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Household effects of electrification through mini-grids: Evidence from Tanzania

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Abstract

Mini-grids are emerging as a key solution to electrify access-deficit communities, yet their effectiveness in improving energy access and household welfare remains underexplored. This paper provides novel evidence from Tanzania, where a policy reform doubled the number of mini-grids since 2008. Exploiting spatial and temporal variation created by the distance to the households in proximity to mini-grids and the timing of their deployment, and using data from two different nationally representative surveys, we find that mini-grids increase local electrification rates by 10-23 percentage points —a result corroborated by a surge in nighttime light intensity near newly deployed projects. We also show that mini-grids reduce reliance on polluting fuel-based lighting and drive the uptake of electric-powered devices. Back-of-the-envelope calculations suggest the surplus generated by renewable-based mini-grids nearly offsets their costs.

JEL Classification Numbers: L94, O13, Q48, Q56, Q58.

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1 Introduction

As of 2025, approximately 750 million people, about three-quarters of whom are in Sub-Saharan Africa (SSA), do not have access to modern energy services. Lack of access to electricity is often associated with lower household income, indoor pollution, and poor health outcomes (Dinkelman, 2011; Van de Walle et al., 2013; Barron and Torero, 2017). Enabling universal access to electricity by 2030 is the UN's Sustainable Development Goal #7. However, despite the efforts of many institutions to reduce energy poverty, achieving this goal remains a costly challenge, which the International Energy Agency (IEA) estimates will require about $49 billion per year. Therefore, evaluating the effectiveness of the different infrastructure options is essential for the optimal allocation of investment and aid.

The debate surrounding the provision of power-related infrastructure, like other projects targeted by development assistance, has often been limited to two opposing approaches: large-scale, centralized projects (national grid) and small-scale, decentralized options (home-based solar panels); see Deichmann et al. (2011) and Lee et al. (2016). In fact, various research articles document the impact of both centrally-planned grid expansion projects —e.g., in India (Burlig and Preonas, 2024), Brazil (Lipscomb et al., 2013), and South Africa (Dinkelman, 2011)— and home-based, off-grid solutions —e.g., in Kenya (Lee et al., 2020b) and Rwanda (Grimm et al., 2020)—, often presenting mixed evidence. Neither type of project is likely to bring *per se* any additional investment in generation capacity or power-related facilities to local communities.

However, many developing countries have recently witnessed massive investment in mini-grids, which are a "middle ground" infrastructure option between large-scale and small-scale approaches aimed at spurring a faster and greener path toward universal electrification (Suri, 2020) that also contribute to the creation of jobs at the local level (Joshi, 2021; Pueyo et al., 2022). This trend has been particularly marked in SSA, where, according to ESMAP (2019), there are approximately 1,500 existing mini-grids (representing a total investment of about $4 billion) with an additional 4,000 mini-grids in the planning stages, accounting for almost two-thirds of the total number planned globally.[1] Despite the significant financial investment and aid initiatives directed toward mini-grids (e.g., the World Bank allocated $1.6 billion to these projects between 2015 and 2019, with additional commitments of more than

[1]The COVID-19 pandemic slowed down the growth of this sector in 2020 and 2021. Still, as explained by AMDA (2022), mini-grid developers in Africa almost doubled the number of connections between 2019 and 2021.

$1.3 billion in the coming years) their effectiveness in promoting electrification and, more generally, household well-being lacks empirical evidence.

In this paper, we close the gap in the literature by estimating the impact of mini-grids in the context of a groundbreaking policy reform that encouraged massive investment in the Tanzanian mini-grid sector. Following this reform, the number of mini-grids in Tanzania doubled between 2008 and 2018, making this country the regional leader in mini-grid development (Odarno et al., 2017). This setting is, therefore, particularly appropriate for studying ongoing electrification efforts, as it provides a unique opportunity to extract insights on the benefits of promoting mini-grid investment for other countries with similarly low electrification rates.

Empirically, we combine geo-localized data on the universe of mini-grids deployed in Tanzania until 2017 with two different household-level survey datasets, namely, four waves of the National Panel Survey (NPS) of Tanzania 2008-2014 and seven waves of the Demographic and Health Survey (DHS) 1999-2017. Using this data, we estimate the impact of mini-grids on household electricity access and other welfare-related outcomes by exploiting spatial and temporal variation in mini-grid deployment. A key challenge arises because communities selected for mini-grid installation are not randomly chosen. Consequently, direct comparisons of household outcomes between communities with and without mini-grids would yield biased and inconsistent estimates. To address this, our identification strategy leverages household proximity to a mini-grid within very narrowly defined geographical zones. Within these zones, the precise location of mini-grids is largely determined by topographic features, such as surface roughness, the slope of nearby water bodies, and other terrain characteristics. We exploit this fact to define treated households (those closer to a mini-grid) and control households (those farther away).

Our empirical strategy is, thus, closely related to that used in a standard generalized difference-in-differences design, as we compare households located relatively close to mini-grids (treated) with those located farther away (control) before and after mini-grid deployment.[2] In the main specification of our regression model, we further control for unobservable differences between mini-grids powered by different technologies, household characteristics, and region-wide (temporally dependent) shocks. Moreover, we also provide evidence of the parallel trends assumption, by showing that pre-deployment trends in key outcomes are similar for treated and control households, indicating that the estimated

[2] In a related context, a very similar strategy is used, for example, by Benshaul-Tolonen (2019) and Bazillier and Girard (2020), who exploit the distance to mines to study the impact of the mining sector on household welfare in SSA.

effects are unlikely to be driven by a previously existing trend.

Our estimates suggest that households concentrated within 5 km from a deployed mini-grid are on average about 10-23 percentage points more likely to have an electricity connection in the post-deployment period, while this effect vanishes as households are located farther away from a mini-grid. These results are remarkably stable across various model specifications that include a rich set of socio-demographic controls and region-specific time trends using both the NPS and the DHS datasets. Moreover, the results using both datasets remain robust when we use alternative estimation strategies that takes into account potential spillovers between treated and control units and to the use of a propensity score matching procedure that corrects minor imbalances in some of the household characteristics across the two groups. Finally, the effect on the increase in electricity connections that we document is further supported with satellite data, as we detect an increase in nighttime light radiance in areas close to the mini-grids during the "post-treatment" period that is not observed as we move farther away from them.

An electricity connection, however, is not inherently valuable but is rather a means of achieving a variety of benefits for households, such as increased wealth and access to appliances. Therefore, we then ask if the deployment of mini-grids is also causally associated with improvements in these outcomes. First, we provide evidence that, among the households that gained energy access through mini-grids, there is also a significant increase in the use of electricity as the main lighting source, to the detriment of fuel-based lighting devices such as oil lamps or paraffin. These lighting technologies, which are popular across SSA (Choumert-Nkolo et al., 2019), contribute to indoor pollution and, therefore, are associated with respiratory diseases (Hanna et al., 2016; Imelda, 2018). Our estimates suggest that mini-grids have the potential to reduce the prevalence of health issues associated with indoor pollution. Second, we find a significant increase in the DHS wealth index among households located relatively close to a deployed mini-grid.[3] This finding is further supported by additional evidence that shows that treated households also result in increased ownership of selected electrical appliances, such as refrigerators and televisions.

As mentioned above, previous empirical studies focus on large-scale (Dinkelman, 2011; Moneke, 2020; Thomas et al., 2020; Schmidt and Moradi, 2025) and small-scale electrification projects (Lee et al., 2020b; Grimm et al., 2020). However, despite the increase in mini-grids, relatively little is known about their impact. Moreover, the evidence in previous studies is mixed and often contradictory. According

[3] As explained on the DHS website, this wealth index is a "composite measure of a household's cumulative living standard" and is calculated "using data on a household's ownership of selected assets".

to Fetter and Usmani (2024) and Lee et al. (2020a), this could be due to the fact that large-scale (grid extension) and small-scale (home-based) initiatives may not have a meaningful impact unless they are combined with "complementary investments" at the local level or target "households that are positioned to take actions" and may "exploit new business opportunities". This concern is of less importance in our context because part of the rationale for mini-grids is precisely to bring investment that leads to new economic opportunities at the local level, as mini-grids involve routine operation and maintenance tasks (e.g., managing a generator, billing collection, etc.) that are performed by the communities (Eras-Almeida and Egido-Aguilera, 2019; Joshi, 2021; Pueyo et al., 2022). While we do not explicitly test labor-market effects, this institutional feature distinguishes mini-grids conceptually from both centralized grid expansion and home-based electrification technologies.

To our knowledge, this is the first paper to provide causal empirical evidence on the impacts of mini-grids in the context of Africa. This setting is particularly relevant given that mini-grids feature prominently in the national electrification strategies of many African countries, where they are often intended to serve as the primary (or sole) source of electricity in access-deficit areas. By contrast, the closest related studies focus on India, a context in which large-scale national electrification programs and grid expansion had already been implemented and coexisted with micro-grids (Burlig and Preonas, 2024). For example, Burgess et al. (2020) show that household surplus from electrification tripled following the deployment of solar micro-grids, but also document that demand for these connections was strongly influenced by the presence of the central grid. Similarly, Fowlie et al. (2019) find that demand for solar mini-grid connections is relatively low due to households' expectations that future grid expansion would be subsidized by the government.[4]

This paper also complements previous studies that provide descriptive analysis (based on case studies and/or survey data) documenting the effect of mini-grids on communities in different countries. For example, Kirubi et al. (2009) present descriptive survey data from Kenya that suggests a positive effect of mini-grids on nearby residents, Herbert and Phimister (2019) develop a wind-powered mini-grid case-study also in Kenya to discuss the expected benefits for nearby rural households, and Tenenbaum et al. (2018) discuss the impact of three mini-grids in rural Cambodia on local communities.

The rest of the paper is as follows. In Section 2, we provide some information on mini-grids and the

[4] A very similar conclusion in the context of the Indian electricity sector is made by Comello et al. (2017).

policy implemented in Tanzania. Section 3 presents the regression models, discusses the identification assumptions, and explains the data. Section 4 contains the empirical result, while Section 5 concludes.

2 Background

2.1 Mini-grids and their expansion in developing countries

A mini-grid is a stand-alone network that can operate autonomously without being connected to a centralized grid by using a locally operated and managed small-scale generator that supplies electricity to a relatively limited group of users (Peskett, 2011; Franz et al., 2014). It thus provides an intermediate solution between the national grid, intended to serve a large group of users from several generators, and an off-grid, home-based system, which usually employs a solar panel to serve only one or a few users. A mini-grid can supply up to 15 megawatts (MW) of power and is therefore able to meet the basic needs of households, small businesses, schools, dispensaries, and other users in a few villages (UNFCC, 2014).

The sources harnessed to power the small-scale generators of mini-grids vary widely. Traditional mini-grids use diesel, biomass (agricultural residues or wood), or hydro-power, although in recent years, solar-powered and hybrid mini-grids that combine solar panels with batteries or diesel backup generators are becoming increasingly popular (IRENA, 2020). Other features, such as ownership (which can belong to a utility, a pro-business third party, or an NGO), type of tariff (consumption- or capacity-based; pre- or post-paid), and payment method (cash or mobile payments) may also differ across mini-grids.

In recent years, a substantial investment has been made in mini-grids in the developing world. According to ESMAP (2019), about 19,000 mini-grids exist globally, representing a cumulative worldwide investment of approximately $28 billion. Different international institutions (including the World Bank) have already committed more than $1.3 billion for mini-grid investment in the following years as one of the key strategies to achieve universal access to electricity. This trend has been particularly marked in SSA, where $300 million per year were allocated to these projects both in 2018 and 2019 (SEforALL, 2020), and about 4,000 new mini-grids are being planned for development.

The expansion of mini-grids in SSA as a mainstream solution to provide electricity to local communities is prompted by three main reasons. First, there has been a rapid decline in the capital costs of mini-grids, which are expected to further decrease through 2030 (ESMAP, 2019; Zigah et al., 2023).

Second, there is a lack of national grid networks, leaving numerous communities (especially in rural areas) without access to electricity. Thus, for many countries in SSA, mini-grids have become a least-cost solution to provide "last-mile" infrastructure to electrify villages. Third, contrary to alternative electrification solutions, mini-grids bring investment to the communities in which they are installed, generating job opportunities —according to Power for All (2022), a mini-grid site creates an average of 150 positions for every MW of installed capacity— and economic opportunities at the local level.[5]

2.2 The Tanzanian mini-grids policy reform

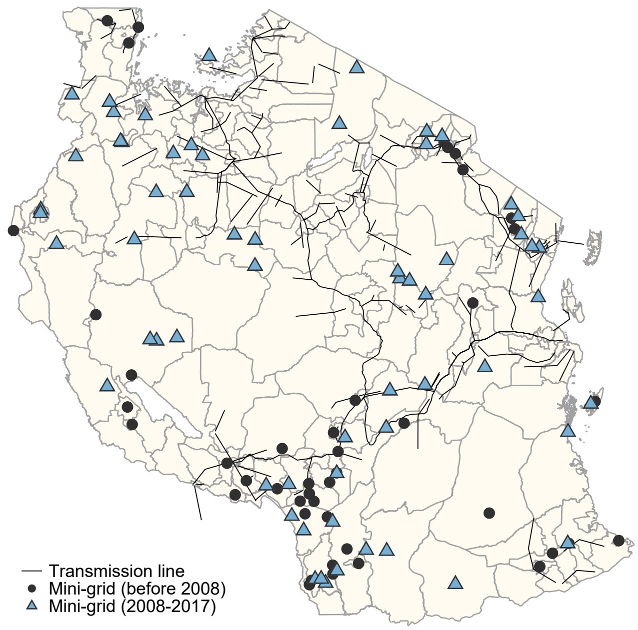
Mini-grids have existed in Tanzania since colonial times. They were built mostly in big cities and near mineral and agricultural facilities (e.g., diamond and gold mines; tea and cotton plantations). In the 1970s, several network expansion projects connected the existing mini-grids, creating the embryo of the current national grid (Odarno et al., 2017). However, the coverage of this network was limited, and many regions remained (and still remain) unserved, as shown in Figure 1.[6] In fact, the electricity access rate has historically been low in Tanzania, reaching just 15% as of 2010. According to ESMAP (2019), Tanzania ranks among the top 20 countries worldwide with the greatest electricity access deficit, with a significant urban-rural gap and a rate almost 10% lower than the average in SSA.

To address the historically low access rate, the Tanzanian government implemented a series of thoroughly designed financial support schemes to attract mini-grid investment from development financial institutions and donor agencies. The key milestone was the *Electricity Act 2008*. Among other things, the act introduced the so-called first-generation feed-in tariff (FiT), which recognized and favored Small Power Producers (SPPs) —private power plants with up to 10 MW of capacity— that supply to mini-grids. This pioneer regulation led the Tanzanian mini-grid sector to launch earlier than those in other countries in SSA. However, policymakers recognized some room for improvement, as the deployment of mini-grids, was fairly concentrated on those that were hydro- and biomass-powered. Thus, to foster

[5]As explained by González Grandón and Peterschmidt (2019) and Sayar (2019), some mini-grids are installed alongside new businesses that process raw materials. These businesses become a secondary revenue source for the mini-grid developer. While we do not explicitly test for employment creation or local economic activity, data on the job creation associated with mini-grid deployment and anecdotal evidence on the local business opportunities that mini-grids can generate can be found in IRENA (2017), ESMAP (2019), AMDA (2020), and Pueyo et al. (2022).

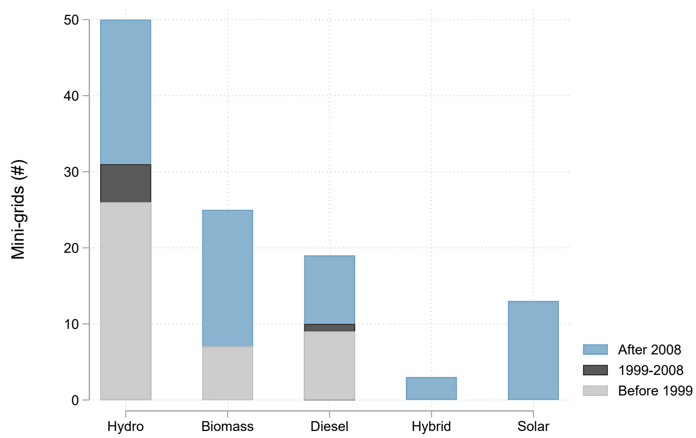
[6]Note that some transmission lines are isolated or not interconnected. This reflects Tanzania's current stage of grid development, in which certain lines are first constructed to serve specific load centers (e.g., mines or towns) located outside the main grid, with the objective of eventual integration into the national grid. In addition, Tanzania is in the process of expanding cross-border interconnections; as a result, some lines are awaiting the completion of planned cross-border links.

Figure 1. Map of mini-grids deployed in Tanzania up to 2017



Note: This figure includes a map of all the mini-grids deployed in Tanzania up to 2017. The 46 mini-grids that were commissioned before 2008 (the year of the implementation of the Electricity Act) are indicated with black circles, while the 51 mini-grids commissioned between 2008 and 2017 are indicated with light blue triangles. The black lines represent the existing high and medium-voltage transmission lines of the Tanzanian national grid as of 2016, obtained from the World Bank Data Catalog, and collected for the Africa Infrastructure Country Diagnostics (AICD). The light gray lines capture the boundaries of the regions of Tanzania.

Figure 2. Total cumulative number of mini-grids in Tanzania by technology up to 2017



Note: This figure displays the cumulative number of mini-grids in Tanzania until 2017 by technology. In light gray, we capture the number of mini-grids deployed before 1999 (the first year for which we have survey data). In black, we capture those built between 1999 and 2008 (the year of the implementation of the Tanzania Electricity Act). Finally, in light blue, we capture those built after 2008.

investment in other technologies (particularly, in solar-powered mini-grids), some changes were implemented by the Tanzanian Energy and Water Utilities Regulatory Authority (EWURA) in 2015; e.g., it created different remuneration mechanisms based on the cost differences between technologies and pegged the FiT to the US dollar to reduce the risk of investment (Odarno et al., 2017).

Due to this policy intervention, the number of mini-grids in Tanzania has doubled since 2008. By 2017, there were 109 mini-grids across the country, representing a total capacity of 157.7 MW and providing connections to about 183,705 customers (Odarno et al., 2017). Figure 1, which contains a map of Tanzania, indicates the mini-grids that were built before the Electricity Act 2008 (indicated with black circles) and after that (light blue triangles). Then, in Figure 2, we show the evolution of mini-grids by technology in Tanzania. It is worth noting that, after 1999 (the first year included in our survey data), there was an increase in the number of mini-grids across all the technologies (particularly, in hydro).[7]

3 Empirical framework and data

3.1 Empirical strategy

The communities where mini-grids are installed are not randomly chosen. Consequently, a linear regression of an outcome of interest (e.g., electricity access) on a dummy that equals 1 for households located in a community where a mini-grid was built and 0 otherwise likely yield biased and inconsistent estimates inasmuch as the (unobservable) characteristics that explain the construction of a mini-grid in the community correlate with the characteristics of the households that live there. Instead, and following Lee et al. (2016), Benshaul-Tolonen (2019), and Bazillier and Girard (2020), we can identify the effect of mini-grids on households by exploiting two key features in our data. The first feature is the location that defines households in proximity to a mini-grid as being either relatively close to or far from it. The second feature is the time effect of the deployment of different mini-grids across Tanzania.

Specifically, our identification strategy relies on the fact that, once a community has been selected as the site for a mini-grid, the precise location of the mini-grid within the community is uncorrelated with factors affecting household electricity access or other outcomes. That is, within a community, mini-grids are not built relatively close to the households that (for pre-existing characteristics) are more likely to receive an electricity connection, and/or far from those less likely to do so. Instead, the exact location of a mini-grid within a community is determined by other (exogenous) factors, such as surface roughness,

[7] According to IRENA (2017), as of 2015, approximately 1,000 people in Tanzania were employed in the construction, operation, and management of hydro-powered mini-grids only.

the slope of the nearest water body, or any other features of the territory.

Appendix A.1 provides supporting evidence for this fact, as it includes several high-resolution maps showing that, even though the mini-grids target certain communities in particular, the exact location of the mini-grids on the premises of the communities responds to different exogenous factors. For example, the location of hydro-powered mini-grids is determined by the presence of a water body and, moreover, are built where there is a sufficiently steep slope and the current is ample.[8] Likewise, the location of solar mini-grids is dictated not only by solar radiance but also by the presence of a sufficiently ample flat terrain that is closely connected to a road. A similar observation is made for biomass mini-grids: as they use (relatively heavy) agricultural waste, biomass mini-grids must be located in areas with agricultural activity and nearby roads. Finally, diesel mini-grids must also be built near primary roads, as diesel must be transported by trucks (there are no refined product pipelines in Tanzania).[9] Appendix A.1 provides a detailed discussion of these features, along with the high-resolution maps that support them.

As noted by Odarno et al. (2017), the cost and fees associated with delivering electricity increase with the distance between a mini-grid and the households it serves —while the reliability of the service tends to decrease over greater distances. Consequently, we could expect that, all else being equal, households relatively close to a mini-grid (whose proximity, as explained above, is determined by exogenous geographic factors) are more likely to connect to the mini-grid than those that are far from it.[10] Further evidence in support of this fact is included in Figure 3, which outlines the average nighttime luminosity captured by Visible Infrared Imaging Radiometer Suite (VIIRS) (in nanoWatts/cm2/sr) across all pixels of different concentric rings around the Segese biomass mini-grid, located in Kahama (Shinyanga Region), the years before and after its deployment. While no radiance is observed the year before the construction of this mini-grid as noted in Figure 3(A), we observe a significant increase the year after it was built (see Figure 3(B)). Moreover, the increase in nighttime radiance is stronger in the concentric circles that are close to the mini-grid, while decreasing in the concentric circles that are far from it.

Figure 3 is merely a case in point to visually illustrate the before-and-after evolution of nighttime

[8] World Bank (2017) provides a list of the exact places in Tanzania that are suitable for small hydro generators, given the characteristics of the terrain and the water bodies.

[9] One may be concerned that, since diesel-fueled mini-grids do not depend on the availability of natural resources and the characteristics of the terrain, their exact location is "less exogenously" dictated than that of, e.g., the solar and hydro ones. Thus, as a robustness check, we provide in Appendix B.3 our main empirical results after excluding them from our sample.

[10] The decline in the probability of electrification for customers farther away from the power infrastructure is also the basis of the empirical strategy of several other papers (Van de Walle et al., 2013; Squires, 2015; Blimpo et al., 2018).

Figure 3. Average nighttime lights around the Segese mini-grid in Kahama (Shinyanga Region) before and after its construction (2014)

(A) Radiance in 2013

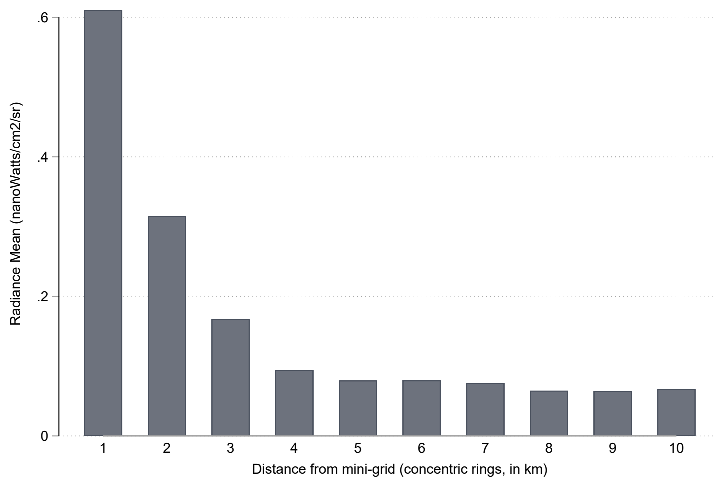
(B) Radiance in 2015

Note: The figure illustrates the change in nighttime luminosity —measured using Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Lights (in nanoWatts/cm2/sr)— across concentric rings (with constant radii increment of 200 m) around the Segese biomass mini-grid, located in Kahama (Shinyanga Region) before and after its construction. Figure 3(A) displays the average radiance across all pixels within each ring in the year preceding construction (2013), while Figure 3(B) displays the corresponding averages for the year following construction (2015). The data was obtained from the National Centers for Environmental Information (WorldPop, 2018).

light intensity across concentric bands surrounding a single mini-grid. However, the same pattern is observed in the rest of the mini-grids in our sample, as we illustrate in Figure 4. This figure captures the average VIIRS Nighttime Lights for different concentric rings (drawn at 1-km intervals) within a radius of 10 km around all the mini-grids included in our sample. It is fairly evident that substantial nighttime radiance is present in the concentric rings that are close to the mini-grids, which disappears as we move far away from them. In fact, the incremental effect of the mini-grids on radiance vanishes for concentric rings that are over 5 km away from the mini-grids. Therefore, this 0-5 km threshold is the one that we use in the first empirical approach that we explain below to identify the "treated" households.[11] Moreover, as we thoroughly explain below, the observed decline in nighttime radiance as the distance from the mini-grid increases also motivates our alternative empirical strategy, in which we exploit a "continuous treatment" approach, along the lines of Huet-Vaughn (2019) and Gavrilova et al. (2019) (among others).

[11]This threshold is not only reasonable in accordance with Figure 4 but also technically convenient: the DHS suggests using buffers of at least 5 km, given that the geo-localization of the households is slightly (randomly) displaced from their true location to preserve their anonymity (Perez-Heydrich et al., 2013). The same randomization procedure was also applied to the localization of the households in the NPS (TNBS, 2011).

Figure 4. Average nighttime lights in different concentric rings around all the mini-grids in Tanzania



Note: The figure captures the average nighttime luminosity —measured using Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Lights (in nanoWatts/cm2/sr)— for different concentric rings around all the mini-grids included in our sample. We consider all the concentric rings (drawn at 1-km intervals) within a radius of 10 km from each of these mini-grids. Each concentric ring has a surface of $\pi[r^2 - (r-1)^2]$, for $r \in \{1, \cdots, 10\}$, where r denotes the corresponding ring (from closest to farthest from the mini-grids).

3.2 Regression model

Bearing the previous ideas in mind, we now present the regression model that we use to examine how the rollout of mini-grids across Tanzania has impacted energy- and wealth-related outcomes at the household level. To do so, we exploit variation both in the timing of the deployment of different mini-grids and in the distance from them, comparing outcomes before and after their deployment in treated units (those geographically closer to a mini-grid) relative to control units, as defined below. The empirical strategy is thus based on a generalized difference-in-difference (*DiD* hereafter) approach, in which our main regression model is as follows:

$$y_{i,c,r,t} = \beta_0 + \beta_1 \mathrm{MG}_{c,r} \times post_t + \boldsymbol{X}_{i,c,r,t} + \alpha_r + \sigma_r \times t + \delta_t + \varepsilon_{i,c,r,t}, \tag{3.1}$$

where an outcome $y_{i,c,r,t}$ of household i in cluster c,[12] region r, at year t is regressed on the interaction between $MG_{c,r}$ (which captures the treatment variable) and $post_t$ (which takes a value of 1 if the mini-grid is active at year t and 0 otherwise). In our first approach, we consider households as treated if they are within a radius of less than 5 km to a mini-grid, while households within a radius of 5-10 km to a

[12] A cluster is the smallest (anonymized) geographical unit defined by groupings of households in the surveys. Both surveys use a fixed number of households per cluster, with an average of 23 households for the DHS and 9 households for the NPS.

mini-grid provide our control group. Hence, in this binary-treatment version, $MG_{c,r}$ is defined by the following indicator function: $MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}$ for all $d_{c,r} \in [0,10]$, where $d_{c,r}$ is the distance (in km) between households in cluster c and the closest mini-grid. This threshold is based on the information in Figure 4 (and later in Figure 5), as we see that the incremental average nighttime radiance around mini-grids vanishes for concentric rings that are more than 5 km away from the mini-grids.

Even though this 5-km threshold allows us to implement a standard *DiD* regression based on a binary treatment, one might still be concerned that the threshold is somehow arbitrarily chosen or that it is not the appropriate one for all the mini-grids in our sample (as the presence of nighttime radiance up to 5 km away might be driven only by a few of them). If this were the case, then households dwelling near the 5-km threshold would contaminate our empirical results.[13] To overcome these concerns, we follow previous literature (Acemoglu et al., 2004; Cicala et al., 2019; Gavrilova et al., 2019; Huet-Vaughn, 2019) and alternatively use a continuous-treatment version by defining the degree of exposure to the treatment (i.e., begin close to a mini-grid) based on the (inverse) distance between households and mini-grids. That is, $MG_{c,r} = 1 - \frac{d_{c,r}}{10}$, for all $d_{c,r} \in [0,10]$, and where $d_{c,r}$ is as defined above.

The coefficient associated with the interaction between $MG_{c,r}$ and $post_t$, denoted by β_1, captures the impact of mini-grid installation on the selected household outcomes, and is, therefore, the one of interest in this study. More precisely, in the binary-treatment version, β_1 captures the impact on outcome $y_{i,c,r,t}$ for households within 5 km of the closest mini-grid (relative to households within 5-10 km) following its deployment, while in the continuous-treatment version, β_1 measures the marginal increase in the outcome when decreasing the distance to the closest mini-grid by 1 km after its deployment.

Finally, the right-hand side (RHS) of equation (3.1) also includes a vector of household and mini-grid characteristics ($\boldsymbol{X}_{i,c,r,t}$), and a battery of fixed effects. Namely, we include head of household characteristics (age, education, and gender); dummy variables indicating the technology of the closest mini-grid (solar, hydro, biomass, hybrid or diesel); the dummy variable $MG_{c,r}$ (not interacted with $post_t$); year fixed effects (δ_t), which control for changes over time that affect all households similarly (e.g., national policies and growth); and region fixed effects (α_r), which control for all time-invariant differences between regions (e.g., ethnic and cultural backgrounds). In an alternative specification of our model, we

[13]Given these concerns, and following Benshaul-Tolonen (2019), as an additional robustness check, we include in Appendix B.4 our main results using the aforementioned binary treatment approach but excluding households in the 4-6 km area.

replace the latter by cluster fixed effects (α_c),[14] which control for a wide range of cluster-specific characteristics that may affect the outcomes of interest —helping to support the robustness of our empirical results. In both cases, we also include region linear time trends ($\sigma_r \times t$) in some specifications to control for potential time-varying shocks that may affect certain regions specifically (e.g., droughts).

3.3 Identification

The identification of the causal effect on $y_{i,c,r,t}$ captured by the coefficient of interest β_1 relies on the following identifying assumptions. First, our empirical strategy requires the parallel trends assumption to hold for the main outcomes of interest between households located close to and far from mini-grids. That is, in the absence of mini-grid deployment, outcomes for all households on the premises of the mini-grids would have followed similar trends over time. We provide substantial evidence in support of this assumption, including tests for parallel trends and for the absence of differential pre-trends, which support that the estimated effects do not stem from pre-existing trends. All this supporting evidence is presented in a stand-alone "validity" sub-section in light of our main empirical results (Section 4).

Second, another assumption necessary for validity is that no other policy changes coinciding with mini-grid deployment differentially affect households located closer to versus farther from mini-grids. Because our analysis is conducted within narrowly defined geographic areas within the same administrative jurisdictions, it is unlikely that contemporaneous policy interventions would both coincide with mini-grid construction and also systematically affect households based on their proximity to the mini-grid. Next, a third identifying assumption is the absence of anticipation effects; that is, that treated and control households do not delay investments in alternative electrification options in expectation of an upcoming mini-grid. Given that mini-grids are deployed in access-deficit locations, where households typically lack viable alternative electrification options, anticipation effects are unlikely to be a significant concern in this setting.

Finally, because our analysis is restricted to households in communities where a mini-grid is installed, it is also important (in order to support the interpretation that communities where mini-grids have not yet been deployed would experience similar effects upon installation) to show that the timing of mini-grid roll-out is uncorrelated with the economic development of targeted communities. This

[14]The inclusion of α_c implies that time-invariant cluster-specific variables, such as $MG_{c,r}$, are dropped.

assumption is standard in our context, given the well-documented constraints that shape electrification project deployment (Schmidt and Moradi, 2025). In fact, Odarno (2017) and Odarno et al. (2017) document that mini-grid developers in Tanzania often experience administrative delays and other financial and engineering constraints that lag their investment projects. Nonetheless, we provide explicit empirical support for this claim in Appendix A.2. Specifically, we show that there is no statistically significant relationship between economic wealth (using both data at the household level and also at the community level) and the timing of mini-grid construction (Table A.2).

3.4 Data

We assemble a unique dataset that combines geo-localized information obtained from different sources both on mini-grids and households. First, we obtain data from the World Resources Institute (WRI) on all the mini-grids deployed in Tanzania. This dataset contains detailed information (geo-localization, year of commission, capacity, and technology) for the 109 mini-grids deployed in this country from the 1930s to 2017. However, we exclude 12 of the mini-grids for which either the commissioned year or the geo-location is missing. Figure 1 provides the location of all the mini-grids across Tanzania before and after 2008 (the year that the Electricity Act was implemented) that are included in our final sample, while Figure 2 displays the evolution of the mini-grids by technology (their average capacity is 1.6 MW).

This information is combined with household-level (secondary) data from two nationwide surveys, namely, four biennial waves of the National Panel Survey (NPS) between 2008 and 2014 and seven cross-sectional rounds of the Demographic and Health Survey (DHS) between 1999 and 2017 (National Bureau of Statistics of Tanzania, 2020; IPUMS, 2020). A rich set of socio-economic and demographic characteristics (including geo-localization) for up to 2,231 and 39,483 representative households across the country are included in the NPS and the DHS, respectively.[15] Bearing in mind that each of the two surveys presents specific advantages and drawbacks (the sample size of the NPS is relatively small and covers a shorter period of time, while the DHS contains information for a larger set of households over a longer time window) we separately use data from both surveys to estimate the regression model above in order to confer robustness to our empirical results.

We use the geo-localization of the households in these survey datasets to calculate their distance (as

[15] The number of households that are repeatedly included in multiple rounds of the NPS is fairly low. This precludes us from estimating equation (3.1) by also including household fixed effects.

the crow flies) to the nearest mini-grid. Using this distance, we define the sample that we use to estimate equation (3.1), which is restricted to households within 10 km from a mini-grid (3,992 households in the DHS and 1,053 in the NPS). Following the 2008 policy reform, the construction of new mini-grids led to a reduction in the average distance between households in our sample and the mini-grids. For example, in the NPS, we observe a 56% increase in the number of households that are less than 5 km from the nearest mini-grid after 2008. We exploit this variation in "pre-post" distances to estimate the impact of newly deployed mini-grids on the selected outcomes.

Importantly for our purposes, both surveys include information on the electrification status and other wealth-related characteristics of the households, which we use to define our main outcomes of interest. First, we focus on the impact of a dummy variable that identifies whether a household has an electricity connection. We use the responses to the following question in the DHS to create this dummy variable: "Does the household have electricity?". For the NPS, we instead use the responses to the question on the households' main source of electricity, for which we define our dummy as equal to 1 if an answer to this question is recorded (excluding a few households whose main source of electricity is a car battery, an owned generator, or a motorcycle battery) and 0 otherwise.[16]

Second, the NPS also provides information on the households' primary fuel sources for lighting. Using this information, we create a dummy that equals 1 if a household uses electricity and 0 otherwise (paraffin, oil, firewood, etc.). This variable allows us to study whether the construction of a mini-grid increased the use of electricity as the primary lighting source *in lieu* of other fuel-based devices, such as oil lamps or paraffin, that are popular in Tanzania.[17] This empirical exercise is particularly relevant in light of the indoor pollution problems associated with these devices, which are causally linked to respiratory problems and premature death in developing countries (Hanna et al., 2016; Imelda, 2020).

Finally, we examine different outcomes related to household asset wealth. In particular, we first study whether the construction of mini-grids had an effect on the DHS wealth index, which is a composite measure of the living standards of households that is calculated based on the ownership of selected assets and other amenities (water and electricity access, sanitation facilities, quality of the materials, etc.); see Rutstein (2015). In addition, using both the DHS and the NPS, we examine the impact of mini-grids on the ownership of specific electric-powered appliances, such as refrigerators and televisions. To

[16] In both surveys, we remove from our sample the very few households that own solar panels.

[17] About 71% of households in the NPS use kerosene or oil lamps for lighting, while other sources like gas or solar are rare.

do so, we construct two different dummies that equal 1 if these appliances are owned, and 0 otherwise.

As explained above, we use as controls other variables in these surveys, such as the gender, age, and education of the head of a household (where the latter is captured by a dummy equal to 1 if the head of the household completed primary education), that are likely to confound the selected outcomes. In addition, as control, we use dummies that indicate the technology of the corresponding mini-grid. For both the DHS and the NPS datasets, Table A.1 (Appendix A.2) provides summary statistics for the treated (0-5 km) and the control (5-10 km) households before and after the deployment of the closest mini-grid. The reader should be aware that some of the households in our sample already had an electricity connection before the deployment of the closest mini-grid. This is because a few mini-grids in our sample were built in areas already served by the national grid, as shown in Figure 1. Due to the potential concern that our results might be affected by pre-existing infrastructure, as a robustness check, we provide in Appendix B.2 the main set of empirical results after dropping the mini-grids (and the corresponding households) that are relatively close to the national grid transmission lines.[18]

4 Empirical results

This section presents our main empirical results. We first estimate the impact of mini-grids on household energy-related outcomes and then examine their effects on wealth outcomes.

4.1 Effect of mini-grids on energy outcomes

Main results. We start by providing the results of equation (3.1) (estimated by OLS) on the probability of households being connected to electricity after the deployment of a mini-grid. Table 1 presents in columns (1)-(4) the coefficients of the linear probability model (LPM) using the dummy that defines treated and control households based on the 5-km distance cut-off (binary treatment approach), while using the variable that defines the degree of exposure to the treatment based on the distance between households and mini-grids (continuous treatment approach) in columns (5)-(8). Panel A displays the estimates obtained using the DHS dataset, while Panel B contains the estimates obtained using the NPS.

First, column (1) presents the results of the model specification that includes the full set of controls

[18]Table A.1 (Appendix A.2) reveals slight imbalances in a few characteristics across treated and control households in our sample, e.g., in television ownership (NPS). As a robustness check, we provide in Appendix B.1 the main set of results obtained by using a propensity score matching estimator that helps resolve these slight imbalances in our sample.

Table 1. Impact of mini-grids on household probability of having an electricity connection

	Binary treatment approach $\left(MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}\right)$				*Continuous treatment approach* $\left(MG_{c,r} = 1 - \frac{d_{c,r}}{10}\right)$			
	Panel A. DHS dataset							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.176***	0.163***	0.160***	0.181***	0.255***	0.238***	0.279***	0.281***
	(0.0507)	(0.0556)	(0.0498)	(0.0688)	(0.0788)	(0.0940)	(0.0788)	(0.0940)
R^2	0.209	0.224	0.341	0.363	0.225	0.238	0.342	0.363
N. Observations	3,992	3,992	3,992	3,992	3,992	3,992	3,992	3,992
	Panel B. NPS dataset							
Mini-grid × post	0.206***	0.231***	0.0613*	0.0844*	0.261***	0.307***	0.0954*	0.148**
	(0.0570)	(0.0540)	(0.0358)	(0.0431)	(0.0859)	(0.0908)	(0.0556)	(0.0603)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.245	0.259	0.381	0.398	0.264	0.279	0.381	0.398
N. Observations	1,053	1,053	976	973	1,053	1,053	976	973

Note: The outcome is a dummy equal to 1 if the household has an electricity connection (and 0 otherwise). Linear probability models estimated by OLS using data from the DHS (Panel A) and from the NPS (Panel B) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, in which the variable "Mini-grid" is a dummy one defined as follows $MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}$ for all $d_{c,r} \in [0,10]$, where $d_{c,r}$ is the distance (in km) between households in cluster c and the closest mini-grid; while in columns (5)-(8) we use the continuous treatment approach, in which the variable "Mini-grid" is a continuous one defined as follows $MG_{c,r} = 1 - \frac{d_{c,r}}{10}$, for all $d_{c,r} \in [0,10]$. Columns (1) and (5): full set of control variables —including head of household (log-) age, head of household education, head of household sex, $MG_{c,r}$, and dummy variables indicating the technology of the closest mini-grid (solar, hydro, biomass, hybrid or diesel)—, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables (except $MG_{c,r}$), cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

—age, education, and sex of the head of a household, as well as dummies indicating the technology of the closest mini-grid—, and region and year fixed effects. The coefficient of the interaction term "Mini-grid $\times$ post" using the DHS dataset is significant at the 1% level and suggests a 17.6 percentage point increase in the probability of having an electricity connection among households located within 5 km of a mini-grid after its deployment. Similarly, the effect is positive, significant at the 1% level, and slightly higher in magnitude when using the NPS dataset. In column (2), we add region-specific time-trends, and the results suggest an increase of about 16-23 percentage points in the outcome. Then, in columns (3) and (4), we use the same model specifications as those in columns (1) and (2), respectively, but replace region fixed effects with cluster fixed effects. In this case, the point estimates using the DHS are similar in magnitude to the previous ones, indicating an increase of 16-18 percentage points (significant at the 1% level) in the probability of treated households having a connection. However, when the NPS is used, the magnitude of the impact decreases to approximately 8 percentage points (significant at the 10% level).[19]

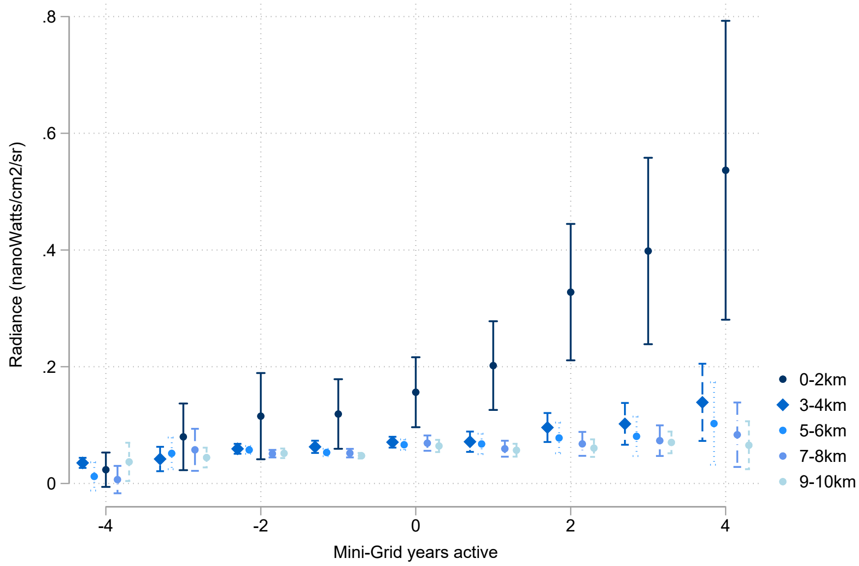
Next, column (5) contains the results of the continuous treatment approach for the model specification that includes the full set of controls as well as region and year fixed effects. The coefficient of interest using both the DHS and the NPS is around 0.26 (significant at the 1% level). This estimate implies that, following mini-grid installation, the probability that an average treated household —located 2.49 km (DHS) or 2.65 km (NPS) from the nearest mini-grid, corresponding to the mean distance among households classified as treated in the binary specification— increases its likelihood of having an electricity connection by roughly 19 percentage points.[20] This effect coincides in magnitude with the estimated (average) effect in column (1). Extremely similar results are also obtained when we add the region-specific trends using both the DHS and the NPS as shown in column (6), and also for the specifications that contain cluster fixed effects using the DHS only, as shown in columns (7)-(8), Panel A. In all these cases, we estimate that the probability of a household having a connection when located 2.49 km from a mini-grid rises by 18-22 percentage points. However, for the latter specification of the regression model estimated using the NPS, the increase in the probability is slightly lower (about 8-10 percentage points). Overall, the results are very similar in magnitude to those obtained using the binary treatment approach.

Validity. In order to evaluate the policy intervention of interest (i.e., the effect of being close to a

[19] The reader should be aware of the relatively low number of observations in the NPS dataset, which may significantly contribute to generating these deviations in the estimated coefficients when different model specifications are used.

[20] This number is obtained as follows: $(0.26) \times \left(1 - \frac{2.49}{10}\right) = 0.195$ (for the DHS average distance of 2.49 km).

Figure 5. Average satellite-based nighttime light (VIIRS radiance) in different concentric rings around mini-grids relative to the year of deployment



Note: The figure captures the average satellite-based nightlight radiance (and the corresponding standard errors around it) for five concentric rings (with constant radii increment of 2 km) around all the mini-grids in our sample that were deployed between 2012 and 2016. These averages are calculated using Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Lights (in nanoWatts/cm2/sr) for 1-hectare pixels —obtained from WorldPop (2018)—, and are plotted for each year relative to the year of the deployment of each mini-grid (ranging from -4 to 4 years).

newly developed mini-grid for any household i) we need to compare outcomes for the household after the deployment of a mini-grid to what the outcomes would have been had the household not been close to the mini-grid (Blundell and Dias, 2009). This treatment effect is captured by the coefficient β_1 in equation (3.1). However, it is important to note that one of the necessary assumptions to identify this effect is that outcomes in treatment and control cohorts would follow the same time trend in the absence of the installation of a mini-grid (see Section 3.1). Given the staggered rollout of the mini-grids in our sample, testing the parallel trends assumption requires collapsing the data in event time, with event time $t = 0$ denoting the year in which a mini-grid becomes operational in a given location. Bearing this in mind, we perform the following tests to support the common trend assumption in our setup and strengthen the validity of our identifying strategy.

First, we provide evidence that there are no differential pre-trends in electricity usage across households in the treatment and control groups. For that purpose, we use average satellite-based nightlight luminosity data obtained from WorldPop (2018) for all the 1-hectare pixels within 10 km of the mini-grids in our sample that were built between 2012 and 2016.[21] Given the large number of pixels, we create five concentric rings around each mini-grid (with a constant radii increment of 2 km) and obtain the mean radiance (and the corresponding standard errors) at each year relative to the year of installation of the mini-grids for each of the rings.

The result of this exercise is presented in Figure 5. First, the five rings around each of the considered mini-grids were on similar trends in terms of average satellite-based nightlight radiance in the years before their installation: radiance levels are not statistically different across rings in the pre-treatment period between t=-4 and t=-1 (inclusive). This pattern thus provides some evidence of the parallel trend assumption, as it suggests that mini-grids were not likely built in rings in which nightlight radiance was already increasing relative to other mini-grids. Moreover, following the deployment of the mini-grids, we observe that the average radiance at different rings evolves differently: there is a stark deviation from the flat trend in the 0-2 km ring (and, to a lesser extent, in the 2-4 km ring) right after the investment phase. This result provides additional evidence of the positive effect of mini-grids on electricity use —captured by an increase in nightlight radiance in areas where our treatment cohort is located (i.e., within a radius of less than 5 km from the closest mini-grid).

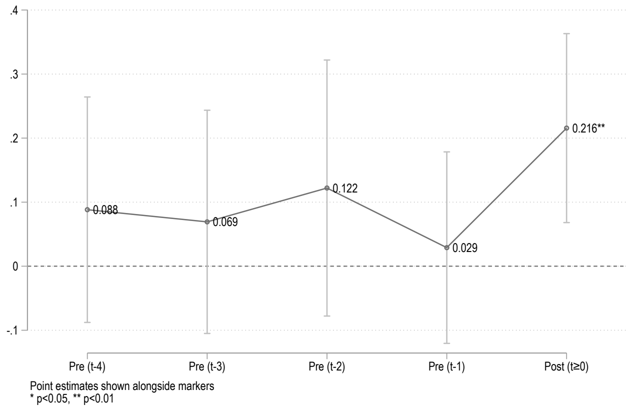
Second, we test for the existence of differential trends in the number of electricity connections among treated households (relative to control households) prior to the installation of a mini-grid to confirm the validity of our identifying strategy. Specifically, we extend our main regression model —equation (3.1), binary treatment version— by including several leads of the treatment variable, in the spirit of Autor (2003). This alternative (year-by-year) regression specification allows us to check whether the uptake of electricity connections documented above comes from the installation of a mini-grid or, alternatively, whether it is stemming from a pre-existing trend among the households in the treated cohort. For the sake of completeness, we estimate this regression using the binary treatment approach for both the specification that includes region fixed effects and also for the one that includes cluster fixed effects.

Figure 6 provides the results obtained by estimating this alternative version of our main regression model augmented with leads of the treatment variable using the DHS.[22] This figure displays the point estimates that capture whether there are pre-trends in the uptake of electricity connections among treated

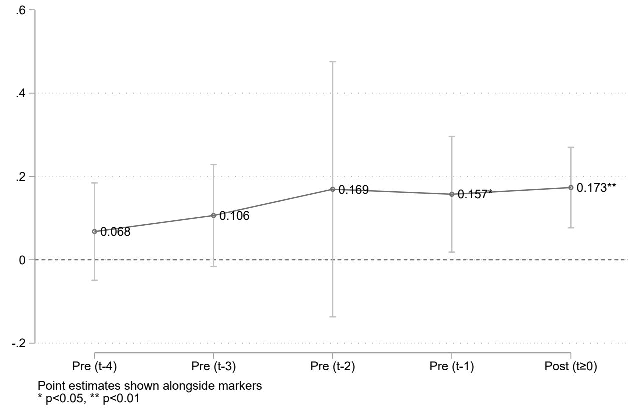
[21] We limit our analysis to mini-grids built between 2012-2016 due to the methodological change in measuring radiance that occurred in 2012. To avoid contamination of luminosity, we drop mini-grids built in areas with pre-existing power-related infrastructure or those connected to the main grid, and pixels potentially connected to the main grid because of their distance.

[22] Due to the limited number of observations, we cannot obtain similar estimates using the NPS.

Figure 6. Estimated impact on the probability of having an electricity connection for treated households relative to control household before (year-by-year) and after the time of installation of the mini-grids



(A) Model specification with Region FE



(B) Model specification with Cluster FE

Note: The figures capture the impact that the deployment of the mini-grids in our sample had on the uptake of electricity connections among treated households —as defined in the binary treatment approach, i.e., those within 5 km from a mini-grid— relative to control households using the DHS dataset. We consider the year-by-year impact four years before the year in which the mini-grids in our sample were deployed. Estimates in Figure 6(A) are obtained using the specification of our regression model (binary treatment approach) including the full set of control variables (head of household age, head of household education, head of household sex, and dummy variables indicating the technology of the closest mini-grid), region fixed effects, and year fixed effects. Estimates in Figure 6(B) are obtained using the specification of our regression model (binary treatment approach) including the full set of control variables, cluster fixed effects, and year fixed effects. Standard errors are clustered at the region-year level. Vertical bands represent 95% confidence intervals for the point estimates.

households (relative to control households) up to four years prior to the deployment of the mini-grids. The treatment effect on the outcome is significant and similar in magnitude (around 17-21 percentage points) to that obtained in Table 1 in the *Post* period both in Figure 6(A) (specification with region fixed effects) and 6(B) (specification with cluster fixed effects). However, except for the $t-1$ lead in Figure 6(B), which suggests that the uptake of connections could have already started in the investment phase, all the lead indicators are statistically indistinguishable from zero, ruling out the existence of such pre-trends. These results further confirm that the increase in the probability of having an electricity connection among treated households occurs only after the installation of the mini-grids and, therefore, is not stemming from a pre-existing trend.

Additional results. The empirical results above suggest that the deployment of mini-grids in Tanzania causally led to a surge in the uptake of electricity connections among treated households. Therefore, the question that follows is whether the mini-grids also increased the *actual* use of electricity for basic needs, such as lighting. This question is of particular relevance considering that about 71% of the households in our sample light their homes using either oil- or paraffin-based devices. These devices, which are popular not only in Tanzania but also in many other developing countries (Choumert-Nkolo et al., 2019), are well-acknowledged sources of indoor air pollution and are causally associated with respiratory problems and premature death (Hanna et al., 2016; Imelda, 2020). Thus, our goal is to check whether the deployment of mini-grids also induced households to light their homes by replacing oil or paraffin devices with electricity, helping to mitigate indoor air quality-related problems.

Hence, we estimate equation (3.1) again using a binary outcome variable that captures whether a household uses electricity instead of fossil fuel-based devices as the main source of lighting —this variable is available only in the NPS dataset (see Section 3.4). The results are presented in Table 2, where columns (1) and (2) show the coefficients obtained using the model specifications with region fixed effects based on the binary treatment approach. The estimates suggest that the installation of a mini-grid raises the probability of electricity use for lighting by 20-23 percentage points, with this effect being significant at the 1% level. However, when we replace region fixed effects with cluster fixed effects, the magnitude of the coefficient decreases to about 9 percentage points (significant at the 10% level).

Next, columns (5)-(8) present estimates using the continuous treatment approach. The most complete specification of our model —columns (6) and (8), which include the full set of controls, year and spatial fixed effects, and region-specific trends— estimates an increase of about 11-22 percent in the probability of electricity use for lighting in a household located 2.5 km away from a mini-grid (significant at least at the 5% level). Overall, our empirical findings suggest that mini-grids increased the use of electricity as the main source of lighting, reducing reliance on fossil fuel-based devices such as oil or paraffin lamps that are popular in Tanzania but have negative effects on indoor air quality.

Robustness checks. So far, we have provided evidence that mini-grids in Tanzania increased the uptake of electricity connections for nearby households and promoted the use of electricity for lighting (to the detriment of pollutant devices). These results are robust to various robustness checks, which are included in Appendix B. Here, we provide a summary of the analysis performed in the appendix.

First, as shown in Table A.1 (Appendix A.2), we acknowledge imbalances in some of the observable characteristics (e.g., education of the head of a household) across the subsets of households in our sample. Consequently, one may be concerned that these imbalances could explain the results that we obtain. To address this concern, we use a propensity score matching procedure that corrects these imbalances. In particular, we proceed as follows. We first estimate the propensity score of being in the treatment group (as defined by the binary treatment approach) using household-level observable characteristics.

Table 2. Impact of mini-grids on household probability of using electricity as the main source of lighting

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.205***	0.230***	0.0628*	0.0854*	0.261***	0.306***	0.100*	0.152**
	(0.0568)	(0.0537)	(0.0357)	(0.0434)	(0.0855)	(0.0902)	(0.0556)	(0.0611)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.248	0.262	0.381	0.397	0.267	0.281	0.381	0.397
N. Observations	1,053	1,053	976	973	1,053	1,053	976	973

Note: The outcome is a dummy equal to 1 if the household uses electricity as the main source of lighting (and 0 otherwise). Linear probability models estimated by OLS using data from the NPS with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, in which the variable "Mini-grid" is a dummy one defined as follows $MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}$ for all $d_{c,r} \in [0, 10]$, where $d_{c,r}$ is the distance (in km) between households in cluster c and the closest mini-grid; while in columns (5)-(8) we use the continuous treatment approach, in which the variable "Mini-grid" is a continuous one defined as follows $MG_{c,r} = 1 - \frac{d_{c,r}}{10}$, for all $d_{c,r} \in [0, 10]$. Columns (1) and (5): full set of control variables —including head of household (log-) age, head of household education, head of household sex, $MG_{c,r}$, and dummy variables indicating the technology of the closest mini-grid (solar, hydro, biomass, hybrid or diesel)—, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables (except $MG_{c,r}$), DHS cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Then, we match treated and control households based on the estimated propensity score. Finally, we re-estimate our main regression model using the subset of matched households. The main empirical results obtained using the matched sample are shown in Appendix B.1. The results, included in Tables B.2 and B.3, are quantitatively and qualitatively similar to those included in Tables 1 and 2, respectively.

Second, we also show in Appendix B that our results are consistent and robust to alternative sample selection and definitions of the treated and control groups. In particular, results in Tables 1 and 2 prove robust *(i)* after we drop from our sample households that are relatively close to the national grid transmission lines (Appendix B.2, Tables B.6-B.7), *(ii)* after we exclude from the set of mini-grids those that are diesel-fueled (Appendix B.3, Table B.10), and *(iii)* after we consider potential spillovers across treated and control households, as defined in the binary treatment approach (Appendix B.4, Tables B.13-B.14).

4.2 Effect of mini-grids on wealth outcomes

Main Results. Next, we turn to present the results from equation (3.1) using the wealth index provided by the DHS as our outcome of interest.[23] As explained extensively in Section 3.4, this wealth index is a composite measure of household living standards and is calculated based on the ownership of selected assets, household access to water and electricity, and other amenities (Rutstein, 2015). Our goal is to check whether the deployment of mini-grids is also reflected as having a positive effect on this index for households that are relatively close to the mini-grids (i.e., among the treated households).

Table 3. Impact of mini-grids on the DHS wealth index

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	2.279	2.722	6.040***	6.454***	3.331	4.176*	8.442***	8.821***
	(1.816)	(2.031)	(1.436)	(1.897)	(2.242)	(2.395)	(1.929)	(2.210)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.314	0.337	0.454	0.466	0.325	0.344	0.451	0.463
N. Observations	3,691	3,691	3,691	3,691	3,691	3,691	3,691	3,691

Note: The outcome is the (log-) DHS wealth index. Linear regression models estimated by OLS using data from the DHS with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, in which the variable "Mini-grid" is a dummy one defined as follows $MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}$ for all $d_{c,r} \in [0,10]$, where $d_{c,r}$ is the distance (in km) between households in cluster c and the closest mini-grid; while in columns (5)-(8) we use the continuous treatment approach, in which the variable "Mini-grid" is a continuous one defined as follows $MG_{c,r} = 1 - \frac{d_{c,r}}{10}$, for all $d_{c,r} \in [0,10]$. Columns (1) and (5): full set of control variables —including head of household (log-) age, head of household education, head of household sex, $MG_{c,r}$, and dummy variables indicating the technology of the closest mini-grid (solar, hydro, biomass, hybrid or diesel)—, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables (except $MG_{c,r}$), DHS cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents estimated coefficients of the linear regression model using both the binary treatment approach —columns (1)-(4)— and the continuous treatment approach —columns (5)-(8). First, columns (1) and (2) contain the estimates for the model specifications that include region fixed effects. The columns indicate that the DHS wealth index increased by about 2.3-2.7 points in the post-deployment

[23] A similar wealth index is not available in the NPS dataset.

period among households within a radius of less than 5 km from a mini-grid, although these coefficients are not statistically significant. However, using the continuous treatment approach, we estimate a very similar increase of about 2.5-3.1 points for treated households in the DHS wealth index (these numbers are obtained using the calculation explained in footnote 20), which is significant at the 10% level in the most complete specification included in column (6). Moreover, this coefficient is also positive, higher in magnitude, and significant at the 1% level in columns (3)-(4) and (7)-(8), where we replace the region fixed effects with cluster fixed effects. In all these cases, the estimated average impact on the DHS wealth index among treated households is about 6-6.6 points. Therefore, these results suggest that mini-grids increased the wealth of nearby households.

The DHS wealth index is a composite measure of household living standards. However, it could also be informative to study the particular effect that mini-grids have on the ownership of electric-powered appliances. Therefore, as an additional empirical exercise, we examine whether the deployment of mini-grids in Tanzania had a positive impact on the uptake of two basic appliances, namely, refrigerators and televisions (Lee et al., 2016; Wen et al., 2023). Specifically, relying on data from both the DHS and the NPS, we estimate equation (3.1) using as our outcome of interest a dummy variable that is equal to 1 if a household owns the appliances (and 0 otherwise). Table 4 contains the estimation results. For the sake of expositional clarity, we include in this subsection the results using only the binary treatment approach, while the same set of results using the continuous treatment approach are in Appendix C.1 (with additional robustness checks using this approach in Appendix C.2).

First, Panel A shows the estimates using the "refrigerator" dummy as the outcome variable. The coefficient of the "Mini-grid$\times$post" interaction term is positive, significant at the 1% level, and extraordinarily similar in magnitude across all the specifications of our regression model using both the DHS (Panel A1) and the NPS (Panel A2). With the DHS, our results suggest an increase between 5 (for the least robust model specification) and 11 percentage points (for the most robust model specification) in the uptake of refrigerators among treated units relative to the control ones. When we use the NPS instead, the least and the most robust model specifications suggest an increase of about 8 and 5 percentage points, respectively. Then, we include in Panel B the results using as our outcome of interest the probability that certain households own a television. This probability increases by about 8-13 percentage points for treated households in the post-treatment period —being significant at least at the 5% level—

Table 4. Impact of mini-grids on household probability of owning selected appliances (refrigerator and television)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0480***	0.0636***	0.0958***	0.109***
	(0.0152)	(0.0164)	(0.0355)	(0.0333)
R^2	0.0834	0.113	0.161	0.188
N. Observations	3,987	3,987	3,987	3,987
	Panel A2. NPS dataset			
Mini-grid × post	0.0807***	0.0831***	0.0504***	0.0365***
	(0.0207)	(0.0225)	(0.0141)	(0.0105)
R^2	0.107	0.113	0.137	0.180
N. Observations	1,053	1,053	976	973

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.0898***	0.0795**	0.112***	0.134***
	(0.0310)	(0.0325)	(0.0382)	(0.0488)
R^2	0.175	0.190	0.257	0.269
N. Observations	3,991	3,991	3,991	3,991
	Panel B2. NPS dataset			
Mini-grid × post	0.189***	0.215***	0.0211	0.0260
	(0.0595)	(0.0542)	(0.0350)	(0.0369)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.248	0.263	0.351	0.389
N. Observations	1,053	1,053	976	973

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (Panels A1 and B1) and from the NPS (Panels A2 and B2) with standard errors clustered at region-year level. In all these columns we use the binary treatment approach, in which the variable "Mini-grid" is a dummy one defined as follows $MG_{c,r} = \mathbb{1}_{\{d_{c,r}<5\}}$ for all $d_{c,r} \in [0,10]$, where $d_{c,r}$ is the distance (in km) between households in cluster c and the closest mini-grid. Column (1): full set of control variables —including head of household (log-) age, head of household education, head of household sex, and dummy variables indicating the technology of the closest mini-grid (solar, hydro, biomass, hybrid or diesel)—, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

if we use the DHS (Panel B1). A slightly higher effect (of about 15-23 percentage points) is obtained if we instead use the NPS dataset. However, while this effect is significant at the 1% level for the model specifications that include region fixed effects —Columns (1)-(2)—, it is not significant for the model specifications that contain cluster fixed effects —Columns (3)-(4).

Robustness checks. The above results on the effects of mini-grids on wealth-related outcomes are robust to a battery of robustness checks, which can be found in Appendix B. First, we deal with the unbalanced sample problem by showing that our estimates remain extraordinarily similar when we use the matching technique explained in Section 4.1 (Appendix B.1, Tables B.4-B.5). Second, we find that the wealth-related effects of mini-grids are not affected after excluding from our sample households that are relatively close to the transmission lines of the national grid (Appendix B.2, Tables B.8-B.9). Third, these results also prove robust when we exclude from our sample diesel-fueled mini-grids (Appendix B.3, Tables B.11-B.12) and when we drop households that are likely affected by spillovers in the binary treatment approach (Appendix B.4, Tables B.15-B.16). Finally, we also show that the deployment of a mini-grid does not result in increased adoption of assets unaffected by electricity (e.g., bicycles). This placebo-based falsification test is available in Appendix C.3 (Table C.5).

5 Conclusion

In recent years, a substantial influx of funding from private companies, international institutions, and donor agencies has been dedicated to the deployment of mini-grids, which have emerged as the predominant "last-mile" solution to electrify villages in regions where access to the national grid network is limited (ESMAP, 2019; AMDA, 2022). This trend is particularly pronounced in SSA, where nearly 4,000 mini-grids are slated for development, accounting for nearly two-thirds of the planned installations globally (SEforALL, 2020). Despite this growing momentum, our understanding of the effectiveness of mini-grids in stimulating household electricity access and usage and their consequent impacts on household welfare remains underexplored and largely uncertain.

To the best of our knowledge, this is the first study that provides causal evidence on the economic implications of mini-grids. Our analysis leverages a groundbreaking policy reform introduced in Tanzania in 2008, which resulted in a doubling of the country's mini-grid count from 2008 to 2016. Using a comprehensive dataset comprising geolocalized information on all mini-grids in Tanzania and household-level data from two distinct sources —encompassing four waves of the NPS and seven waves of the DHS— we investigate the impact of mini-grid installations. We assess changes in the number of electricity connections, the adoption of electricity as the primary lighting source, as well as wealth-related outcomes. To compare the outcomes of households that are relatively close to and those that are relatively far from mini-grids, our empirical approach exploits variation both in the temporal rollout of mini-grids and their distance to nearby households (largely dictated by exogenous features like surface roughness or the slope of the nearest water body). This methodology avoids the inclusion of households that are "too far away" from the treated ones as control units.

Our analysis reveals that relative to households located at a greater distance from a mini-grid, households located in close proximity to a mini-grid are significantly more likely (approximately 10-23 percentage points) to have an electricity connection following the installation of a mini-grid. Moreover, our empirical results demonstrate a similarly positive impact on the DHS wealth index among treated households, indicating a higher probability of households owning selected electric-powered appliances as well as of using electricity as their primary lighting source. As a result, our findings have direct implications on the role of mini-grids in reducing indoor pollution, which are supported by the reduction of alternative fuels that are commonly used for lighting purposes in SSA households (Choumert-Nkolo et al., 2019).

We emphasize that our results do not imply that mini-grids should be scaled universally or viewed as a one-size-fits-all substitute for grid extension or off-grid solutions. Rather, our findings complement the growing literature on least-cost electrification planning, which highlights that the optimal technology choice depends on factors such as population density, expected demand, and geographic constraints. In this context, a key policy implication of our analysis is the importance of improved coordination between mini-grid developers and national grid expansion strategies. In many settings, these actors currently operate as competitors rather than complements, a dynamic that can undermine investment incentives and hinder efficient long-run planning.

Moreover, to further provide context for our empirical results, we present a cost-benefit analysis in Appendix D, comparing the gains that result from the installation of renewable-based mini-grids (solar, hydro, or biomass) and their corresponding total (lifespan) costs.[24] Our analysis unveils a close

[24]We acknowledge the potential for future researchers to engage in technology-specific empirical analyses (an avenue that our study could not pursue due to limitations in available data) aiming to further refine the cost-benefit analysis accordingly.

alignment between the benefits derived from mini-grid installations and the total costs incurred over the project's lifespan. This result stands even under conservative assumptions regarding gains, as we focus solely on the surplus derived from household electricity access while omitting other considerations, such as potential positive health effects from improved lighting and the potential benefits of electricity consumption by local businesses. In conclusion, our findings demonstrate that mini-grids have the potential to significantly impact the pervasive "vicious cycle" of energy poverty (Burgess et al., 2020), contributing to the betterment of underserved communities.

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Appendix A: Additional background information

A.1 Evidence on the geography of mini-grid locations

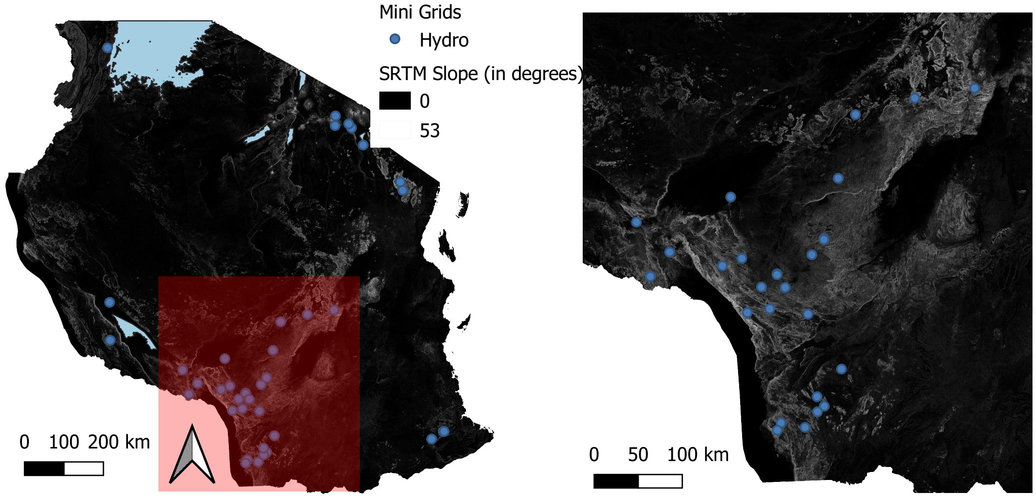
In this appendix, we provide additional detailed evidence supporting that, while the selection of communities in our sample for mini-grid installation was not random, the exact location of the mini-grids within the premises of these communities (in a radius of 10 km) was primarily determined by geographical and terrain-related factors. To demonstrate this, we provide several high-resolution maps that document the (presumably exogenous) factors that primarily determined the placement of different types of mini-grids.

First, as discussed in Section 3.1 in the main text, the exact location of hydro-powered mini-grids is determined not only by the presence of a water source with an ample current (such as a river) but also by the terrain's topography (Okot, 2013). This is because the hydroelectricity is generated through an elevation difference: the mini-grid channels part of the stream that falls down a hillside through a powerhouse, after which the water rejoins the main river. Therefore, the speed of the flow, which is critical for the turbine to generate electricity, depends on the elevation of the terrain. As such, mini-grids must be constructed where there is a sufficiently steep slope (US Department of Energy, 2023).

This mechanism is in line with the evidence presented in the map in Figure A.1, which displays the location of all hydro-powered mini-grids in Tanzania included in our sample. This map also includes the elevation of the terrain —obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model—, where areas with lower slopes are shaded in a darker color and, conversely, those with higher slopes are shaded in a lighter color. To further examine the site selection of these mini-grids, we zoom in on a snapshot of the lower part of the map where a significant number of hydro-powered facilities are located. As evident from the map, the mini-grids are located in areas that are shaded in white or light gray, indicating the steepest slopes of the terrain. This is also consistent with the information in World Bank (2017), which has identified the specific areas in Tanzania that are most suitable for small hydro generators based on the characteristics of the terrain and water bodies. Thus, when installing a hydro-powered mini-grid in a community, the exact location in the premises of it is determined, to a large extent, by the gradient of the terrain.

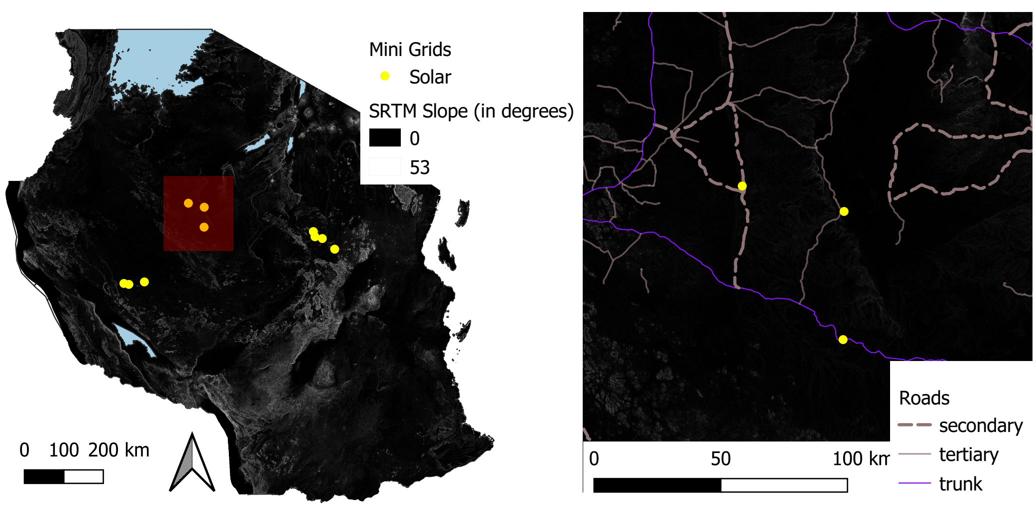
The opposite feature is observed when we turn to examine the location of solar mini-grids. For these

Figure A.1. Map of the location of hydro-powered mini-grids and slope of the terrain in Tanzania



Note: This figure includes a map of all the hydro-powered mini-grids deployed in Tanzania up to 2017, indicated with blue circles. The image shows the topographic slope (in degrees) using a heatmap, in which darker means less slope, obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model (WorldPop, 2018). Areas shaded in black indicate that the terrain is flat, while areas shaded in white indicate that the slope reaches the maximum one (53 degrees). The bottom part of the map, where most of the hydro-powered mini-grids are located, was zoomed in to better appreciate the slope of the terrain there.

Figure A.2. Map of the location of solar-powered mini-grids, slope of the terrain, and roads in Tanzania



Note: This figure includes a map of all the solar-powered mini-grids deployed in Tanzania up to 2017, indicated with yellow circles. The image shows the topographic slope —in degrees— by a color ramp that goes from its minimum (flat terrain in black) to its maximum (53 degrees) in white (WorldPop, 2018). Secondary roads are indicated with a dashed, thin gray line, tertiary roads are indicated with a solid, thin gray line, and truck roads are indicated with a solid, thin purple line. The middle part of the map, where most of the solar-powered mini-grids are located, was zoomed in to better appreciate the slope of the terrain and the road access there.

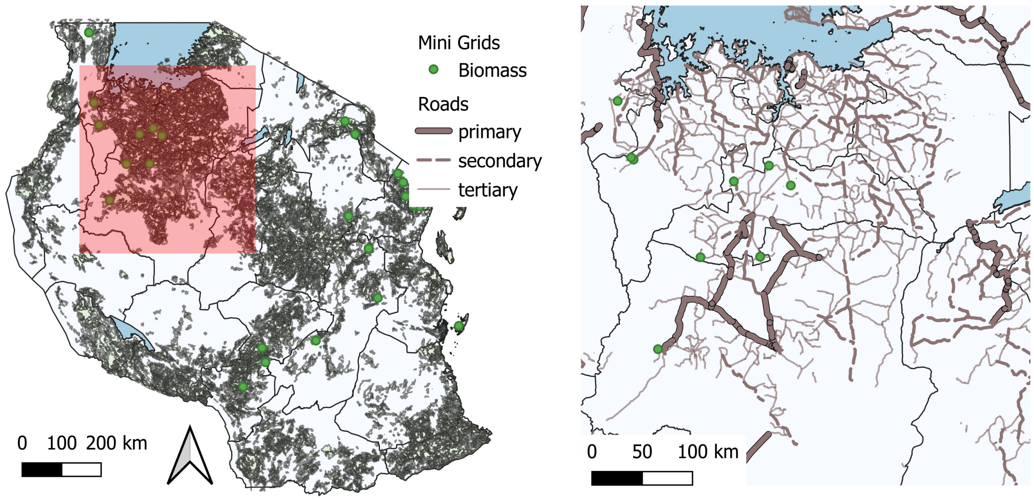
mini-grids, location is primarily determined by solar radiance which, however, is relatively uniform across Tanzania, and has little variability within small areas (Moner-Girona et al., 2016; Zigah et al., 2023). Nevertheless, there are two additional key ingredients (besides solar radiance) that explain the exact location of a solar-powered mini-grid. First, the solar panels used to generate electricity must be installed where there is sufficiently ample flat terrain: it is estimated that a 1 megawatt (MW) solar generator (using photovoltaic panels) occupies around 5.5-6 acres or about 0.023-0.024 square kilometers (Kochendoerfer and Thonney, 2021; Abashidze and Taylor, 2023). Second, because solar PV panels are relatively heavy —the average weight per square meter of panel is about 33 pounds or 15 kilograms (Wu et al., 2017)—, they must also be located in a field that is connected to a road in order to facilitate their transportation and replacement (in case of damage).

These observations are supported by the information presented in Figure A.2, which displays a map containing all of the solar mini-grids included in our sample. As with the previous map, we show again the slope of the terrain and also include the roads in Tanzania in the zoomed-in portion to the right. In this map, it is fairly evident that the solar mini-grids in our sample are located in areas that are essentially flat, indicated on the map by black shading. Additionally, all these mini-grids are located near an existing road, be it a primary, a secondary, or a tertiary road (Chen et al., 2021).

Next, we turn to investigate the geographical distribution of biomass-powered mini-grids. These systems utilize agricultural waste, such as residues or wood, and share some similarities with the previously discussed mini-grids. Specifically, their location is not only constrained by the availability of biomass materials but also (as is the case for solar mini-grids) by the transportation logistics of the relatively heavy waste. Consequently, they tend to be located in areas with substantial agricultural activity and convenient access to major roads for transportation (Felix and Gheewala, 2011). Consistently, as shown in Figure A.3, the location of all biomass mini-grids in our sample corresponds to areas with agricultural land cover, indicated by light green shading on the map —this information was obtained from FAO (2002). Moreover, we can see in the zoomed-in portion of the map to the right that all of them are easily accessed by either a primary road, a secondary road, or a tertiary road.

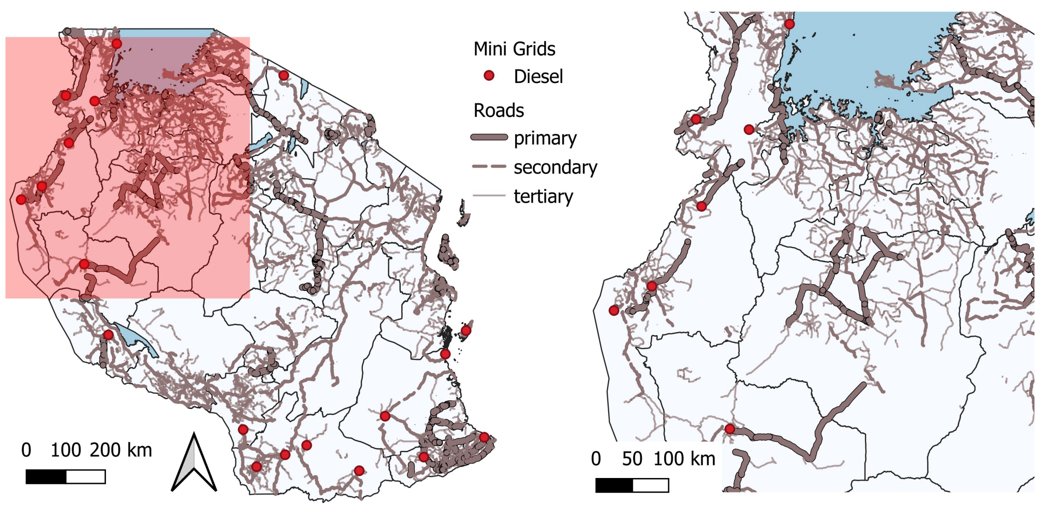
Finally, something similar occurs with diesel-fueled mini-grids: they also require proximity to primary (truck-accessible) roads that can be accessed by tank trucks for the delivery of diesel, as there are no pipelines in Tanzania for transporting this fuel (Szabo et al., 2011). Again, we can observe in the map

Figure A.3. Map of the location of biomass-powered mini-grids, agricultural land cover, and roads in Tanzania



Note: This figure includes a map of all the biomass-powered mini-grids deployed in Tanzania up to 2017, indicated with green circles. Agricultural land cover (FAO, 2002) is indicated in light green. Primary roads are indicated with a solid, thick gray line; secondary roads are indicated with a dashed, thin gray line, and tertiary roads are indicated with a solid, thin gray line. The solid, thin black lines represent the boundaries of the regions. The top-right part of the map, where most of the biomass-powered mini-grids are located, was zoomed in to better appreciate the road access and the agricultural land cover there.

Figure A.4. Map of the location of diesel-powered mini-grids and roads in Tanzania



Note: This figure includes a map of all the diesel-powered mini-grids deployed in Tanzania up to 2017, indicated with red circles. Primary roads are indicated with a solid, thick gray line; secondary roads are indicated with a dashed, thin gray line, and tertiary roads are indicated with a solid, thin gray line. The solid, thin black lines represent the boundaries of the regions. The top-right part of the map, where most of the diesel-powered mini-grids are located, was zoomed in to better appreciate the road access there.

provided in Figure A.4 that all the diesel mini-grids in our sample are located nearby primary roads.

A.2 Additional background tables

This appendix provides additional tables to offer further context and clarity for the reader. First, Table A.1 presents summary statistics for households located within 0–5 kilometers of a mini-grid (treated group) and those within 5–10 kilometers (control group), both before and after the deployment of the nearest mini-grid. The summary statistics are reported separately for the DHS dataset (Panel A) and the NPS dataset (Panel B).

Second, we test whether there is a statistically significant relationship between the economic wealth of households in the communities where mini-grids are installed and the timing of mini-grid construction. To do so, we focus on the communities that experienced the installation of a mini-grid at some point during the period 2008-2017. We define an "early installation" binary variable, which equals 1 if the mini-grid was commissioned in or before a specified cutoff year, and 0 otherwise. To ensure the robustness of our analysis, we vary the cutoff year used to define "early installation", testing thresholds such as 2010, 2011, and 2012. We then estimate a regression model in which the dependent variable is the "early installation" indicator and the key independent variable is the (log-) DHS wealth index, measured both at the community level and at the household level. To focus on relevant time frames, we restrict the sample to observations where the difference between the commissioning year and the observation year is less than one. The model also includes year and region fixed effects to account for temporal and regional variations.

The regression results are presented in Table A.2. Columns (1)–(3) show estimates using the DHS wealth index aggregated at the community level, while columns (4)–(6) report the corresponding results using the household-level DHS wealth index. Across all specifications, the estimated coefficients of the (log-) wealth index (whether measured at the community or household level) are close to zero and not statistically significant. These findings support the claim made in the main text: there is no statistically significant relationship between the economic wealth of a community and the timing of mini-grid construction.

Table A.1. Summary statistics by distance to the closest mini-grid before and after its deployment

	(1) Control (5-10 km)	(2) Treated (0-5 km)	(3) Control (5-10 km)	(4) Treated (0-5 km)	(5) Diff-in-diff
	Panel A. DHS dataset				
	Panel A1. Before		*Panel A2. After*		
Electricity (d)	0.014	0.074	0.081	0.327	0.187***
	(0.119)	(0.262)	(0.273)	(0.469)	(0.000)
(log-) Age of Hoh	3.813	3.732	3.774	3.685	-0.007
	(0.359)	(0.358)	(0.350)	(0.346)	(0.788)
Education of head (d)	0.702	0.761	0.814	0.890	0.017
	(0.458)	(0.427)	(0.389)	(0.313)	(0.587)
Sex of head (d)	0.753	0.765	0.753	0.712	-0.053
	(0.432)	(0.424)	(0.432)	(0.453)	(0.102)
Wealth index	-7.061	-2.289	-4.331	3.756	3.315***
	(8.205)	(10.695)	(9.749)	(10.395)	(0.000)
Television (d)	0.022	0.067	0.071	0.251	0.135***
	(0.148)	(0.251)	(0.258)	(0.434)	0.000
Refrigerator (d)	0.004	0.007	0.014	0.079	0.063***
	(0.064)	(0.081)	(0.116)	(0.270)	(0.000)
N. Observations	490	459	1,330	1,713	3,992
	Panel B. NPS dataset				
	Panel B1. Before		*Panel B2. After*		
Electricity (d)	0.091	0.081	0.053	0.352	0.310***
	(0.289)	(0.273)	(0.225)	(0.478)	(0.000)
Elect. lightning (d)	0.091	0.081	0.056	0.355	0.310***
	(0.289)	(0.273)	(0.231)	(0.479)	(0.000)
(log-) Age of Hoh	3.787	3.716	3.835	3.749	-0.016
	(0.293)	(0.330)	(0.348)	(0.349)	(0.718)
Education of head (d)	0.640	0.644	0.527	0.708	0.176***
	(0.481)	(0.480)	(0.500)	(0.455)	(0.006)
Sex of head (d)	0.731	0.698	0.740	0.700	-0.007
	(0.445)	(0.461)	(0.439)	(0.459)	(0.911)
Television (d)	0.113	0.081	0.044	0.324	0.312***
	(0.317)	(0.273)	(0.206)	(0.469)	(0.000)
Refrigerator (d)	0.027	0.020	0.006	0.104	0.105***
	(0.162)	(0.141)	(0.077)	(0.306)	(0.000)
N. Observations	186	148	337	382	1,053

Note: Summary statistics for all households included in the sample. Panel A: DHS dataset —Panel A1: before the deployment of the closest mini-grid; Panel A2: after the deployment of the closest mini-grid. Panel B: NPS dataset —Panel B1: before the deployment of the closest mini-grid; Panel B2: after the deployment of the closest mini-grid. Column (1) and (3): means for the subgroups of households within a radius of 5-10 km to the closest mini-grid (control households in the binary treatment approach). Column (2) and (4): means for the subgroups of households within a radius of 5 km to the closest mini-grid (treated households in the binary treatment approach). Column (5): raw diff-in-diff estimator, and p-value in parenthesis. All dummy variables are indicated with a (d).

Table A.2. Impact of (community- and household-level) wealth on the timing of mini-grid construction

	Outcome: Early Installation					
	Community-level			*Household-level*		
	(1)	(2)	(3)	(4)	(5)	(6)
(log-) DHS wealth	0.00705	0.00938	0.00938	0.00183	0.000950	0.00160
	(0.00849)	(0.0106)	(0.0106)	(0.00159)	(0.00174)	(0.00157)
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
R^2	0.546	0.892	0.936	0.651	0.873	0.956
N. Observations	46	46	46	1,311	1,311	1,311

Note: The sample includes all communities where a mini-grid was commissioned after 2008. The outcome variable "Early Installation" is a binary indicator that equals 1 if the mini-grid was commissioned before year x, and 0 otherwise. In columns (1) and (4), x is 2010; in columns (2) and (5), x is 2011; and in columns (3) and (6), x is 2012. Standard errors are jackknife estimated in columns (1) to (3) —i.e., in the regression is at the community level (due to the relatively low number of observations). Standard errors are clustered at region-year level in columns (4) to (6) —i.e., in the regression is at the household level. The significance levels are as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Robustness checks

Even though the empirical strategy explained in Section 3 in the main text is well-founded to support the causal interpretation of our estimates, we acknowledge that there are alternative procedures to estimate the effect of the installation of a mini-grid on households, other definitions of the treatment and control groups, and also alternative samples that we could have been employed instead. Hence, this appendix presents an extensive procedure of robustness checks to confirm that our results are not sensitive to the choices used throughout the paper.

B.1 Matching

We first recognize that there is an imbalance in some observable characteristics across the different subsets of households in our sample. For example, Table A.1 in Appendix A.2 indicates that the dummy capturing the education level of the head of household is not well-balanced across the treated and the control groups (as defined in the binary treatment approach) both in the DHS and in the NPS. Moreover, Table B.1 (Panel A), in which we include the mean value of selected variables for both the treated and the control cohorts —and also the p-value of the test under the null hypothesis that the difference between them is equal to zero—, shows that there are also minor imbalances in some characteristics, such as in the age of the head of households. Therefore, one may be concerned that these differences might also explain the empirical results that we obtain.

To address this potential concern, we use a matching technique that can help resolve the unbalanced sample problem before implementing our estimation methodology. In particular, we proceed as follows. First, we estimate the propensity score of being in the treatment group (i.e., less than 5 km away from a mini-grid) using the observable characteristics of the head of the household (age, education, and sex), and also a dummy that captures whether the household lives in a rural setting.[1] Then, we match treated and control households based on the propensity score. Finally, we re-estimate our regression model using the subset of households that have been matched

In Table B.1 (Panel B) we examine the quality of the matching by comparing the mean of these variables for treated and control households after the matching. Again, this table includes the p-value

[1]Due to the presence of cluster fixed effects, this dummy variable cannot be included in our main regression model.

Table B.1. Balance of household characteristics before and after matching

	Panel A: Before matching					
	DHS dataset			*NPS dataset*		
	Mean in treated	Mean in untreated	Difference (p-value)	Mean in treated	Mean in untreated	Difference (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
(log-) Age of Hoh	3.787	3.698	-0.088***	3.818	3.735	-0.084***
	(0.356)	(0.350)	(0.000)	(0.329)	(0.346)	(0.000)
Hoh primary educ (d)	0.784	0.863	0.079***	0.567	0.690	0.123***
	(0.412)	(0.344)	(0.000)	(0.496)	(0.463)	(0.000)
Hoh sex (d)	0.748	0.731	-0.017	0.738	0.703	-0.035
	(0.434)	(0.443)	(0.169)	(0.440)	(0.457)	(0.197)
N. Observations	2,254	2,803	5,057	527	545	1,072
	Panel B: After matching					
	DHS dataset			*NPS dataset*		
	Mean in treated	Mean in untreated	Difference (p-value)	Mean in treated	Mean in untreated	Difference (p-value)
(log-) Age of Hoh	3.725	3.726	0.000	3.722	3.731	0.009
	(0.345)	(0.348)	(0.978)	(0.337)	(0.342)	(0.770)
Hoh primary educ (d)	0.828	0.826	-0.003	0.674	0.682	0.008
	(0.377)	(0.380)	(0.870)	(0.470)	(0.467)	(0.846)
Hoh sex (d)	0.765	0.755	-0.010	0.760	0.744	-0.017
	(0.424)	(0.430)	(0.562)	(0.428)	(0.437)	(0.674)
N. Observations	1,176	1,176	2,352	242	242	484

Note: Balance of selected household characteristics. Panel A: before the matching procedure. Panel B: after the matching procedure. Columns (1) and (4): means for the subgroups of households within a radius of 0-5 km to the closest mini-grid (treated households in the binary treatment approach) in the DHS and in the NPS respectively. Columns (2) and (5): means for the subgroups of households within a radius of 5-10 km to the closest mini-grid (control households in the binary treatment approach) in the DHS and in the NPS respectively. The standard deviation of each variable is displayed in parentheses. Columns (3) and (6): difference in means and the p-value (in parenthesis) of a simple t-test in means difference. The significance levels of this test are as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All dummy variables are indicated with a (d).

of the test under the null hypothesis that this difference equals zero —see columns (3) and (6). As we can see, no imbalances remain in these variables after implementing the matching methodology both in the DHS and in the NPS (although this lack of imbalances comes at the cost of losing approximately half of our sample).

Finally, we provide the same set of empirical results that we present in the main text (Tables 1-4) using our matched sample of households. These results are included in Tables B.2-B.5 respectively. Regarding the coefficients obtained using the DHS, all of them remain positive, significant at least at the 10% level —except for that in Table B.4, column (2), and a couple of them in Table B.5— and similar in magnitude to those included in the analog tables in the main text. This is also the case for most of the coefficients obtained using the NPS dataset. However, the reader should be aware that in some cases the estimated coefficients lose significance (particularly in the model specifications that include cluster fixed effects), likely due to the lack of observations and statistical power to estimate them; see columns (3)-(4) and (7)-(8) in Tables B.2 and B.3, and columns (1)-(3), Panel A2, and columns (3)-(4), Panel B2, in Table B.5. Overall, these results offer additional evidence that the deployment of mini-grids positively impacted the uptake of electricity connections, the use of electricity as the main source of lighting, the DHS wealth index, and the probability of having appliances among nearby households.

Table B.2. Impact of mini-grids on the household probability of having an electricity connection using a matching procedure

	Binary treatment approach				*Continuous treatment approach*			
	Panel A. DHS dataset							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.160***	0.130**	0.149**	0.170**	0.290***	0.238***	0.284**	0.307**
	(0.0506)	(0.0526)	(0.0581)	(0.0776)	(0.0762)	(0.0743)	(0.108)	(0.126)
R^2	0.207	0.244	0.431	0.457	0.225	0.258	0.432	0.458
N. Observations	2,351	2,351	2,351	2,351	2,351	2,351	2,351	2,351
	Panel B. NPS dataset							
Mini-grid × post	0.182***	0.197***	-0.0414	-0.0558	0.235*	0.261*	-0.0354	-0.0525
	(0.0653)	(0.0729)	(0.0481)	(0.0803)	(0.121)	(0.140)	(0.0845)	(0.132)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.185	0.205	0.427	0.424	0.189	0.211	0.427	0.424
N. Observations	482	482	437	434	482	482	437	434

Note: The outcome is a dummy equal to 1 if the household has an electricity connection (and 0 otherwise). Linear probability models estimated by OLS using data from the DHS matched sample (Panel A) and from the NPS matched sample (Panel B) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3. Impact of mini-grids on the household probability of using electricity as the main source of lighting using a matching procedure

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.176**	0.197***	-0.0414	-0.0558	0.225*	0.261*	-0.0354	-0.0525
	(0.0657)	(0.0729)	(0.0481)	(0.0803)	(0.122)	(0.140)	(0.0845)	(0.132)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.195	0.215	0.427	0.424	0.199	0.221	0.427	0.424
N. Observations	482	482	437	434	482	482	437	434

Note: The outcome is a dummy equal to 1 if the household uses electricity as the main source of lighting (and 0 otherwise). Linear probability models estimated by OLS using data from the NPS (matched sample) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, DHS cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4. Impact of mini-grids on the DHS wealth index using a matching procedure

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	2.449*	2.710	5.084***	6.281***	4.607**	5.124**	7.489***	9.102***
	(1.442)	(1.780)	(1.606)	(2.107)	(2.061)	(2.333)	(2.214)	(2.657)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.247	0.274	0.428	0.446	0.252	0.275	0.426	0.444
N. Observations	2,135	2,135	2,135	2,135	2,135	2,135	2,135	2,135

Note: The outcome is the (log-) DHS wealth index. Linear regression models estimated by OLS using data from the DHS (matched sample) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in Columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, DHS cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5. Impact of mini-grids on the household probability of owning selected appliances (refrigerator and television) using a matching procedure

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0252**	0.0346***	0.0485	0.0818*
	(0.0105)	(0.0128)	(0.0316)	(0.0414)
R^2	0.0730	0.107	0.146	0.172
N. Observations	2,348	2,348	2,348	2,348
	Panel A2. NPS dataset			
Mini-grid × post	0.0528	0.0550	0.0565	0.0465*
	(0.0321)	(0.0331)	(0.0399)	(0.0272)
R^2	0.0483	0.0774	0.122	0.160
N. Observations	482	482	437	434

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.0827**	0.0589	0.107**	0.132**
	(0.0372)	(0.0392)	(0.0419)	(0.0504)
R^2	0.173	0.204	0.291	0.311
N. Observations	2,350	2,350	2,350	2,350
	Panel B2. NPS dataset			
Mini-grid × post	0.197***	0.223***	0.00316	-0.0297
	(0.0721)	(0.0807)	(0.0452)	(0.0613)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.211	0.233	0.385	0.423
N. Observations	482	482	437	434

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS matched sample (Panels A1 and B1) and from the NPS matched sample (Panels A2 and B2) with standard errors clustered at region-year level. In all these columns we use the binary treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Dropping households close to the grid transmission lines

As extensively explained in the main text, mini-grids are stand-alone networks that can operate autonomously without being connected to a centralized grid (Peskett, 2011; Franz et al., 2014). Hence, they are usually located where the centralized grid has not (yet) arrived. However, as can be seen in Figure 1, due to the evolution of the Tanzanian national grid, a few mini-grids in our sample are relatively close to existing high and medium-voltage transmission lines —they were either fully integrated into or built as part of the existing grid (Odarno et al., 2017). In fact Table A.1 in Appendix A.2 shows that some of the households in our sample already had an electricity connection before the deployment of the closest mini-grid. Consequently, one might be concerned that our findings are not arising from the installation of a mini-grid, but they might rather be explained by the presence of the national grid infrastructure.

To address this potential additional concern, we provide in this appendix (as an additional robustness check) our main set of empirical results after dropping the households that are relatively close to the national grid transmission lines. More precisely, and for the sake of consistency, we exclude from our sample households that are less than 10 km far from the existing transmission lines as of 2016 (see Figure 1).[2] The results of this additional empirical exercise are included in Tables B.6-B.9.

First, Table B.6 contains the results on the probability with which households are connected to electricity after the deployment of a mini-grid. The coefficient of the interaction "Mini-grid $\times$ post" in Panels A (using the DHS dataset) and B (using the NPS dataset) for all the model specifications considered are extraordinarily similar to those included in Table 1 in the main text. In all these cases the point estimates are positive and significant —except for that in column (2), Panel B—, suggesting that the deployment of mini-grids increased the uptake of electricity connections among the nearby households. The same pattern is observed in Table B.7, whose estimates are again very similar to those in the analog table in the main text (Table 2). These results confirm that mini-grids increased the use of electricity for lighting purposes while decreasing that of pollutant devices.

Next, we turn to present the results using the DHS wealth index as our outcome of interest. These results are included in Table B.8. Consistent with those in Table 3 in the main text, the estimates in columns (1)-(2) and (5)-(6) —obtained for the model specifications that include region-fixed effects using both the binary treatment approach and the continuous treatment approach— are not significant.

[2] Data on the geographical expansion of the transmission lines for previous years is not available.

Table B.6. Impact of mini-grids on the household probability of having an electricity connection dropping households close to the grid transmission lines

	Binary treatment approach				*Continuous treatment approach*			
	Panel A. DHS dataset							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.117**	0.107	0.142**	0.161**	0.196**	0.190**	0.308***	0.321***
	(0.0580)	(0.0716)	(0.0556)	(0.0751)	(0.0789)	(0.0941)	(0.0794)	(0.103)
R^2	0.228	0.247	0.303	0.326	0.245	0.264	0.308	0.329
N. Observations	2,963	2,963	2,963	2,963	2,963	2,963	2,963	2,963
	Panel B. NPS dataset							
Mini-grid × post	0.143***	0.167***	0.0799**	0.110***	0.196**	0.244***	0.115*	0.174***
	(0.0520)	(0.0540)	(0.0361)	(0.0332)	(0.0776)	(0.0869)	(0.0629)	(0.0626)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.254	0.269	0.329	0.347	0.263	0.277	0.328	0.346
N. Observations	643	643	597	595	643	643	597	595

Note: The outcome is a dummy equal to 1 if the household has an electricity connection (and 0 otherwise). Linear probability models estimated by OLS using data from the DHS (Panel A) and from the NPS (Panel B) with standard errors clustered at region-year level, and excluding households within 10 km far from the grid transmission lines. In Columns (1)-(4) we use the binary treatment approach, while in Columns (5)-(8) we use the continuous treatment approach. Column (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Column (2) and (6): same as the previous columns but also including region-specific linear time trends. Column (3) and (7): full set of control variables, cluster fixed effects, and year fixed effects. Column (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, all the coefficients obtained for the model specifications that include cluster fixed effects are positive, significant, and very similar to those in Table 3. The same pattern is observed in the appliance regressions, whose results are shown in Table B.9: the point estimates are again positive, while only a few of them are not significant (as is also the case in Table 4). All in all, these findings further suggest that mini-grids positively impact the uptake of electric-powered appliances.

Table B.7. Impact of mini-grids on the household probability of using electricity as the main source of lighting dropping households close to the grid transmission lines

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.137**	0.161***	0.0799**	0.110***	0.187**	0.233***	0.115*	0.174***
	(0.0516)	(0.0533)	(0.0361)	(0.0332)	(0.0774)	(0.0861)	(0.0629)	(0.0626)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.270	0.283	0.329	0.347	0.279	0.291	0.328	0.346
N. Observations	643	643	597	595	643	643	597	595

Note: The outcome is a dummy equal to 1 if the household uses electricity as the main source of lighting (and 0 otherwise). Linear probability models estimated by OLS using data from the NPS with standard errors clustered at region-year level, and excluding households within 10 km far from the grid transmission lines. In Columns (1)-(4) we use the binary treatment approach, while in Columns (5)-(8) we use the continuous treatment approach. Column (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Column (2) and (6): same as the previous columns but also including region-specific linear time trends. Column (3) and (7): full set of control variables, DHS cluster fixed effects, and year fixed effects. Column (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8. Impact of mini-grids on the DHS wealth index dropping households close to the grid transmission lines

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.184	-0.0431	5.654***	5.901***	1.734	1.816	9.588***	9.888***
	(1.613)	(1.873)	(1.568)	(2.053)	(1.954)	(2.129)	(1.823)	(2.234)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.388	0.421	0.481	0.501	0.406	0.434	0.482	0.503
N. Observations	2,754	2,754	2,754	2,754	2,754	2,754	2,754	2,754

Note: The outcome is the (log-) DHS wealth index. Linear regression models estimated by OLS using data from the DHS with standard errors clustered at region-year level, and excluding households within 10 km far from the grid transmission line. In Columns (1)-(4) we use the binary treatment approach, while in Columns (5)-(8) we use the continuous treatment approach. Column (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Column (2) and (6): same as the previous columns but also including region-specific linear time trends. Column (3) and (7): full set of control variables, DHS cluster fixed effects, and year fixed effects. Column (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9. Impact of mini-grids on the household probability of owning selected appliances (refrigerator and television) dropping households close to the grid transmission lines

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0404**	0.0779***	0.121***	0.150***
	(0.0173)	(0.0208)	(0.0445)	(0.0452)
R^2	0.100	0.133	0.184	0.215
N. Observations	2,958	2,958	2,958	2,958
	Panel A2. NPS dataset			
Mini-grid × post	0.0616***	0.0609**	0.0433***	0.0333***
	(0.0216)	(0.0251)	(0.0136)	(0.0108)
R^2	0.105	0.122	0.140	0.208
N. Observations	643	643	597	595

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.0507	0.0461	0.115**	0.141***
	(0.0314)	(0.0389)	(0.0443)	(0.0513)
R^2	0.192	0.208	0.253	0.270
N. Observations	2,962	2,962	2,962	2,962
	Panel B2. NPS dataset			
Mini-grid × post	0.118*	0.138**	0.0357	0.0444
	(0.0592)	(0.0620)	(0.0324)	(0.0311)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.270	0.278	0.333	0.363
N. Observations	643	643	597	595

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (Panels A1 and B1) and from the NPS (Panels A2 and B2) with standard errors clustered at region-year level, and excluding households within 10 km far from the grid transmission line. In all these columns we use the binary treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Excluding diesel mini-grids

As explained in the main text, another concern might arise due to the potential endogenous location of some mini-grids. Recall that our empirical strategy rests on the assumption that, within relatively narrowly defined geographical areas (i.e., within a radius of 10 km), the exact location of a mini-grid is uncorrelated with factors affecting electricity access and other development outcomes of the households on their premises (conditional on the household characteristics and the battery of fixed effects that we consider) but is rather explained by other geographical factors (e.g., the roughness of the terrain, the slope of the nearest water body, and other features of the territory). Additional explanations and substantial evidence that support this assumption are provided in Appendix A.1, which contains several maps showing that the location of different types of mini-grids mostly responds to (exogenously given) geographical characteristics.[3]

The assumption above presumably holds for all the mini-grids in our sample that depend on the availability of natural resources (such as hydro, solar, or hybrid). However, one could potentially argue that this assumption is not as likely to hold for the mini-grids that do not depend on the natural resources at hand and, by contrast, that are powered by a fuel that can be purchased in the market and that is relatively easily transportable (such as diesel-powered ones). Still, this type of mini-grids cannot be installed "anywhere" within these relatively narrowly defined geographical zones, as they must be located where there is easy and adequate road access for the tank trucks to deliver the fuel (there are no pipelines in Tanzania). Note moreover that, as explained by Dumas and Játiva (2020), the road density in Tanzania is very low in comparison with that of the adjacent countries (it was about 97 meters per square km back in 2008, whereas in Kenya and Uganda was about 300), and the few existing roads are in very poor conditions (only 36.63% of the road network was paved or sealed back in 2008).

Nevertheless, in order to address the concern arising due to the potential endogenous location of non-renewable resource-based mini-grids, we estimate our main regression model excluding the diesel-fueled ones in this appendix. The reader should be aware, though, that we can do so using just the DHS dataset but not the NPS dataset. In the latter case, due to the lack of observations, we do not have sufficient statistical power to estimate our regression model after dropping the diesel-fueled mini-grids

[3] In line with this idea, World Bank (2017) discusses the exact places in Tanzania where the characteristics of the terrain are appropriate for the installation of hydro-powered mini-grids (i.e., places in which the water body has a sufficiently steep slope or the current is adequate and ample).

Table B.10. Impact of non-diesel fueled mini-grids on the household probability of having an electricity connection (DHS only)

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	0.183***	0.183**	0.188**	0.340**	0.364***	0.419***	0.310*	0.343*
	(0.0622)	(0.0728)	(0.0909)	(0.165)	(0.0947)	(0.116)	(0.173)	(0.202)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.197	0.221	0.468	0.510	0.208	0.234	0.466	0.505
N. Observations	2,176	2,176	2,176	2,176	2,176	2,176	2,176	2,176

Note: The outcome is a dummy equal to 1 if the household has an electricity connection (and 0 otherwise). Linear probability models estimated by OLS using data from the DHS (dropping all the households that are less than 10 km far from a diesel mini-grid) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

from our sample. Our main empirical results are included in Tables B.10-B.12.

First, Table B.10 includes the estimated impact of mini-grid deployment on the likelihood of having an electricity connection at home for nearby households. On the one hand, the coefficients across columns (1)-(4) (i.e., those obtained using the binary treatment approach) are extremely similar to those in Table 1 (Panel A) in the main text. On the other hand, those included in columns (5)-(8) (i.e., using the continuous treatment approach) are slightly higher in magnitude (about 0.1 points higher) relative to the analog ones included in Table 1. In both cases, these results further suggest that the installation of mini-grids positively impacted the uptake of electricity connections among nearby households.

Then, Table B.11 shows the point estimates associated with the DHS wealth index. These estimates are again positive and similar in magnitude to those displayed in Table 3 in the main text for the model specifications included in columns (1)-(3) and (5)-(7) (in some cases they are not significant at the 10% level though). However, for the two specifications that include cluster fixed effects and region-specific time trends —see columns (4) and (8)—, the magnitude of the coefficient of interest is above that obtained in Table 3, suggesting that these coefficients are likely overestimated in these two cases when we drop the diesel mini-grids. Still, our main conclusion qualitatively holds, as we see that the installation of mini-grids is associated with a higher DHS wealth index.

Table B.11. Impact of non-diesel fueled mini-grids on the DHS wealth index

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	1.425 (2.487)	3.112 (3.440)	6.331** (3.095)	24.94*** (3.977)	2.151 (3.968)	6.427 (5.408)	5.097 (4.749)	19.05* (10.87)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.198	0.216	0.368	0.397	0.192	0.211	0.362	0.381
N. Observations	1,988	1,988	1,988	1,988	1,988	1,988	1,988	1,988

Note: The outcome is the (log-) DHS wealth index. Linear regression models estimated by OLS using data from the DHS (dropping all the households that are less than 10 km far from a diesel mini-grid) with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in Columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, DHS cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Something similar is observed in Table B.12, which contains the results for the appliance regressions. Panels A and B, in which we include the impact that the deployment of a mini-grid had on the probability of owning a refrigerator and a television (respectively), show that all the point estimates are again positive but slightly lower in magnitude than those in Table 4 (Panels A1 and B1) in the main text. There are two main reasons that explain this pattern in our empirical results. First, the fact that non-diesel-powered mini-grids are generally less reliable than those powered by diesel (which are excluded from the sample here) due to the intermittency problem (Borenstein, 2012; Gowrisankaran et al., 2016; Liebensteiner and Wrienz, 2020). Second, because the capacity (in MW) of the former is also on average lower than the capacity of diesel-powered mini-grids and, thus, they are presumably less appropriate to power higher voltage appliances, such as refrigerators and televisions. All in all, even though these estimates are not significant at the 10%, their sign still provides suggestive evidence that mini-grids positively impacted the uptake of these appliances.

Table B.12. Impact of non-diesel fueled mini-grids on the household probability of owning selected appliances (refrigerator and television; DHS only)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
Mini-grid × post	0.0132	0.0121	0.0240	0.0616*
	(0.0127)	(0.0127)	(0.0207)	(0.0369)
R^2	0.0263	0.0333	0.0560	0.0660
N. Observations	2,174	2,174	2,174	2,174
	Panel B. Outcome: has a television?			
Mini-grid × post	0.0585	0.0291	0.0856	0.206
	(0.0547)	(0.0593)	(0.0752)	(0.144)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.147	0.162	0.269	0.291
N. Observations	2,176	2,176	2,176	2,176

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (dropping all the households that are less than 10 km far from a diesel mini-grid) with standard errors clustered at region-year level. In all these columns we use the binary treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Dropping potential spillovers

In the main text, we present two different approaches to estimate our regression model, namely, the binary treatment approach and the continuous treatment approach. The former, for which we define treated and control households in our sample using the 5 km threshold following the information in Figures 4 and 5, allows us to implement a standard generalized *DiD* regression based on a binary treatment. However, this threshold creates a sharp break between the treated cohort (0-5 km) and the control cohort (5-10 km) for all the mini-grids in our sample, regardless of their generation capacity (in MW). Thus, one may have the potential concerns that this threshold is not the appropriate one for all the mini-grids in our sample, as some of them (say, those with higher capacity) may have an impact on households slightly beyond the 5 km threshold and, conversely, some others (say, those with lower capacity) may not have an impact on households located just below the 5 km threshold. In these cases, the treated and the control group would contaminate (bias) our estimates.

To address this potential concern, we follow Benshaul-Tolonen (2019) and estimate again our main regression model (using the binary treatment approach) taking potential spillovers into account by dropping from our sample all the households that are within 4-6 km far from a mini-grid. The empirical results of this additional robustness check are included in Tables B.13-B.16.

To begin with, Table B.13 includes the estimated effect of mini-grid deployment on households' likelihood of having an electricity connection. The estimates across the four model specifications obtained using both the DHS (Panel A) and the NPS (Panel B) are positive, significant at least at the 5% level —except for the model specification in column (3) in Panel B—, and comparable in magnitude to those obtained in the first four columns in Table 1 in the main text. Something similar is observed in Table B.14 (the analog of Table 2), which displays the estimated impact of mini-grids on the probability of using electricity (rather than fossil fuel-based devices) as the main source of lighting (recall that this information is available in the NPS dataset only). The same pattern is also observed in Tables B.15 and B.16, in which the effect of mini-grid deployment on the DHS wealth index and on the ownership of appliances are qualitatively and quantitatively similar to those included in Tables 3 and 4 in the main text, respectively. A few exceptions are worth noting, though.

First, the coefficient on interest in columns (1) and (2) in Table B.15, where the dependent variable is the DHS wealth index, are positive but not significant. Notice, though, that they were not significant

Table B.13. Impact of mini-grids on the household probability of having an electricity connection dropping spillovers in the binary treatment approach

	Panel A. DHS dataset			
	(1)	(2)	(3)	(4)
Mini-grid × post	0.196***	0.191***	0.161**	0.224**
	(0.0568)	(0.0671)	(0.0632)	(0.0894)
R^2	0.221	0.232	0.333	0.350
N. Observations	3,221	3,221	3,221	3,221
	Panel B. NPS dataset			
Mini-grid × post	0.145**	0.199***	0.0768	0.147***
	(0.0641)	(0.0638)	(0.0495)	(0.0398)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.278	0.293	0.352	0.378
N. Observations	880	880	813	812

Note: The outcome is a dummy equal to 1 if the household has an electricity connection (and 0 otherwise). Linear probability models estimated by OLS using data from the DHS (Panel A) and from the NPS (Panel B) with standard errors clustered at region-year level, using the binary treatment approach, and excluding households within 4-6 km far from a mini-grid. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous columns but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14. Impact of mini-grids on the household probability of using electricity as the main source of lighting dropping spillovers in the binary treatment approach

	(1)	(2)	(3)	(4)
Mini-grid × post	0.143**	0.197***	0.0793	0.150***
	(0.0638)	(0.0634)	(0.0494)	(0.0402)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.280	0.294	0.352	0.377
N. Observations	880	880	813	812

Note: The outcome is a dummy equal to 1 if the household uses electricity as the main source of lighting (and 0 otherwise). Linear probability models estimated by OLS using data from the NPS with standard errors clustered at region-year level, using the binary treatment approach, and excluding households within 4-6 km far from a mini-grid. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous columns but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

either in Table 3 in the main text (additional explanations on this result are provided in Section 4.2). This is also the case in Table B.16, Panel B2, columns (3)-(4), regarding the impact of mini-grids on the uptake of televisions (interested readers may refer to Section 4.2 for further details).

Overall, we can confirm that the results obtained taking potential spillovers into account by excluding from our sample all the households within 4-6 km far from a mini-grid are extremely similar to those obtained using the full sample of households. Thus, we find evidence once again that mini-grids positively impacted the uptake of electricity connections and the use of electricity at home, and also suggestive evidence of a lower incidence of infectious diseases that are associated with poor food safety and preservation.

Table B.15. Impact of mini-grids on the DHS wealth index dropping spillovers in the binary treatment approach

	(1)	(2)	(3)	(4)
Mini-grid × post	3.042	2.124	6.833***	6.819***
	(2.080)	(2.576)	(1.484)	(1.847)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.359	0.380	0.478	0.488
N. Observations	3,015	3,015	3,015	3,015

Note: The outcome is the (log-) DHS wealth index. Linear regression models estimated by OLS using data from the DHS with standard errors clustered at region-year level, using the binary treatment approach, and excluding households within 4-6 km far from a mini-grid. Column (1) and: full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous columns but also including region-specific linear time trends. Column (3): full set of control variables, DHS cluster fixed effects, and year fixed effects. Column (4): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.16. Impact of mini-grids on the household probability of owning selected appliances (refrigerator and television) dropping spillovers in the binary treatment approach

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0703***	0.0818***	0.135***	0.134***
	(0.0233)	(0.0204)	(0.0373)	(0.0384)
R^2	0.0914	0.118	0.197	0.216
N. Observations	3,218	3,218	3,218	3,218
	Panel A2. NPS dataset			
Mini-grid × post	0.0698***	0.0696***	0.0629***	0.0440***
	(0.0220)	(0.0248)	(0.0170)	(0.0135)
R^2	0.111	0.119	0.129	0.174
N. Observations	880	880	813	812

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.115***	0.0961**	0.113**	0.134**
	(0.0332)	(0.0384)	(0.0492)	(0.0590)
R^2	0.183	0.190	0.262	0.272
N. Observations	3,222	3,222	3,222	3,222
	Panel B2. NPS dataset			
Mini-grid × post	0.115*	0.170***	0.0265	0.0666
	(0.0607)	(0.0533)	(0.0478)	(0.0422)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.280	0.295	0.325	0.373
N. Observations	880	880	813	812

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (Panels A1 and B1) and from the NPS (Panels A2 and B2) with standard errors clustered at region-year level, using the binary treatment approach, and excluding households within 4-6 km far from a mini-grid. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C: Additional empirical results

C.1 Main estimates for appliances (continuous treatment approach)

For the sake of clarity of exposition, in Section 4.2 in the main text we present the empirical results of the impact of mini-grid deployment on appliance (refrigerator and television) ownership using just the binary treatment approach —see Table 4. However, for the sake of completeness, in this appendix we include the same set of empirical results using the continuous treatment approach to confirm that our results remain consistent if we use this alternative approach instead. These results are included in Table C.1.

First, Panel A in Table C.1 displays the estimates using the "refrigerator" dummy as the outcome variable. The coefficient of interest across all the model specifications included in this panel are positive and significant at the 1% level when we use both the DHS dataset (Panel A1) and the NPS dataset (Panel A2). In the former case, this coefficient is between 0.08 and 0.16, which implies that the probability of having a refrigerator in the "post" period for a household located 2.5 km far from a mini-grid (the household "in the middle" among those in the treated group, as defined by the binary treatment variable) increases by about 6-12%. These figures coincide with the estimated (average) effect obtained using the binary treatment approach displayed in Table 4 (Panel A1). Extremely similar results are obtained when we use the NPS dataset instead, as can be seen in Table C.1 (Panel A2) and in Table 4 (Panel A2) in the main document.

The same pattern is also observed in Panel B in Table C.1, which contains the estimated effect of mini-grids on the uptake of televisions for households that are increasing far from them. All the point estimates are again positive, and most of them are significant at the 1% level. However, as is also the case in Table 4 (Panel B2) in the main text, the coefficient of interest for the model specifications that include cluster fixed effect obtained using the NPS dataset are close to zero and not significant —see Panel B2, columns (3)-(4). For all the other cases, this coefficient is between 0.13 and 0.28, which implies that the likelihood of having a television after the installation of a mini-grid for a household located 2.5 km far from it (the household "in the middle" among those in the treated group) increases by about 10-21%. These figures are again extraordinarily similar to those included in Table 4 (Panel B), obtained using the binary treatment approach.

Table C.1. Impact of mini-grids on the household probability of owning selected appliances (refrigerator and television; continuous treatment approach)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0791***	0.101***	0.160***	0.141***
	(0.0278)	(0.0271)	(0.0397)	(0.0341)
R^2	0.0878	0.116	0.162	0.185
N. Observations	3,987	3,987	3,987	3,987
	Panel A2. NPS dataset			
Mini-grid × post	0.111***	0.122***	0.0735***	0.0633***
	(0.0253)	(0.0279)	(0.0250)	(0.0172)
R^2	0.114	0.121	0.137	0.180
N. Observations	1,053	1,053	976	973

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.136***	0.126***	0.186***	0.193***
	(0.0452)	(0.0474)	(0.0592)	(0.0679)
R^2	0.181	0.194	0.257	0.269
N. Observations	3,991	3,991	3,991	3,991
	Panel B2. NPS dataset			
Mini-grid × post	0.226***	0.279***	-0.000557	-0.00226
	(0.0789)	(0.0805)	(0.0527)	(0.0534)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.268	0.283	0.351	0.389
N. Observations	1,053	1,053	976	973

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (Panels A1 and B1) and from the NPS (Panels A2 and B2) with standard errors clustered at region-year level. In all these columns we use the continuous treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Robustness checks for appliances (continuous treatment approach)

Next, we include in the present appendix the same set of robustness checks that we consider in Appendix B for the appliance regression using the continuous treatment approach. Note that the tables in Appendix B include the robustness checks for these regressions using only the binary treatment approach in order to make them consistent with the format of the analog tables in the main text (i.e., to facilitate the visual comparison between the tables in the main text and those in Appendix B).

First, we provide estimates of the impact of mini-grids on appliance ownership using our matched sample of households (see Appendix B.1 for further details on the matching procedure). These results are included in Table C.2. The estimated coefficient of interest across all the model specifications in Panel A (refrigerator ownership) and Panel B (television ownership) using both the DHS dataset and the NPS dataset are extraordinarily similar in magnitude to those included in Table B.5. The only difference is that, while the estimates for refrigerator ownership using the DHS-matched sample in columns (1) and (2) are significant at the 5% level in Table B.5, they are significant only at a level of confidence slightly above 10% when using the continuous treatment approach —see Table C.2, Panel A2.

Second, we present the results obtained after dropping from our sample the households that are relatively close to (i.e., less than 10 km far from) the national grid transmission lines. Table C.3 displays the estimated impact on appliance ownership using the continuous treatment approach. The point estimates of the coefficient of interest across all the model specifications are positive and significant at least at the 10% level —except for those obtained using "television ownership" as the outcome variable in Panel B2, columns (3) and (4). The magnitude of them is again consistent with that of the point estimates in Table B.9 (obtained using the binary treatment approach).

Finally, we provide the estimates for the appliance regression using the DHS dataset after excluding from our sample the diesel-fueled mini-grids. These empirical results are included in Table C.4. Once again, the coefficient of interest across all the columns in this table are positive and comparable in magnitude to those included in the analog table in Appendix B (see Table B.12). However, as it also occurs in the latter, the estimated effect is frequently not significant. This is because, as explained in Appendix B.3, the non-diesel-powered mini-grids in our sample are presumably less appropriate to power higher voltage appliances (see that appendix for further details). Overall, the empirical results in Tables C.2-C.4 further confirm that our estimates obtained using the continuous treatment approach are consistent

Table C.2. Impact of mini-grids on the household probability of owning selected appliances using a matching procedure (refrigerator and television; continuous treatment approach)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0535***	0.0694***	0.109***	0.118***
	(0.0187)	(0.0205)	(0.0387)	(0.0378)
R^2	0.0774	0.109	0.149	0.170
N. Observations	2,348	2,348	2,348	2,348
	Panel A2. NPS dataset			
Mini-grid × post	0.0511	0.0731	0.0614	0.0338
	(0.0514)	(0.0535)	(0.0769)	(0.0563)
R^2	0.0533	0.0840	0.121	0.158
N. Observations	482	482	437	434

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.164***	0.131**	0.198***	0.223***
	(0.0532)	(0.0544)	(0.0647)	(0.0708)
R^2	0.179	0.206	0.291	0.311
N. Observations	2,350	2,350	2,350	2,350
	Panel B2. NPS dataset			
Mini-grid × post	0.236*	0.299**	-0.0266	-0.0842
	(0.120)	(0.145)	(0.0766)	(0.0961)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.215	0.240	0.385	0.423
N. Observations	482	482	437	434

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS matched sample (Panels A1 and B1) and from the NPS matched sample (Panels A2 and B2) with standard errors clustered at region-year level. In all these columns we use the continuous treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3. Impact of mini-grids on the household probability of owning selected appliances (refrigerator and television) dropping households close to the grid transmission lines (continuous treatment approach)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
	Panel A1. DHS dataset			
Mini-grid × post	0.0845**	0.125***	0.207***	0.196***
	(0.0322)	(0.0330)	(0.0482)	(0.0495)
R^2	0.108	0.139	0.186	0.211
N. Observations	2,958	2,958	2,958	2,958
	Panel A2. NPS dataset			
Mini-grid × post	0.0978***	0.0952***	0.0733***	0.0577***
	(0.0290)	(0.0338)	(0.0210)	(0.0182)
R^2	0.110	0.126	0.139	0.208
N. Observations	643	643	597	595

	Panel B. Outcome: has a television?			
	(1)	(2)	(3)	(4)
	Panel B1. DHS dataset			
Mini-grid × post	0.102**	0.105*	0.228***	0.240***
	(0.0464)	(0.0550)	(0.0648)	(0.0763)
R^2	0.201	0.215	0.256	0.271
N. Observations	2,962	2,962	2,962	2,962
	Panel B2. NPS dataset			
Mini-grid × post	0.170*	0.215**	0.0253	0.0391
	(0.0898)	(0.0975)	(0.0540)	(0.0577)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.291	0.300	0.333	0.363
N. Observations	643	643	597	595

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS (Panels A1 and B1) and from the NPS (Panels A2 and B2) with standard errors clustered at region-year level, and excluding households within 10 km far from the grid transmission line. In all these columns we use the continuous treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

with those obtained using the binary treatment approach for the appliance regressions.

Table C.4. Impact of non-diesel fueled mini-grids on the household probability of owning selected appliances (refrigerator and television; continuous treatment approach; DHS only)

	Panel A. Outcome: has a refrigerator?			
	(1)	(2)	(3)	(4)
Mini-grid × post	0.0257	0.0279	0.0595	0.0630
	(0.0190)	(0.0212)	(0.0358)	(0.0446)
R^2	0.0265	0.0335	0.0570	0.0649
N. Observations	2,174	2,174	2,174	2,174
	Panel B. Outcome: has a television?			
Mini-grid × post	0.136*	0.126	0.167	0.219
	(0.0787)	(0.0994)	(0.125)	(0.147)
Full set of controls	✓	✓	✓	✓
Region FE	✓	✓		
Cluster FE			✓	✓
Year FE	✓	✓	✓	✓
Region-specific time-trend		✓		✓
R^2	0.147	0.162	0.270	0.290
N. Observations	2,176	2,176	2,176	2,176

Note: The outcome is a dummy equal to 1 if the household owns a refrigerator (and 0 otherwise) in Panel A, while it is a dummy equal to 1 if the household owns a television (and 0 otherwise) in Panel B. Linear probability models estimated by OLS using data from the DHS dataset (dropping all the households that are less than 10 km far from a diesel mini-grid) with standard errors clustered at region-year level. In all these columns we use the continuous treatment approach. Column (1): full set of control variables, region fixed effects, and year fixed effects. Column (2): same as the previous column but also including region-specific linear time trends. Column (3): full set of control variables, cluster fixed effects, and year fixed effects. Column (4): same as the previous column but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Falsification (placebo) test

In this final appendix, we perform a sensitivity analysis by estimating a placebo test using an outcome that is unlikely to be affected by the installation of a mini-grid. Specifically, we use a dummy variable indicating whether a household owns a bicycle (obtained from the DHS), which is an asset that does not require electricity and is likely not affected by income shocks —even poor households may own one (Aggarwal, 2018; Nakanwagi et al., 2021). The rationale behind this test is that we do not expect to observe differences between treated and control groups, as the outcome considered is unlikely to be affected by the installation of a mini-grid nearby. Therefore, any estimates significantly different from zero would support the validity of our research design.

We present the results of this placebo test in Table C.5. The coefficient of the "Mini-grid × post" interaction term is not statistically significant and is close to zero (with no consistent positive or negative effect observed) across all model specifications using both the binary treatment approach —columns (1)-(4)—- and continuous treatment approach —columns (5)-(8). These results provide further support for the validity of our research design, as we find no evidence of treatment effects on outcomes that are unlikely to be influenced by the installation of a mini-grid.

Table C.5. Impact of mini-grids on household probability of owning a bicycle

	Binary treatment approach				*Continuous treatment approach*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mini-grid × post	-0.0241	-0.0186	-0.00733	-0.00714	0.00725	0.0347	-0.0677	-0.0755
	(0.0459)	(0.0493)	(0.0317)	(0.0319)	(0.0633)	(0.0654)	(0.0554)	(0.0588)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓			✓	✓		
Cluster FE			✓	✓			✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region-specific time-trend		✓		✓		✓		✓
R^2	0.154	0.164	0.230	0.235	0.156	0.166	0.230	0.236
N. Observations	3,990	3,990	3,990	3,990	3,990	3,990	3,990	3,990

Note: The outcome is a dummy equal to 1 if the household owns at least one bicycle (and 0 otherwise). Linear regression models estimated by OLS using data from the DHS with standard errors clustered at region-year level. In columns (1)-(4) we use the binary treatment approach, while in columns (5)-(8) we use the continuous treatment approach. Columns (1) and (5): full set of control variables, region fixed effects, and year fixed effects. Columns (2) and (6): same as the previous columns but also including region-specific linear time trends. Columns (3) and (7): full set of control variables, cluster fixed effects, and year fixed effects. Columns (4) and (8): same as the previous columns but also including region-specific linear time trends. The significance levels are as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D: Welfare analysis

In this appendix, we perform a back-of-the-envelope cost-benefit analysis of installing a mini-grid. To do so, we combine our empirical estimates with technology-specific cost data and additional parameters obtained from various sources.

We consider the installation of a mini-grid intended to serve 190 households that lack access to electricity. This figure is derived from the average population size of the 35,000 settlements identified within Tanzania by World Bank (2016).[4] We assume that the primary objective of the mini-grid is to provide electricity to meet essential household needs, such as lighting, cell phone charging, and basic appliance usage (e.g., a television or a fan). Therefore, we tailor the load profile to reflect residential demand, excluding electricity consumption for productive purposes. Specifically, we assume an average daily household consumption of 1 kilowatt-hour (kWh), which is sufficient to meet these basic domestic electricity requirements.[5] In addition, based on the fieldwork in Tanzania by Wen et al. (2023), we assume that, on average, households are willing to pay $7.4 per month for the level of electricity service we consider here.

To meet this electricity demand, we consider the installation of a mini-grid with a total peak capacity of 0.01 MW–or, equivalently, 10 kilowatts (kW). This capacity level, which is well-suited to serve the aforementioned electricity needs of an average household, closely matches the median (0.015 MW) and mode (0.008 MW) capacities of renewable-based mini-grids in our sample. Consequently, we focus our analysis first on these types of mini-grids.[6] By contrast, diesel-powered mini-grids typically present significantly higher average capacities, making them better suited for powering high-voltage appliances (beyond basic household needs) and catering to commercial consumers. Therefore, we provide a stand-alone analysis tailored to diesel-powered mini-grids at the end of this appendix. Next, following the information by Zigah et al. (2023), we assume a 25-year lifespan for the mini-grid and a discount rate of 10%. Based on these assumptions, we proceed to compare the (lifespan) benefits and costs of three different renewable technology options, namely, solar, hydro, and biomass. For each of these technology

[4] In particular, we calculate this number using the average population within these clusters and the average size of the households in our sample.

[5] A similar consumption profile is considered by other scholars in the context of Tanzania, such as Banerjee et al. (2017).

[6] As per the 2015 policy reform in Tanzania, mini-grids with a capacity of up to 1 MW are entitled to specific benefits, such as the flexibility to select their own tariff scheme (Odarno et al., 2017).

options, we make the following cost assumptions.

To begin, we obtain estimates of the cost of capital for a solar-powered mini-grid from two distinct sources. First, ESMAP (2022) provides an estimate of the total capital cost for a 10 kW solar mini-grid at \$25,000. Second, the Global Electrification Platform (GEP) estimates a total cost of \$2,950 per kW of peak power (World Bank, 2019).[7] In addition, following Zigah et al. (2023), we assume that annual operational and maintenance costs for a solar mini-grid represent approximately 25% of their total capital costs. Next, for a hydro-powered mini-grid, we rely on the figures by World Bank (2019), which estimates that total capital costs are \$3,000 per kW of peak power. Moreover, following IRENA (2012), we consider that total capital costs for a biomass mini-grid are \$2,543 per kW. In both cases, we assume that annual operational and maintenance costs account for 5% and 10% of the respective total capital costs IRENA (2012).[8]

Based on these parameters, Figure D.1 displays the estimated net present value of the total surplus (defined as the difference between consumer surplus and total costs) generated by a 10 kW renewable-based mini-grid for the different technologies considered. These values are obtained using the average increase in connection rates following the installation of the mini-grid that we estimate in this paper — which stands at approximately 20%. To account for potential deviations arising from different specifications of our main regression model, we allow for a margin of +/- 5% in the actual increase in connection rates. In most cases, the net present value of the total surplus is negative. However, solar mini-grids exhibit a modestly positive or nearly "break-even" surplus. By contrast, hydro and biomass mini-grids maintain a negative net present value of the investment, although the gap between this value and zero narrows for the most optimistic household connection rate estimates. It is worth noting, though, that these latter technologies have significantly different capacity factors compared to solar, potentially resulting in excess energy generation that may go unused.[9]

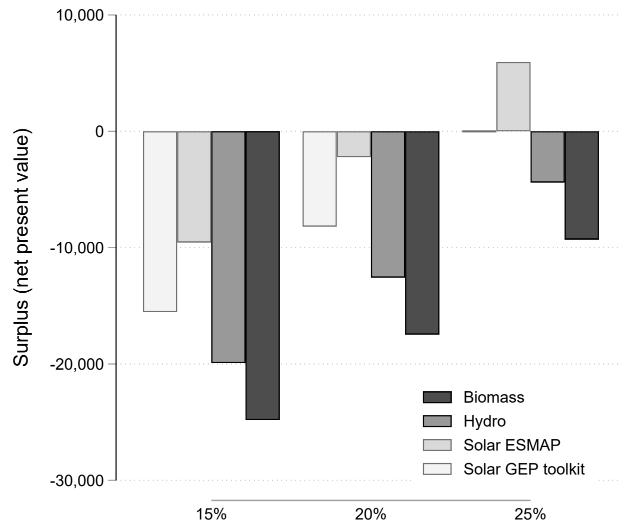
Finally, we turn to examine diesel-powered mini-grids. For this type of mini-grid, following Zigah et al. (2023), we assume that the total capital cost is \$5,000 per kW and that the (net present value

[7] The kW of peak power refers to the maximum electrical power that can be supplied under standard conditions, such as normal temperature and sunlight for solar power or consistent water flow for hydropower.

[8] The cost estimates provided by IRENA (2012) apply to large-scale projects. However, cost estimates from Banerjee et al. (2017) for smaller systems (ranging from approximately \$2,000-\$3,000 per kW) are very similar to our assumed figures.

[9] As an alternative approach to comparing the generation costs of these technologies, we can use the Levelized Cost of Electricity (LCOE), which takes into account the capacity factor of each technology. When accounting for the differences in capacity factors of a 10 kW power plant, our calculations of the LCOE (in \$/kWh) for these technologies result in \$0.25 for solar, \$0.14 for hydro, and \$0.11 for biomass.

Figure D.1. Estimated net present value of the total surplus of a 0.01-MW renewable-based mini-grid for different technologies



Note: Estimated net present value of the total net surplus from a renewable energy-based mini-grid. We examine three different mini-grid technology options: solar (under two alternative cost assumptions), hydro, and biomass. The mini-grid is assumed to have a total (peak) capacity of 0.01 MW. The total net surplus is calculated as the difference between the total annual household surplus over the lifespan of the mini-grid (assumed to be 25 years) and the total (lifespan) cost of the mini-grid, considering a 10% discount rate. Additional assumptions on costs and other parameters are provided in the text.

of) operation and maintenance costs are $99,000.[10] With these figures in mind, and under the same demand assumptions considered above, we calculate a negative net present value of total surplus that is four times larger than that of a biomass mini-grid. In fact, as noted by Agenbroad et al. (2018), diesel generators exhibit a Levelized Cost of Electricity (LCOE) ranging from $0.35 to $0.70 per kWh, values that substantially exceed our assumed household willingness-to-pay of $0.25 per kWh.[11] This result reveals that, as previously explained, diesel mini-grids are a more appropriate option only at higher capacity levels and are, therefore, more suitable for densely populated areas —i.e., in clusters with a population exceeding the average of those in our sample— that include both residential and commercial or industrial consumers.[12] In any case, it is important to note that this welfare analysis does not account for the environmental damages associated with diesel exhaust, mainly due to the challenges associated with estimating the social cost of carbon (Tol, 2023). These damages can make diesel-powered mini-grids a less desirable option. For example, assuming that a diesel generator emits 1 kg of CO_2 per kWh

[10]These operation and maintenance costs also account for expenses related to fuel and other replacement costs. Following Zigah et al. (2023), we assume a diesel cost of $1 per liter (l) and a heat rate of 0.45 l per kWh. For additional details on these costs, refer to Table 7 in Zigah et al. (2023).

[11]For our 10 kW mini-grid with a 25% household connection rate scenario, the capacity is utilized at 20%, resulting in an LCOE of $0.76/kWh. However, if the capacity were used at 75% power capacity (equivalent to a village with 720 households or 3,600 inhabitants under a 25% household connection rate), the LCOE would decrease to $0.36/kWh.

[12]Consistently, the average power capacity of the nine diesel mini-grids in our sample deployed after 2008 is 2 MW.

of electricity generated (SEforALL, 2021), we estimate that the LCOE increases by approximately 1 cent for every $10 increase in the cost per ton of carbon dioxide produced.

In summary, if we set aside diesel-powered mini-grids, we remark that renewable mini-grids are nearing a social surplus "break-even" point, even under our fairly conservative assumptions (particularly on the demand side). We also should emphasize that these findings hold true despite the omission in our cost-benefit analysis of other positive externalities associated with mini-grids that are documented in our paper —e.g., replacing paraffin and oil lamps—, and others documented in previous literature —e.g., generating employment opportunities within the local economy Pueyo et al. (2022); Fabra et al. (2023). When we take these elements into account, the overall welfare impact is likely to become positive.

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