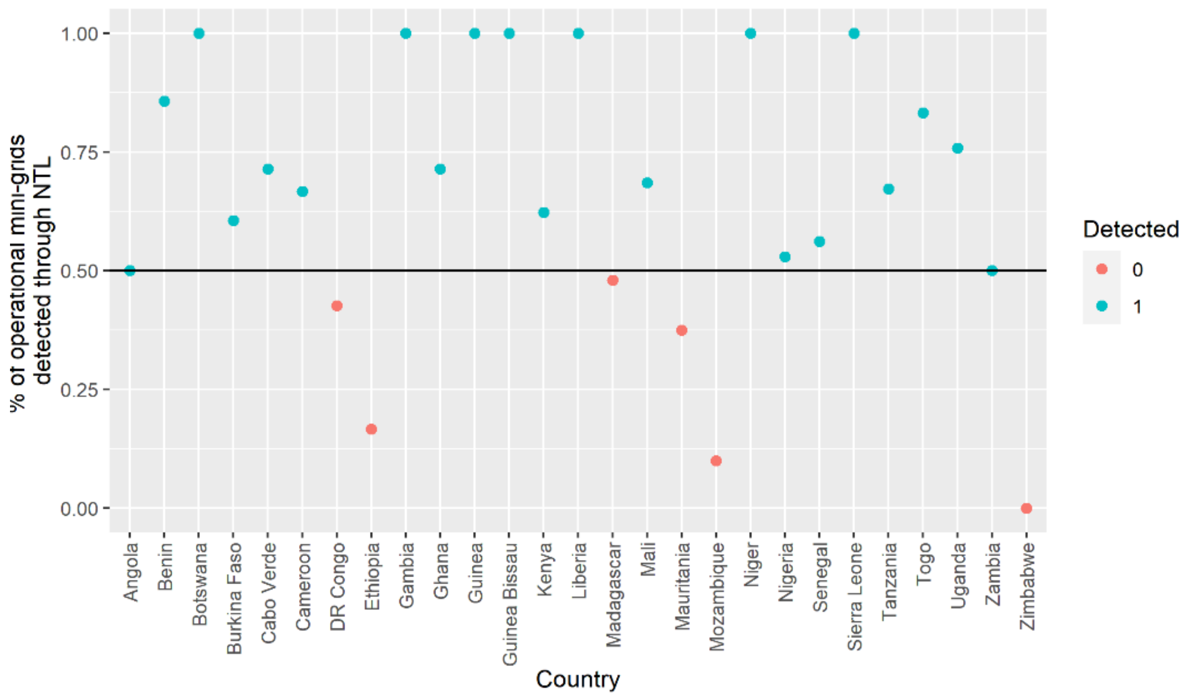

Figure 2. Share of (operational) minigrid sites detected by nighttime light data.

Notes: Each dot represents the percentage of mini-grids in the CLUB-ER database where non-zero NTL radiance is detected in the surroundings of the mini-grid location, net of NTL data noise-floor adjustment. Blue (red) dots identify countries where at least (less than) 50% of mini-grid sites are successfully detected by NTL.

The main feature of minigrids is the ability to operate independently, which enables them to be set up in remote locations that the main grid does not reach. Although most installed mini-grids in remote areas are isolated, they can also be grid-connected (SEforAll, 2020). One concern is that nighttime luminosity attributed to the minigrids might be due to on-grid electrification as some minigrids are likely to be constructed in the proximity of the distribution lines. Figure 3 depicts minigrids installed at a maximum distance of 2-km from the grid system and more than 2 km far away, indicated by red and green dots, respectively. Georeferenced information about the presence of the grid is derived from Arderne et al. (2020). As shown in the map, the majority of the minigrids are installed relatively far from the grid system. Figures A.2 in the appendix showing the same map for selected countries, including Kenya, DR Congo and West Africa corroborates this observation.

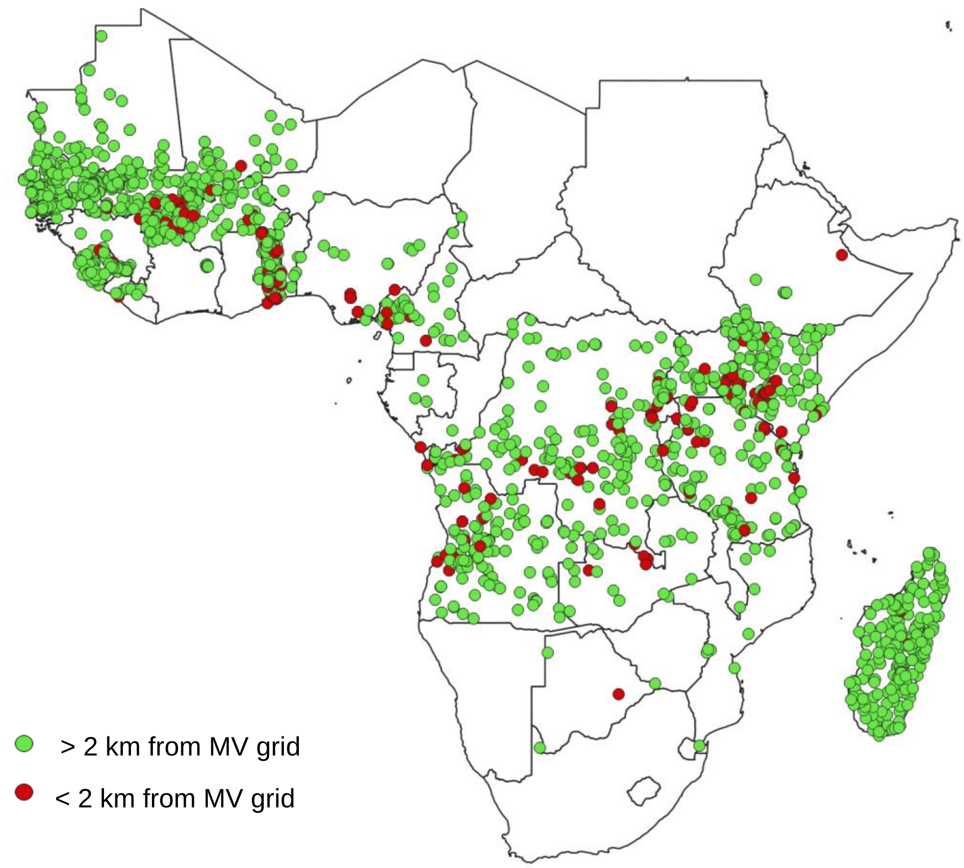

Figure 3. Minigrids installed in SSA within and outside the 2-km proximity to grid lines

Notes: The map is produced by the authors based on Arderne et al. (2020). The green and red dots represent minigrids in the proximity of a grid more than 2km and within a 2km-distance far away, respectively. Note that grid distance data are also used in the PSM as a balancign covariate.

Moreover, given that the NTL data are measured between midnight and 3 am, it is possible that nighttime brightness captured by satellite data might be coming from streetlights rather than dwellings or workplaces. To address the issue, using geo-coordinates, we merge the minigrid-NTL data with data from a ground-based survey carried out in Senegal by Peters at al. (2019) and investigate both energy access issues and availability of public lighting. About 90% of the 86 locations covered in the survey data have at least one minigrid, which are outside the reach of a grid system. About 76% of the minigrid sites have public lighting and 34% have a streetlight operational at the time of the survey. Based on a two-sample t-tests, we compare the NTL radiance in sites with and without operational streetlights, and we find no evidence of a statistically significant difference of the mean (at a 95% level of significance). This finding is interpreted as evidence that in the context of communities served by minigrids, the presence of streetlights might not be determinant for light detection via NTL data[10].

Effectiveness of minigrids in increasing nighttime brightness

Next, we analyze whether installing minigrids leads to a meaningful increase in electricity access and consumption density at community level. The yearly median value of the NTL radiance is used as a proxy for the electrification level. Considering the same OLS and FE regressions as described in Table 5, we find that communities become brighter by an average increase of up to 38 percent following the electrification through mini-grids, after controlling for minigrid and community characteristics. The magnitude of the effect drops to 23 percent once minigrid-level time-constant heterogeneity is controlled (Table 5, right panel). We also check the heterogeneity of the results across countries. As displayed in Figure 4 (left panel), the estimated effect exhibits a cross-country variation, ranging from approximately 0.1 in Congo to 0.5 in Kenya. Furthermore, we replicate the duration analysis to estimate the impact on the NTL measure (i.e., natural logarithm of yearly median) following the specification introduced for Figure 1. Similar to the results of vegetation index, the positive impact comes with a lag but to a lesser extent. As shown in the right panel of Figure 4, the positive impact starts to be seen following the first year of

[10] The street light data from Senegal are not publicly available, however, related calculations are available upon the request from the authors.

installation and increases over time. This finding implies that it takes about at least one year for communities to take up electric lighting after the minigrid was commissioned.

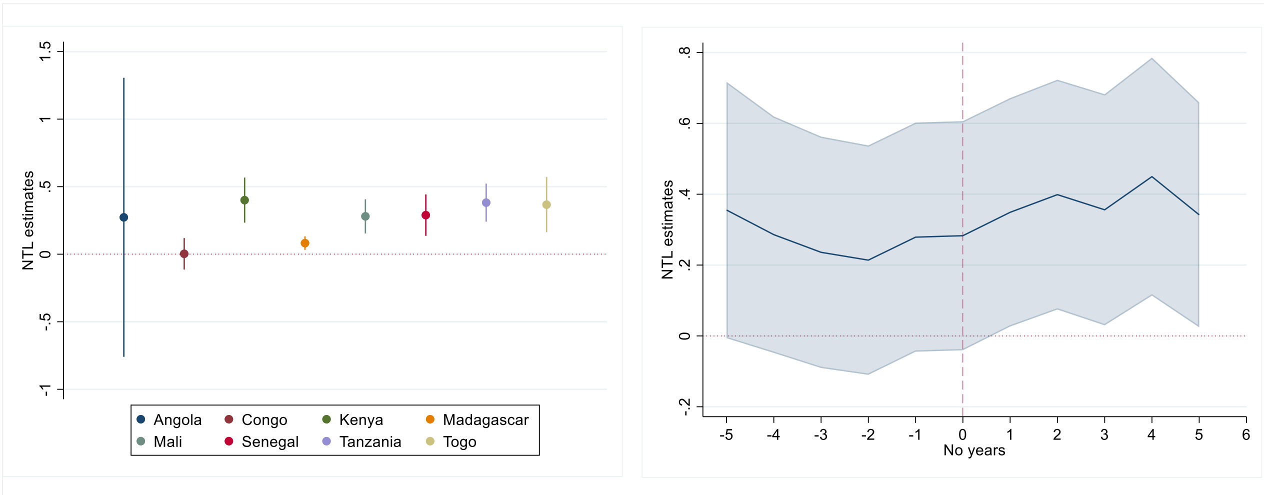

Figure 4. Effects of minigrid electrification on nighttime brightness across SSA and over time

Notes: Estimation is based on an OLS regression controlling for minigrid and community characteristics, as well as country dummies. The key regressor is *post-installation*, which is a time treatment binary indicator for years following the year of commission of the minigrid. The graph on the left hand side displays point estimates on the post-installation variable per country for a selected sample of countries, where more than a hundred minigrids are installed. The graph on the right hand side displays the results of the duration analysis for the entire set of 27 countries. The x-axis of the right panel shows the year difference between when the NTL was measured and when the minigrid was installed. While zero indicates that the NTL was measured in the year when minigrid was installed, a positive (negative) number refers to how many years after (before) the minigrid installation the NTL was measured.

6.2. Robustness checks

In this subsection, we first check the robustness of the DiD results by relying on a subset of matching covariates that satisfy the balancing property. While estimating the propensity score to match the treated group with comparable control communities, the probabilistic model for receiving the treatment conditions on covariates including population density, urban dummy, distance to the grid, travel time to the nearest city center, cropland share, and the number of healthcare centers. As can be seen in Table 4, for each covariate the mean difference between treated and control groups, despite its statistical significance, becomes substantially lower after matching compared to the mean difference in the unmatched sample. The balancing property is not satisfied when we include all the six covariates. We replicate the DiD analysis based on a matched sample using a subset of matching covariates that satisfy the balancing property.[11] This subset includes three covariates, namely an urban dummy, the number of healthcare centers, and cropland share. The remainder of the covariate set including population density, travel time to the center, and distance to the grid are used as additional control variables in the DiD specification. The results are shown in Table 6.

Table 6. Effects of minigrid electrification on household welfare and agricultural employment
DiD results on a matched sample using kernel method satisfying the balancing property

	(1) Electricity uptake	(2) Fridge ownership	(3) TV ownership	(4) Radio ownership	(5) Cash job	(6) Employed all year	(7) Employed	(8) Employed agriculture	(9) Vegetation index
Dtime	0.067***	-0.034**	0.202**	-0.000	0.084	0.178**	0.146	0.104	-0.006
	(0.024)	(0.013)	(0.079)	(0.087)	(0.052)	(0.075)	(0.114)	(0.103)	(0.005)
Dtreat	0.194***	0.104***	0.263***	0.014	0.055	0.201***	-0.116	-0.150**	-0.020***
	(0.038)	(0.021)	(0.050)	(0.059)	(0.057)	(0.064)	(0.088)	(0.067)	(0.006)
Dtime*Dtreat	0.168***	0.018	0.045	-0.182**	0.028	0.013	0.033	0.094	0.024***
	(0.050)	(0.023)	(0.074)	(0.078)	(0.070)	(0.083)	(0.106)	(0.093)	(0.009)
Constant	0.109**	-0.008	-0.028	0.598***	0.713***	0.341***	0.734***	0.417***	0.208***
	(0.051)	(0.028)	(0.101)	(0.121)	(0.122)	(0.131)	(0.143)	(0.146)	(0.012)
Observations	15,067	15,076	15,074	15,076	10,215	10,221	15,043	12,704	9,743

N*otes:* Estimation is retstricted to a matched sample, using weights obtained from Kernel matching method based on a subset of covariates that satisfy the balancing property including the urban dummy, cropland share, and the number of healthcare centers. Each column controls for community characteristics including population density, travel time to city, distance to grid; household characteristics including household size, age, gender, and education level of the household head; as well as country dummies. While Dtime and Dtreat refer to dummy variables for time and group indicators, Dtime*Dtreat is the interaction term between the two variables. The covariates population density, distance to the grid, and travel time to city are scaled by 1/100. While the household level dependent variables presented in columns (1) to (8) are dummy variables, the community level dependent variable in column (9), the enhanced vegation index ranges within a scale of [-1, 1]. Robust standard errors clustered at community level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[11] This analysis makes use of the STATA program *pscore*, which explicitly reports whether the balancing property is satisfied. Among all the combinations, the subset of urban dummy, number of healthcare centers, and cropland share is the only one satisfying the balancing property. On the other hand, we use the program *psmatch2* for the propensity score matching and its post-command *pstest* to report the mean differences and the corresponding t-test results before and after matching.

In general, the results are similar to those presented in Table 4, however the magnitude of the treatment effect (i.e., coefficient of the interaction term) gets smaller when the balancing property is satisfied. The largest drop is observed for the TV ownership (column 3) and agricultural employment (column 8), which turns the estimates into statistically insignificant. The statistical inference for the agricultural employment is also sensitive to selection of the matching algorithm. The use of radius matching makes its coefficient estimate statistically insignificant (see Table A.4 in the appendix). On the other hand, the coefficient estimate on the vegetation index is robust both to the choice of the matching covariates and the matching technique and remains strongly positive (column 9 of Table 6 & Table A.4).

Finally, we check the robustness of the results to the choice of the treatment year. Based on the stylized facts in the minigrids market report, the analysis sample was restricted to the minigrids installed from 2010 onwards and hence the treatment time indicator was coded 1 for the survey years following 2010. In an alternative specification, we check the DiD results comparing two sub-periods before the reference year of 2010. This sample restriction reduces the number of observations to about one third of the entire sample size. In this case, the time dummy is coded 1 for survey years between 2006 and 2009, and zero for earlier years between 2001 and 2005. The treatment group indicator is considered the same as described in the main specification of Eq. (1). The results presented in Table 7 show that the treatment effect is statistically insignificant when two pre-treatment periods are compared. The null effect from the comparison of two pre-treatment periods justifies the selection of the reference year of 2010 as the treatment year.

Table 7. DiD results comparing two pre-treatment periods earlier to 2010
(based on a matched sample using weights from kernel matching)

	(1) Electricity uptake	(2) Fridge ownership	(3) TV ownership	(4) Radio ownership	(5) Cash job	(6) Employed all year	(7) Employed	(8) Employed agriculture	(9) Vegetation index
Dtime	0.102	0.065**	-0.048	-0.360**	0.448**	-0.910***	0.311**	-0.120	-0.020
	(0.070)	(0.032)	(0.076)	(0.152)	(0.175)	(0.079)	(0.146)	(0.102)	(0.020)
Dtreat	0.081	0.033	0.008	-0.049	0.348***	-0.138*	-0.051	-0.187*	0.039*
	(0.075)	(0.032)	(0.069)	(0.096)	(0.107)	(0.082)	(0.106)	(0.103)	(0.021)
Dtime*Dtreat	0.107	-0.004	0.088	0.462	-0.538	0.352	-0.277	0.031	-0.044
	(0.097)	(0.052)	(0.086)	(0.346)	(0.374)	(0.213)	(0.172)	(0.117)	(0.032)
Constant	-0.031	-0.101	0.041	0.319*	-0.065	0.899***	0.725***	0.822***	0.239***
	(0.149)	(0.070)	(0.119)	(0.163)	(0.148)	(0.149)	(0.155)	(0.139)	(0.018)
Observations	4,836	4,842	4,844	4,842	3,338	3,334	4,814	4,279	4,008

Notes: Estimation is retstricted to a matched sample, using weights obtained from Kernel matching method based on covariates including population density, urban dummy, distance to the grid, travel time to city, cropland share, the number of healthcare centers. Each column controls for household characteristics including household size, age, gender, and education level of the household head in addition to the country dummies. While Dtime and Dtreat refer to dummy variables for time and group indicators, Dtime*Dtreat is the interaction term between the two variables. The covariates population density, distance to the grid, and travel time to city are scaled by 1/100. While the household level dependent variables presented in columns (1) to (8) are dummy variables, the community level dependent variable in column (9), the enhanced vegation index ranges within a scale of [-1, 1]. Robust standard errors clustered at community level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7. Conclusion

We empirically evaluate the effectiveness of minigrid systems in empowering remote communities in a large set of SSA countries. Our study is the first to seek a causal impact estimation of minigrid electrification with potential external validity, namely beyond a single case or country study. Our estimation results indicate that minigrids contribute to households electrification and improve access to low-power electrical appliances, such as a television after the minigrid installation, when compared to counterfactual households in pre-installation years. By contrast, we find that minigrid electrification does not increase the likelihood for households owning highly consuming appliances, such as fridges, which might be linked with the higher appliance cost or social norms. In addition, minigrid electrification improves vegetation health over cropland surrounding the mini-grid community (a proxy for agricultural productivity), and in turn, also increases agricultural employment. These two agricultural impact estimates are consistently positive for both the remotely-sensed and the survey-based outcomes, rendering the finding more robust. Yet, the effect on vegetation health shows a great heterogeneity across countries.

We do not find minigrid electrification to play a statistically robust role in changing the overall employment probability and earning type of households. This finding is consistent with the struggle to find statistically robust evidence of structural socio-economic transformations following rural electrification in Africa (e.g., Bensch et al., 2011; Peters & Sievert, 2016), and in India (e.g., Burlig & Preonas, 2016). This finding highlights that further conditions beyond the availability of electricity are likely needed to unleash community-wide structural change. Similarly, minigrid electrification is estimated to be unassociated with the choice of cooking fuels.

An array of robustness checks raises confidence about the reliability of the results, which are robust to different matching algorithms as well as to the choice of the treatment year. We are confident that the satellite-based nighttime data are a satisfactory proxy for electrification levels, despite their limitations. Although we account for self-selection and country differences, we still interpret the results with caution for a causal inference, given the potential confounding factors arising from the location and timing of minigrid installation, as well as the inability to control for time-variant macro-economic and regional characteristics due to data unavailability. Yet, the present work provides important evidence, first of its kind, in evaluating the effectiveness of minigrid electrification across countries of SSA. We encourage future data collection efforts and further research evaluating welfare consequences of minigrid electrification.

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Appendix

1. Figures

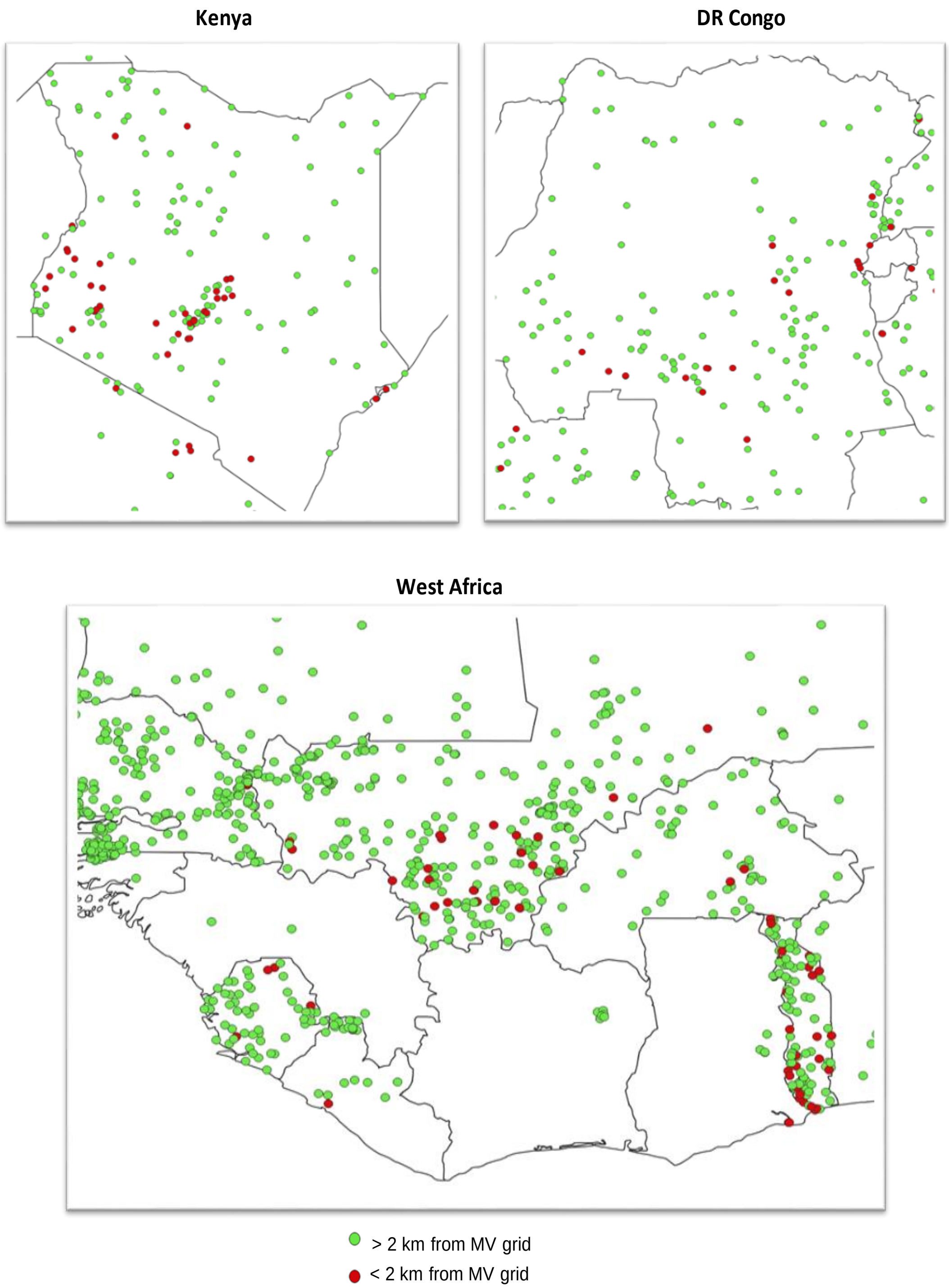

Figure A.1. Minigrids installed in sub-Saharan Africa within and outside the 2-km proximity to grid lines

Source: The map is produced by the authors based on (Arderne et al., 2020)

2. Tables

Table A.1. Power requirements of selected income-generating appliances

Sector	Appliance	Power required (kW)
Primary industries (agriculture, fishing)	Egg incubator	80 to 160 W
	Grinder for pulses and beans	5.2 kW
	Water irrigation pump	3.7 to 22.4 kW
	Sterilizer (for dairy processing)	3 to 6 kW
	Packager	250 W to 3 kW
Light manufacturing	Electronic welding machine	3 to 7.5 kW
	Jigsaw	400 W
	Electric drilling machine	400 W
	Popcorn maker	1.5 to 2.1 kW
Commercial and retail activities	Computer	15 to 100 W
	Printer/scanner	0.5 to 2 kW
	Sewing machine	200 W
	Television for local cinemas and bars (including decoder)	50 to 200 W

Source: (AMDA, 2020: 40)

Table A.2. Tier system for measuring energy access (according to Global Tracking for SE4ALL)

Energy access	**Basic**	**Advanced**			
Attributes	**Tier 1**	**Tier 2**	**Tier 3**	**Tier 4**	**Tier 5**
Services	Task light & phone charging	General lighting & television & fan	Tier-2 & any low-power appliances	Tier-3 & any medium power appliances	Tier-4 & any higher power appliances
Peak available capacity (Watts)	> 1 W	> 20W/50W	> 200W/500W	> 2000 W	> 2000 W
Duration (hours)	> 4 hours	> 4 hours	> 8 hours	> 16 hours	> 22 hours
Evening supply (hours)	> 2 hours	> 2 hours	> 2 hours	> 4 hours	> 4 hours
Affordability		Yes	Yes	Yes	Yes
Formality (Legality)			Yes	Yes	Yes
Quality (Voltage)			Yes	Yes	Yes
Indicated minimum technology	**Nano-grids/micro-grids**, pico-PV/solar lantern	**Micro-grids/mini-grids**, rechargeable batteries, solar home systems	**Micro-grids, mini-grids**, home systems	**Mini-grids** & grid	**Mini-grids** & grid

Source: (EUEI PDF, 2014: 24)

Table A.3. Effects of minigrid electrification on household welfare and agricultural productivity
DiD results based on matched sample using weights from radius matching method

	(1) Electricity uptake	(2) Fridge ownership	(3) TV ownership	(4) Radio ownership	(5) Cash job	(6) Employed all year	(7) Employed	(8) Employed agriculture	(9) Vegetation index
Dtime	0.047	0.075	0.090	-0.018	0.180**	0.037	0.312***	-0.198**	-0.042***
	(0.088)	(0.080)	(0.080)	(0.070)	(0.089)	(0.086)	(0.085)	(0.087)	(0.010)
Dtreat	0.200***	0.035	0.134**	0.089	0.183**	0.019	-0.074	-0.337***	-0.019**
	(0.065)	(0.034)	(0.059)	(0.068)	(0.085)	(0.062)	(0.077)	(0.080)	(0.008)
Dtime*Dtreat	0.344***	0.030	0.159**	-0.100	-0.034	0.173*	-0.133	0.126	0.048***
	(0.081)	(0.067)	(0.076)	(0.072)	(0.097)	(0.094)	(0.088)	(0.086)	(0.013)
Constant	0.084	-0.199**	0.109	0.362***	0.459***	0.457***	0.544***	0.859***	0.238***
	(0.134)	(0.093)	(0.130)	(0.125)	(0.146)	(0.131)	(0.126)	(0.125)	(0.009)
Observations	14,834	14,843	14,844	14,843	10,106	10,112	14,810	12,552	9,733

N*otes:* Estimation is retstricted to a matched sample, using weights obtained from Radius matching method based on covariates including population density, urban dummy, distance to the grid, travel time to city, cropland share, the number of healthcare centers. Each column controls for household characteristics including household size, age, gender, and education level of the household head in addition to the country dummies. While Dtime and Dtreat refer to dummy variables for time and group indicators, Dtime*Dtreat is the interaction term between the two variables. Robust standard errors clustered at community level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4. Effects of minigrid electrification on household welfare and agricultural productivity
DiD results on a matched sample using radius method satisfying the balancing property

	(1) Electricity uptake	(2) Fridge ownership	(3) TV ownership	(4) Radio ownership	(5) Cash job	(6) Employed all year	(7) Employed	(8) Employed agriculture	(9) Vegetation index
Dtime	0.076***	-0.042***	0.147**	-0.016	0.034	0.065	0.080	0.112	-0.010**
	(0.023)	(0.012)	(0.060)	(0.078)	(0.051)	(0.067)	(0.090)	(0.095)	(0.004)
Dtreat	0.185***	0.098***	0.235***	0.002	0.041	0.136**	-0.146**	-0.159**	-0.021***
	(0.037)	(0.019)	(0.045)	(0.051)	(0.055)	(0.058)	(0.068)	(0.063)	(0.005)
Dtime*Dtreat	0.145***	0.032	0.004	-0.182***	0.045	0.106	0.094	0.102	0.022***
	(0.051)	(0.022)	(0.066)	(0.070)	(0.070)	(0.082)	(0.087)	(0.089)	(0.008)
Constant	0.139***	0.010	0.067	0.605***	0.721***	0.562***	0.748***	0.464***	0.204***
	(0.046)	(0.025)	(0.087)	(0.113)	(0.113)	(0.097)	(0.130)	(0.124)	(0.011)
Observations	15,067	15,076	15,074	15,076	10,215	10,221	15,043	12,704	9,761

N*otes:* Estimation is retstricted to a matched sample, using weights obtained from Radius matching method based on a subset of covariates that satisfy the balancing property including urban dummy, cropland share, the number of healthcare centers. Each column controls for community characteristics including population density, travel time to city, distance to grid; household characteristics including household size, age, gender, and education level of the household head; as well as country dummies. While Dtime and Dtreat refer to dummy variables for time and group indicators, Dtime*Dtreat is the interaction term between the two variables. Robust standard errors clustered at community level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1