Powering Progress: Assessing the Impacts of Solar Mini-Grids on Energy Access and Human Capital Accumulation in India

Margarita Petrusevich*

January 6, 2025

Click here for the most recent version.

Emerging green technologies, such as solar mini-grids, are changing the global electrification frontier, providing access to electricity for remote rural communities. This work aims to examine the short- and medium-term effects of mini-grid-driven electrification on energy access and the accumulation of human capital in rural India. To identify the causal impact of the mini-grid installations, I exploit the staggered rollout of solar mini-grids across villages from 2014-2022. Utilizing remote imagery data in combination with conventional survey data and a difference-in-differences approach, I find that the installation of mini-grids results in a measurable 21% improvement in energy access (as measured by night-time brightness). The effects are driven primarily by medium and large-scale mini-grid installations. This translates into improved educational outcomes for children in affected communities, with the most pronounced effects observed in high school children. This paper shows that the key channel of these effects is enhanced energy access within households rather than schools. This research suggests that solar mini-grids can offer a cost-effective solution for electrifying remote communities.

Keywords: Electricity access, Solar mini-grids, India, Human capital, Development, Solar cells, Renewable energy, Education outcomes, Remote sensing

JEL Codes: I25, J24, O13, Q42

Many developing countries still face under-provision of reliable energy, especially in remote rural areas. To address this issue, there is growing interest in utilizing emerging renewable energy technologies like solar mini-grids to facilitate electricity access. These efforts are being supported by substantial investments from developing countries themselves, along with mini-grid aid initiatives from the World Bank, which has allocated over \$3 billion since 2015 (ESMAP, 2022). The underlying belief is that these technologies hold the potential for win-win outcomes—stimulating development without compromising environmental quality (Barrett et al., 2023; IEA, 2017).

However, there is still a scarcity of empirical evidence regarding the effectiveness of stand-alone mini-grids (hereafter, mini-grids) in promoting energy access and rural community development. A mini-grid is an integrated system that operates autonomously without being connected to a centralized grid and supplies energy to remote rural communities, for which being connected to the central grid is economically unviable. Existing evidence on mini-grids largely relies on descriptive analyses and case studies of individual mini-grid projects (Kirubi et al., 2009; Mishra & Behera, 2016; Tenenbaum et al., 2018; Yadav et al., 2019).

Early literature on electrification has primarily focused on large-scale projects such as central grid extension, which have shown significant positive effects on development (Dinkelman, 2011; Rud, 2012; Lipscomb et al., 2013). However, studies of central grid-based electrification may not be a good guide to the impact of investing in mini-grids, notably lighter-touch interventions. A fundamental distinction that sets mini-grids apart from their central grid counterparts is the limited generation capacity inherent in small-scale, decentralized, renewable-based mini-grids.[1] Consequently, it remains uncertain ex-ante whether the energy supplied by mini-grids will be sufficient to drive substantial economic changes.

This paper aims to investigate the impact of solar mini-grids on energy access and rural development, where rural development is proxied by the accumulation of human capital, specifically educational attainment.[2] To assess the effectiveness of mini-grids,

---

[1]It is not uncommon for operators of mini-grids to impose restrictions on the quantity of power allocated per customer.

[2]This choice is driven by the fact that education functions as a cornerstone for numerous other outcomes, spanning from enhanced health and expanded employment opportunities to an overall improved quality of life. Therefore, through an investigation into education, one can discern early indicators of broader positive changes in the community.

I employ the Difference-in-Differences approach that exploits the staggered adoption of mini-grids in Indian villages between 2014 and 2022. Specifically, I compare villages that are relatively close and those that are further away from newly installed mini-grids, before and after the installation of the nearest mini-grid. This strategy allows me to estimate the potentially very localized impacts of mini-grids.[3] Additionally, since I am interested in estimating the dynamic effect of mini-girds over time, I employ an estimator that accounts for potential biases that may arise when treatment effects vary over time (Callaway & Sant'Anna, 2021).

India presents an important context for studying the effectiveness of mini-grids in promoting energy access. First, there exists a substantial electricity gap between rural and urban areas, with a significant portion of the population in India lacking access to electricity. Additionally, India benefits from a favorable climate for solar energy generation, which combined with the sharply decreasing costs of solar cells over the last 20 years (Banares-Sanchez et al., 2024), makes solar mini-grids an increasingly affordable technology. As of 2022, India has the third-largest mini-grid program globally, boasting 3,200 installations (ESMAP, 2022).

To analyze the effects of mini-grids' installation on energy access and human capital accumulation, I combine data sources on mini-grid characteristics, and energy access, as well as village and school-level data. A key feature these datasets share is their detailed spatial coverage, enabling a granular analysis of the local effects of mini-grids. Since no comprehensive data on the locations of mini-grids exists, I use a combination of satellite-derived data sources, Open Street Maps data, Bloomberg data, and World Resource Institute data. The use of multiple sources enables me to overcome the data limitations of previous papers and expand the scope of the study. To analyze the effect of mini-grids on electricity access outcomes, I use changes in nighttime brightness as a proxy for electricity access.[4]

---

[3]To establish causality, the key assumption of this approach is that the distance to the mini-grid is exogenous within narrowly defined geographical zones. That is, at the local level, mini-grids are not built close to the households that (for pre-existing characteristics) are more likely to get an electricity connection, and/or far from those less likely to do so. Instead, the exact location of a mini-grid within a narrowly defined geographical area is likely determined by other (exogenous) factors, such as surface roughness, solar irradiance, climatic conditions and presence of a sufficiently ample flat terrain. I empirically test this assumption and examine the robustness of the results using alternative definitions of control and treatment groups. The results remain consistent.

[4]The use of a proxy is appropriate in this context given the lack of detailed official energy consumption data at the village level. Furthermore, this measure has been previously adopted in a wide range of studies

To estimate the effects of mini-grids on human capital accumulation outcomes, I focus on indicators of educational attainment. The school data for this study is obtained from the District Information System for Education (DISE), which represents an annual census of schools in India.[5] This is the only source of education data in India that contains precise village identification information and allows me to link it back to the village data. To capture the social characteristics of villages, I utilize the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), which offers detailed spatial coverage of all census villages.[6] These data are used to control for trends in population characteristics, as well as to check if local trends in population characteristics can explain the adoption of mini-grids.

I find that the installation of mini-grids results in a measurable increase in energy access. Particularly, there is a growth of approximately 21% in nighttime brightness within the affected communities.[7] This finding is consistent with previous research on central grid electrification projects in developing country contexts, which have reported similar effects sizes on energy access (Burlig & Preonas, 2024; Machemedze et al., 2017; Min et al., 2013). When conducting a heterogeneity analysis based on mini-grid size, I further discover that the observed effects are primarily driven by medium and large-scale mini-grid installations.

I find that improved energy access translates into enhanced educational outcomes for children. Specifically, I estimate an approximate 8% increase in student enrollment at the village level. These observed impact sizes are comparable to the influence of other infrastructure projects on educational investments, such as central grid electrification programs (Khandker et al., 2014; Van de Walle et al., 2013; Khandker et al., 2013) and school-based sanitation improvement programs (Adukia, 2017). While the effect sizes are similar for both girls and boys, there is strong heterogeneity of effects by school type. Specifically, the results indicate that the enrollment effects are primarily driven by high school students. The baseline results are not sensitive to a

on electrification (Machemedze et al., 2017; Burlig & Preonas, 2024).

[5]As compared to other education data in India, DISE data have the most detailed temporal and spatial coverage.

[6]This is beneficial for the study since the empirical analysis is based on being able to identify the distances between mini-grids and villages. In addition to detailed spatial data, SHRUG also contains rich social and economic census data.

[7]The estimated effect size is equivalent to installing 15 additional streetlights or providing electricity to 60 more homes in a village Min & Gaba (2014).

range of robustness tests. The results remain consistent when I include a wide range of controls, apply alternative sample restrictions, and use different measurements for treatment variables as well as alternative estimation strategies.

To understand the factors contributing to the observed results on education, I investigate mechanisms related to *the supply of education* (educational infrastructure, teacher quality and quantity, number of schools) and *demand for education* (time allocation, health, income, and social attitudes toward education). While electrification through mini-grids could enhance learning environments in schools, the study finds limited evidence of mechanisms associated with the supply of education. This suggests that the primary drivers of change are demand-side mechanisms.

When investigating demand-side mechanisms, I find that mini-grids significantly enhance residential energy access, with the most compelling evidence stemming from changes in agricultural production. Mini-grids support the use of electricity for pumps and irrigation systems, contributing to the mechanization of labor and increased agricultural output (Best, 2014; Burke & Lobell, 2017; Gupta, 2019). This technological advancement facilitates labor-capital substitution, reducing reliance on manual labor, particularly among older youth who were previously engaged in agricultural work.[8] Additionally, increased agricultural production boosts household incomes, which may drive the adoption of additional electric appliances, further enhancing household welfare through multiple channels. Specifically, ownership of low-load electric appliances, such as cell phones, radios, TVs, and electric fans, also increases. The rise in electric fan ownership suggests potential health benefits, such as reduced exposure to extreme heat (Garg et al., 2022; Masuda et al., 2021), while the increased ownership of cell phones, radios, and TVs indicates greater media exposure. This enhanced media access may sensitize individuals to the importance of education, potentially encouraging greater parental investment in their children's education (Cheung, 2012; Ferrara et al., 2012; Jensen & Oster, 2009; Keefer & Khemani, 2011).

This paper makes several contributions. First, this study contributes to the literature on the impact of electricity infrastructure projects on development, by analyzing the renewable energy technology of solar mini-grids. They present a large departure

---

[8]As a result, these children can return to school, leading to improvements in educational outcomes (Self & Grabowski, 2008; Thévenon & Edmonds, 2019).

from traditional electrification infrastructure, such as centralized grids based on fossil fuel, nuclear or hydroelectric sources, due to their relatively low-cost, smaller capacity, environmentally sustainable and decentralized nature. While early research on electrification has predominantly focused on large-scale infrastructure projects, such as central grid extensions with significant positive effects on development (Dinkelman, 2011; Rud, 2012; Lipscomb et al., 2013; Barron & Torero, 2017; Fetter & Usmani, 2020; Moneke, 2020; Burlig & Preonas, 2024), smaller-scale projects like solar mini-grids might have lower potential to foster broad community development for several reasons. First, mini-grids might rely on generation sources with capacities insufficient to drive significant economic changes. Second, as mini-grids often serve remote and rural communities, other constraints to growth may exist beyond electricity access. Third, there could be a perception among the population that mini-grids are inferior to grid electrification (Burgess et al., 2020), resulting in lower adoption. Consequently, it remains uncertain ex-ante whether mini-grids can foster community development.

This paper demonstrates that despite these challenges, solar mini-grids have the potential to improve energy access and societal outcomes in communities they serve. Specifically, I find that mini-grids offer comparable energy and school enrollment improvements at lower costs compared to central grid expansion projects in developing countries like India, Senegal, and South Africa (Burlig & Preonas, 2024; Machemedze et al., 2017; Min et al., 2013; Khandker et al., 2014; Van de Walle et al., 2013; Khandker et al., 2013). A back-of-the-envelope calculation for the first 20 years of project operation reveals that an average-sized mini-grid project (100 kWp capacity) yields a 17% internal rate of return (IRR) and initial expenditures are recouped within a 5-year period.[9]

Second, this study adds to prior work on electrification via renewable technologies by providing first causal evidence on longer-term effects of solar mini-grids expansion at scale. Prior work on mini-grids mainly relies on descriptive analyses and case studies of individual mini-grid projects (Kirubi et al., 2009; Mishra & Behera, 2016; Tenenbaum et al., 2018; Yadav et al., 2019).[10]

---

[9]17% IRR is above the 10–12% threshold for social discount rate commonly used to benchmark cost-effectiveness (Asian Development Bank, 2013; Bonzanigo & Kalra, 2014).

[10]For instance, Kirubi et al. (2009) present descriptive survey data from Kenya suggesting a positive effect of mini-grids on nearby residents. The study by Tenenbaum et al. (2018) explores the impact of three mini-grids

There are only a few causal investigations of mini-grids' effects, primarily from a small number of randomized controlled trials (Aklin et al., 2017, 2018). For instance, Aklin et al. (2017) find that providing standalone community mini-grids to 81 unelectrified habitations in Uttar Pradesh leads to increased electrification rates and daily hours of access to electricity, as well as reduced monthly kerosene expenditure. However, they found no systematic evidence for changes in savings, spending, business creation, time spent working or studying, or other broader indicators of socioeconomic development one year after the mini-grid construction. Importantly, given the nature of RCTs, these studies are based on a relatively small number of mini-grid projects and have short follow-up periods, enabling researchers to detect only immediate effects.

To surmount the data limitations inherent in prior investigations of mini-grids, this paper creates a comprehensive data set of mini-grid placement by utilizing a combination of satellite-derived data sources, OpenStreetMap data, Bloomberg data, and World Resources Institute data to examine mini-grids at scale, potentially enhancing external validity and improving the precision of estimated effects. This study also adopts a longer time horizon, which is crucial given the anticipated dynamic effects of mini-grids in practice.[11] Understanding the effects at scale over time is particularly important, given that recent literature has shown that results from small-scale randomized control trials or field experiments often cannot be replicated when policies or interventions are expanded to larger contexts or different settings (Andrabi et al., 2020; Barrera-Osorio & Linden, 2009; Bold et al., 2018; Kumaranayake, 2008; Kurowski et al., 2007; List, 2022; Mobarak, 2022; Monroe-DeVita et al., 2012).[12]

Third, this paper advances the growing literature on the impacts of technology adoption and use on human capital in developing countries by examining the effects

___

on local communities in rural Cambodia.

[11]People require time to learn about the benefits the technology offers, adopt it, and for new norms to evolve, which shorter-term studies may overlook. As a result, the benefits of mini-grid adoption might be underestimated in shorter-term analyses. Indeed, I find this to be the case in the study, where improvements take time to emerge. For example, school enrollment showed only slight signs of improvement one year after the construction of the mini-grid (less than 2%, statistically insignificant), but improved significantly by 8-10% after five years.

[12]Banerjee et al. (2017) identifies six main reasons for the failure of policies or interventions scaling up: market equilibrium effects, spillovers, political reactions, context dependence, randomization or site-selection bias, and piloting bias.

of solar mini-grids on educational outcomes.[13] Existing research typically focuses on specific educational technologies, such as radio (Jamison et al., 1981), cell phones (Aker et al., 2012), satellite internet (Bianchi et al., 2022), remote lessons (Banerjee & Duflo, 2014; Alpert et al., 2016; Bettinger et al., 2017; Goodman et al., 2019), interactive videoconferencing (Johnston & Ksoll, 2022), expert-led video integration (Beg et al., 2022), and TV-schools (Fabregas & Navarro-Sola, 2024; Borghesan & Vasey, 2024). These studies have generally demonstrated positive effects on school attendance, test scores, and later-life earnings. In contrast, this study highlights the critical role of solar mini-grids as a foundational technological infrastructure that enables the adoption of subsequent technologies. The findings reveal that mini-grids facilitate the uptake of various electric appliances, such as TVs, radios, cell phones, and electric water pumps, which can have their own distinct effects on educational attainment. The findings emphasize the importance of considering mini-grids as a fundamental building block for technological progress, with potential cascading effects on human capital development.

1. Background

1. Setting

A stand-alone mini-grid is an integrated system that operates autonomously without being connected to a centralized grid, supplying energy to remote rural communities where extending the central grid is economically unviable. Intuitively, a mini-grid provides an intermediate infrastructure solution between the national grid —intended to serve a large group of users from several generators— and an off-grid, home-based solar system serving just one or a few users.

India's setting is ideal for studying mini-grids' effectiveness in promoting energy access given several factors: (1) India's historical lack of electricity access and substantial size of the unelectrified population, (2) favorable climate for solar energy generation, and (3) decreasing costs of solar mini-grid sub-components that have made solar mini-grids an affordable technology to be introduced in a developing country setting.

---

[13]For reviews, please see Bulman & Fairlie (2016); Escueta et al. (2017).

To illustrate the first point, in India, per the most recent Census data as of 2011, electricity access was highly uneven with 32.4 % of the population being unelectrified. Moreover, even for the population connected to the grid, the reliability of electricity varied substantially.[14] Figure A1 shows that this issue was particularly pronounced for Indian states in Central and Eastern zones where the average hours of electricity per day varied from 3 to 12 hours depending on specific location.[15]

To support the second point, Figure A12 illustrates the map for the average solar generating potential at the district level. The Figure shows that India has a high solar energy generation potential with abundant solar radiation during most of the year. The most productive regions include Western, Central, and parts of North India.[16]

Finally, the decreasing costs of solar cells driven primarily by the Chinese government's subsidies to the solar energy industry in recent decades have made solar mini-grids an affordable technology.[17]

All of these developments have culminated in India's establishment of the world's third-largest mini-grid program, with 3,200 installations as of 2022 (ESMAP, 2022). India's vision for the future is even more ambitious, with plans for 18,900 additional mini-grid projects, positioning the country as the global leader in terms of planned projects.

2. Solar mini-grids

Mini-grid system description

A standalone mini-grid includes generation, energy storage devices, power conversion equipment, and distribution infrastructure (Peskett, 2011; Franz et al., 2014). The generation of energy is being conducted with the help of a solar photovoltaic (PV) array – or group of solar panels – that captures and generates electricity from

---

[14]Reliability of electricity is measured in hours per day when energy is available.

[15]In this paper, the East zone consists of the Indian states of Bihar, Jharkhand, Odisha and West Bengal, while the Central zone includes Chhattisgarh, Madhya Pradesh, Uttarakhand and Uttar Pradesh.

[16]Solar energy generation potential, or Photovoltaic power potential (PVOUT), represents the potential for solar energy generation in a given area. It is measured in kilowatt-hours per kilowatt-peak (kWh/kWp), indicating how much electricity a solar panel with a peak capacity of one kilowatt can generate in one year. Intuitively, it shows how productive a solar panel can be based on the amount of sunlight it receives.

[17]Specifically, the fall in component prices is primarily driven by the Chinese government's support of solar energy in terms of production and innovation subsidies. These solar policies helped drive up Chinese firms' entry and production, innovation, and exporting. These changes helped to drive down solar generation costs not just in China but across the world which, in turn, has helped to encourage the global diffusion of solar energy (Banares-Sanchez et al., 2024).

the sun's light. Depending on the energy production and the amount of energy being used by the community, some of the electricity generated is stored in batteries for future use. The batteries ensure that communities have power at night and during stretches of cloudy weather.

A mini-grid can supply up to 10 megawatts (MW) of power and, thus, can meet the basic electricity needs of households, small businesses, schools, hospitals, and other users in one or a few villages. The energy generation capacity is typically decided in advance given the community's energy needs. Depending on the capacity of the system, different uses can be powered. Following Multi-Tier framework of energy access developed by the World Bank and the UN's Sustainable Energy for All (Bhatia & Angelou, 2015) the installation of a mini-grid can move a village from Tier 0 to somewhere between Tier 1 to Tier 4, depending on the capacity of the system and the number of hours per day when electricity is available.

In particular, small-scale systems (Tier 1 systems) are primarily designed for powering task lighting, phone charging, and radios. Medium-sized systems, categorized as Tier 2 and Tier 3, are suitable for operating low-load appliances (like multiple lights, a television, or a fan), as well as medium-load appliances (such as refrigerators, freezers, food processors, water pumps, rice cookers, and air coolers). On the other hand, larger capacity systems are capable of powering high-load appliances (like washing machines, irons, hair dryers, toasters, and microwaves), and even some productive microenterprise uses (such as irrigation of crops).[18]

It is worth noting that the features of mini-grids can vary substantially across projects. Characteristics like ownership and management can fall under the purview of a utility, a third-party entity, an NGO, or the community members themselves. Additionally, the type of tariff, be it consumption-based or capacity-based, pre-paid or post-paid, may differ among mini-grids. In this study, the focus is predominantly on third-generation technology mini-grids due to their increasing prevalence.[19]

---

[18]A typical small size mini-grid is 33 kWe in capacity. It supplies electricity to 1-4 villages (approximately 300-400 households). Power is distributed from the battery banks to clusters of between 20-100 households. Transmission wires are typically limited to keep distribution losses low (typically up to 1.5-2 km). Supply duration totals 5-8 hours per day, concentrated in the early morning and in the evening. Typically, it can power lighting services, based on LED lamps of 2-6 watts (2-3 light points per household), and mobile phone charging.

[19]Compared to first and second-generation mini-grids, these third-generation mini-grids are typically larger and often incorporate battery storage. They tend to implement pre-paid energy cost systems and meter-based

Construction of mini-grids conducted by private firms is financed through grants, debt, and equity investment. Notably, the three largest private mini-grid developers worldwide—Tata Power, Husk Power, and OMC Power—all operate in India. According to reports from developers (Desai, 2020), private developers follow a set of criteria when selecting communities to target:

(1) Solar Potential: Favorable solar conditions, including solar irradiation, temperature, terrain shading, and cloud coverage, are essential considerations.

(2) Rural unelectrified community. Mini-grids are placed in rural areas that are far from the Indian central grid.

(3) Demographics: The number of households and the overall population size play a crucial role. A higher number of households improves the viability of mini-grids. Additionally, high population density and growth are preferable, with individual hamlets located close to each other.[20]

(4) Customer Paying Capacity: This involves assessing the occupation, consumption patterns, and the share of low-income households. Understanding the paying capacity is critical for determining the profitability of mini-grids and designing suitable service packages. Higher non-agricultural economic activity is an indicator of higher income levels and increased electricity demand.

Rural energy alternatives

Mini-grids offer a solution for rural customers that are not connected to the grid since they provide a cheaper approach to energy generation than traditional alternatives. I provide a detailed comparison of rural energy generation alternatives in Table B1.

Traditionally, unelectrified households cope with the situation by using candles, kerosene lamps for lighting, or dry-cell-battery-powered devices (flashlight or radio). Another energy-generating technology is diesel generators. However, diesel generators are highly polluting and less affordable than solar mini-grids because of increasing

---

energy consumption tracking to prevent energy theft. Furthermore, they make use of cutting-edge technologies like smart meters and remote monitoring systems and are usually designed with the ability to connect to the main grid if it becomes available.

[20]Hamlet represents a subpart of a village, typically comprising a few dozen households or fewer.

diesel costs. An environmentally friendly alternative is solar home systems (SHS), which primarily offer lighting and mobile charging services. However, mini-grids are gaining popularity due to their ability to support both basic and productive loads, as well as commercial activities. Typically, mini-grid-produced energy is cheaper than that of standalone SHS due to economies of scale.

Grid electricity, while often unreliable, is often cheaper than mini-grid-produced electricity because of economies of scale and/or administrative pricing that fails to recover the full cost of generation, transmission, and distribution (Blankenship et al., 2019). Comello et al. (2017) compared the Levelized Cost of Electricity (LCOE) for a representative village in the Gujarat state of India. They found that solar mini-grids with a battery at \$0.380 per kWh were relatively more expensive than the central grid that could offer power at \$0.062 per kWh.

Even though high electricity prices remain an important concern among customers, some studies suggest that they are willing to pay a higher price for electricity to obtain a reliable supply (Graber et al., 2018; Alam & Bhattacharyya, 2017; Twerefou, 2014). Moreover, researchers who have looked into solutions to make off-grid operations more cost-effective suggest that apart from long-term technological improvements, the use of energy-efficient appliances, provision of finance to customers to purchase those appliances, use of tariff bundles that allow customers to choose payment plans based on their electricity demand, or progressive tariffs that subsidize poor residential users based on commercial loads can be helpful in the short-term (Muchunku et al., 2018; Azimoh et al., 2017; Zubi et al., 2016).

2. Conceptual framework: Schooling decisions and energy access

In this section, I outline the potential channels through which the installation of mini-grids can impact the accumulation of human capital in India. Broadly speaking, these channels can be classified as related to (1) demand for education and (2) supply of education.[21]

---

[21]Notably, while 67.6% of the population had access to electricity as of the 2011 Census, only 43% of schools had functional energy access in 2011 (DISE, 2011).

1. Demand for education and related channels:

(1) Time Allocation: First, if mini-grids provide lighting, then they extend the effective duration of the day, enabling inter-temporal substitution of tasks. This allows children to do homework and chores in the evening, freeing up daytime for school. Additionally, mini-grids enable other household members to work more efficiently, reducing the task burden on children.

(2) Health Channel: Transitioning from coal and wood for cooking to cleaner electricity reduces indoor pollution and disease incidence, indirectly boosting education.[22] Secondly, mini-grids supply energy for essential heating and cooling services, helping communities better cope with extreme temperature events. This is crucial given the documented detrimental impact of extreme temperatures on cognitive performance and productivity (Garg et al., 2022; Masuda et al., 2021).

(3) Agriculture and Household Income: Mini-grid can increase agricultural yields by supporting the use of electricity for pumps and irrigation systems, enhancing family income through increased agricultural production (Best, 2014; Burke & Lobell, 2017; Gupta, 2019) which enables greater parental investment in their children's education. Previous research also indicates that adopting new agricultural technologies, both mechanical and biochemical, leads to a reduction in child labor, allowing older children to return to school (Self & Grabowski, 2008; Thévenon & Edmonds, 2019).

(4) Migration and Demographic Changes: Electrification can make communities more attractive, potentially motivating inward migration from unelectrified areas.

(5) Knowledge and Beliefs: Ownership of TV, radio, and mobile phones, facilitated by electricity, increases exposure to media, which in turn promotes alternative role models and alters attitudes to education (Cheung, 2012; Ferrara et al., 2012; Jensen & Oster, 2009; Keefer & Khemani, 2011). Secondly, the installation of streetlights enhances the safety of school travel, encouraging parents to send their children to school, particularly girls. Finally, as electrified communities develop, the perceived returns to education may increase.

---

[22]However, this shift requires adequate mini-grid power capacity for powering medium and large load appliances.

2. Supply of education and related channels:

(1) School Infrastructure: Availability of electricity at school acts as an input for the education production function, making students and teachers more productive.

(2) Quantity and Quality of Teachers: Electrification can make communities more attractive, potentially motivating inward migration from unelectrified areas.

(3) Quantity of Schools: Electric tools and equipment often provide higher precision and efficiency, leading to faster construction processes. For instance, electric saws, drills, and welding equipment are more accurate and require less manual effort, resulting in quicker and more precise construction. Access to electricity allows for well-lit construction sites, which can extend working hours into the evening. This increased flexibility can expedite the construction process.

3. Data

To analyze the effects of mini-grids' installation on energy access and human capital accumulation, I combine data sources on mini-grids characteristics, and energy access, as well as village and school-level data. A key feature these datasets share is their detailed spatial coverage, enabling a granular analysis of the local effects of mini-grids. This section provides details on the underlying data sources.

1. Solar mini-grids

Since no comprehensive data on the locations of mini-grids exists, I use a combination of satellite-derived data sources, Open Street maps data, Bloomberg data, and World Resource Institute data. This multi-source approach enables me to overcome the limitations of previous research and broaden the project's scope.

Specifically, I utilize a union of solar installation data from all these sources, recognizing that each has its strengths and weaknesses. Satellite data, for instance, offers objectivity and extensive geographical coverage but may miss smaller installations (those below 10 kW) due to its coarse imagery resolution. In contrast, incorporating data sources based on survey data, government agency information, and crowd-sourced data helps pinpoint the locations of smaller capacity installations. For a more comprehensive description of each of the mini-grid data sources, please refer to Appendix C.

2. Electricity access

To analyze the impact of mini-grids on electricity access, this study employs changes in nighttime brightness as a proxy for measuring electricity access, since direct official electricity access and consumption data at the village level is not available. For these data, the study utilizes the version 1 suite of global average radiance composite images derived from the VIIRS Day/Night Band data, provided by the Earth Observation Group. These images cover the period from 2014 to 2022. The VIIRS data offers several improvements compared to its predecessor, the DMSP-OLS series. These enhancements include a finer spatial resolution of approximately 0.5×0.5 km (near the equator), a wider radiometric detection range to address oversaturation issues in bright urban core centers, and onboard calibration (Elvidge et al., 2013).[23] The data has undergone filtering to exclude information affected by stray light, lightning, lunar illumination, and cloud cover.[24]

Using satellite-derived brightness proxies for electrification at the village level is appropriate, as previous studies have successfully correlated nighttime brightness with electrification rates at the sub-national level. For instance, Min et al. (2013) demonstrated that electrified villages in Senegal and Mali exhibit significantly higher brightness compared to unelectrified villages. Additionally, Min & Gaba (2014) found a strong correlation between nighttime brightness, and streetlights and household electrification in Vietnam. Machemedze et al. (2017) correlated household electrification with brightness in South Africa, and Dugoua et al. (2018) identified strong correlations between brightness and the number of electrified households in rural Indian villages.

To measure the effects of mini-grids on energy access, I construct a yearly brightness panel at the village level. The preferred measure is to assign each village the maximum brightness value across all pixels within the village's shapefile polygon (Burlig & Preonas, 2024). This reflects the typical organizational structure of South Asian villages, with concentrated inhabited regions surrounded by fields. Maximum brightness best captures light emitted from village settlements while avoiding aver-

---

[23]Please, refer to Table B2 for more detailed comparison of VIIRS and DMSP-OLS series.
[24]Monthly VIIRS nighttime lights data were further preprocessed and composited annually.

aging over unlit agricultural land. To test the robustness of the maximum brightness measure, I use alternative measures: the mean and median of village-level brightness. My results are similar in significance but smaller in magnitude when I apply these alternative measures.

3. SHRUG data for village-level characteristics

To obtain village-level social and economic data for this study, I rely on the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). SHRUG offers extensive spatial coverage of all Census villages, which proves advantageous as the empirical analysis hinges on accurately determining the distances between mini-grids and villages. Apart from detailed spatial information, SHRUG also includes comprehensive social and economic census data. In particular, I make use of three consecutive Indian Population Censuses from 1991, 2001, and 2011. These data serve two purposes: controlling for trends in population characteristics and examining whether local population trends can explain the adoption of mini-grids. For the purpose of this study, I limit the sample to villages that lacked access to power for domestic and agricultural needs as of the 2011 Census.

4. DISE data for education outcomes and school characteristics

The school data for this study is obtained from the District Information System for Education (DISE), which represents an annual census of primary and middle schools in India. The data covers the years 2010 to 2022, and provides the most detailed temporal and spatial coverage compared to other education datasets in India. Importantly, DISE is the only source of education data that includes precise village identification information, which enables linking it with village-level data. This dataset, created by the Ministry of Human Resource Development of the Government of India and administered by the National University of Educational Planning and Administration, is designed to comprehensively cover every registered Indian government primary and middle school.

DISE provides information on educational outcomes that are of primary interest to this study: student enrollment, exam performance, and grade repetition. School enrollment is defined as the total number of enrolled students in grades 1-12 across all schools within a village. However, DISE does not provide the total number of

school-age children in a village, making it impossible to calculate enrollment rates. Additionally, DISE collects examination outcomes for states that conduct terminal primary- and middle-school examinations, which are used for promotion decisions and completion verification. This includes data on the number of students who appeared for the exam, passed the exam, and achieved distinction. However, examination data is only available for a subset of years.

Crucially, the DISE dataset includes information on school electrical infrastructure, allowing me to examine school-level energy access as a mechanism for the effects of mini-grids on educational outcomes. Furthermore, the dataset covers various school amenities such as the presence of blackboards, sanitation facilities, water sources, playgrounds, libraries, boundary walls, access to medical checkups, and access ramps. Additionally, data on teacher characteristics include the number of teachers, years of experience, and level of education. Together school amenities and teacher characteristics are utilized to study the mechanisms influencing the demand for educational channels in the empirical analysis.

5. Sample construction

The final sample, covering the years 2014-2022, is constructed by intersecting the data sources and creating a village-level panel dataset. Additionally, the dataset is matched to DISE data through fuzzy matching based on state, district, village names, and zip codes. Further details on sample construction are provided in the Appendix C.

4. Empirical framework

The source of plausibly exogenous variation for this study comes from the staggered adoption of solar mini-grid projects from 2014 to 2022. To study the effectiveness of mini-grids, I use a Difference-in-Differences (DID) approach that compares villages relatively close and further away from newly installed mini-grids, before and after the closest mini-grid installation. The idea behind the strategy is that villages that are relatively close to a mini-grid are more likely to connect to mini-grids and benefit from it than those relatively far away.

1. Baseline model

The standard estimation approach for such a scenario commonly employs the Two-way Fixed Effects (TWFE) estimator. However, recent literature has highlighted the limitations of TWFE when dealing with groups treated at various time points (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021). First, TWFE uses already-treated groups as controls, overlooking potential dynamic treatment effects. In practice, it is conceivable to expect that mini-grids can have a dynamic effect on rural communities, because the longer a village has a mini-grid, the better the communities may adapt to the availability of electricity and develop new behaviors, such as increased use of electrical appliances, changes in work patterns, increased connectivity and changes in traditional practices.[25]

Secondly, even if there is no dynamic effect, TWFE can still introduce bias when there are heterogeneous treatment effects across groups.[26] It is reasonable to expect heterogeneous treatment effects across groups. For example, earlier adoption might signal a higher motivation and higher perceived benefits of increased energy access. To address these issues, I follow the method proposed by Callaway & Sant'Anna (2021) for my baseline analysis. This approach explicitly allows for multiple time periods, variation in the treatment timing, and the parallel trends assumption holding potentially only after conditioning on observed covariates. Thus, I estimate "group-time average treatment effects":

$$(1) \qquad ATT(g,t) = E[Y_t - Y_{g-1}|G_g = 1] - E[Y_t - Y_{g-1}|G_g = 0],$$

where Y_t represents electricity access or human capital outcome in year t. Addi-

---

[25]Additionally, the longer a community is exposed to mini-grids, the more time there is for the benefits to accumulate and have a meaningful effect on various aspects of life, such as income, education, and health. Long-term exposure can contribute to the sustained economic growth of rural communities, fostering entrepreneurship and attracting investments.

[26]The TWFE estimator assigns varying weights to observations within a panel. It gives higher weights to observations in the middle of the panel and lower weights to those at the ends. Consequently, the TWFE estimator calculates a parameter that is specific to the length of the data used, rather than the actual average treatment effect. For an in-depth discussion, refer to Goodman-Bacon (2021). It's important to note that the TWFE estimator is equal to the Average Treatment Effect (ATT) only when all ATTs from different groups are identical. However, in designs with numerous groups and periods that implement treatments in a staggered fashion, such uniformity is unlikely (De Chaisemartin & d'Haultfoeuille, 2020).

tionally, $g \in (2016, 2022)$ is the year the group was first treated (for instance, 2016 corresponds to the village group first treated in 2016, and so on), $t \in (2014, 2022)$ is a point in time, G_g is a binary variable that is equal to one if a unit is first treated in the period g and zero otherwise. I then calculate the overall effect suggested by Callaway & Sant'Anna (2021) of mini-grid installation by aggregating these group-time average treatment effects together:

$$(2) \qquad \delta = \frac{1}{\kappa} \sum_{g=2016}^{2022} \sum_{t=2014}^{2022} w(g,t) ATT(g,t),$$

where $ATT(g,t)$ is defined in Equation 1, g corresponds to the time period when a unit is first treated, and other components are defined as follows:

$$(3) \qquad w(g,t) = I\{t \geq g\} P(G = g | G \leq 2022),$$

$$(4) \qquad \kappa = \sum_{g=2016}^{2022} \sum_{t=2014}^{2022} P(G = g | G \leq 2022),$$

I also conduct the TWFE estimation. I specify it as the following model with binary treatment:

$$(5) \qquad Y_{vt} = \beta_0 + \delta Close_v \cdot Post_t + \beta_1 Close_v + \gamma X_{vt} + \theta_t + \epsilon_{vt},$$

where Y_{vt} represents electricity access or human capital outcome of village v in year t. $Close_v$ is a dummy variable that equals unity if for villages within 0-2 km of mini-grid. $Post_t$ is a dummy variable that equals unity after the closest mini-grid has been constructed. X_{vt} is a vector of village-level controls. Common village time shocks are absorbed by the year indicators θ_t. Standard errors are clustered at village level. The coefficient of interest, δ, estimates an intention to treat (ITT) parameter; even though virtually all villages in the treated group are in close vicinity to the mini-grid,

not all households from treated villages receive a mini-grid connection.

The central identifying assumption of Callaway & Sant'Anna (2021) is limited treatment anticipation.[27] The second assumption is the conditional parallel trends assumption. More specifically, the assumption in this context is that conditional on covariates, the average outcomes for the group first treated in period g and for the "never-treated" group would have followed parallel paths in the absence of treatment.[28]

2. Event-study framework

As discussed above, the empirical strategy relies upon the conditional parallel trend assumption. Thus, before presenting my results, I use a more flexible event-study specification to rule out differential pre-trends. The event-study specification provides a natural test for the identification assumption of the model as differences in pre-trends can be examined visually. The specification is:

$$
(6) \qquad \delta_{es}(e) = \sum_{g=2016}^{2022} \sum_{t=2014}^{2022} I(t-g=e) P(G=g|t-g=e) ATT(g,t),
$$

where $\delta_{es}(e)$ is the average effect of participating in the treatment e periods after the treatment was adopted across all groups that are ever observed to have participated in the treatment for exactly e periods. The event study is also computed using TWFE[29]:

$$
(7) \qquad Y_{vt} = \alpha + \sum_{\tau=-3,\tau\neq-1}^{5} \delta_\tau D_{vt} + \lambda Close_v + \gamma X_{vt} + \theta_t + \upsilon_{vt},
$$

[27]This assumption is likely to hold if treatment path is not apriori known and villages are not the ones that "choose" their treatment status.

[28]In addition, the following set-up specific assumptions of Callaway & Sant'Anna (2021) DiD need to be satisfied. First, the "irreversibility of the treatment" should hold, meaning that once unit becomes treated and it will remain treated. This assumption is met due to the nature of the mini-grid projects roll-out. Once villages get mini-grid, they remain treated. Second assumption is random sampling, imposing that each unit is randomly drawn from population of interest. This implies that the data used for estimation is panel or repeated cross-sectional data. This assumption is satisfied by the longitudinal nature of the VIIRS nighttime brightness and DISE school datasets. With these data, I can follow village outcomes and treatment status over time.

[29]The canonical parallel trend assumption required by TWFE estimator states that the underlying trends of the two groups being considered are similar. In particular, we need to assume that the trends in energy access (human capital) outcomes between the treatment and control villages would have been the same in the absence of a mini-grid.

where D_{vt} are dummy variables indicating the number of years ($\tau = -3, \ldots, 5$) for village v relative to year of mini-grid installation. The omitted variable is $\tau = -1$ and corresponds to one year prior to mini-grid installation. Therefore, each coefficient δ_τ should be interpreted as the average change in outcome of interest in period τ in villages treated with mini-grids relative to the control villages, and all these coefficients should be interpreted relative to period $\tau - 1$. The rest of the parameters are defined as before. I discuss the validity of the parallel trend assumption using the raw data as well as using the event-study framework in the Results Section.

3. Data-driven control and treatment groups

I employ a data-driven approach to select treatment and control groups, aiming to identify affected and unaffected groups with similar observable characteristics. The descriptive analysis relies on raw nighttime brightness data, and Figure 1 presents the corresponding results. The figure displays the difference in maximum nighttime brightness levels (measured in nanoWatts/cm²/sr) before and after mini-grid installation at varying distances from all mini-grids within my study sample. Specifically, each bar represents the difference in maximum brightness within concentric circles (or rings) at 0.5 km intervals. The figure demonstrates that proximity to mini-grids is related to increased light levels after mini-grid installation. Notably, areas immediately adjacent to mini-grids exhibit substantial radiance increases, but this brightness increase diminishes as the distance from the mini-grids increases, stabilizing after a 2 km radius. This observation remains consistent when alternative brightness measures, such as mean and median brightness, are considered (see Figure A2 in the Appendix). Based on this finding, I designate villages within 0-2 km as the treatment group and villages within 2-5 km as the control group for subsequent empirical analysis. The Robustness section further explores the robustness of the results to alternative distance thresholds, yielding consistent findings across different specifications.

4. Balance tests

Finally, my empirical strategy relies upon the assumption that, within relatively narrowly defined geographical zones (as defined above), the location of a mini-grid is uncorrelated with other factors affecting electricity access, human capital, and other related household outcomes. That is, at the local level, mini-grids are not built close
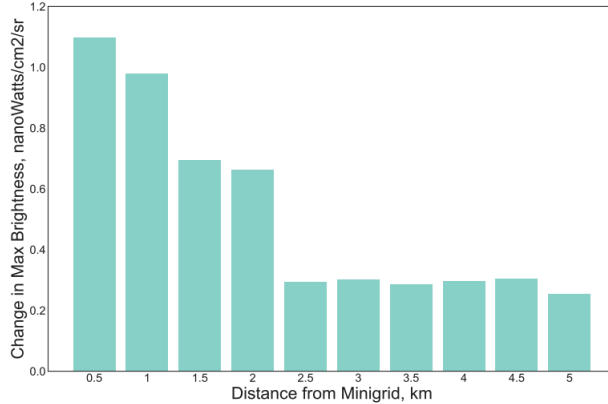
Figure 1. Data-driven control and treatment groups: Maximum brightness

Note: The figure displays the difference in nighttime brightness levels (measured in nanoWatts/cm^2/sr) before and after mini-grid installation at varying distances from all mini-grids within my study sample. In this Figure, each bar represents the maximum recorded brightness value within concentric circles (or rings) at 0.5 km intervals.

to the households that (for pre-existing characteristics) are more likely to get an electricity connection, and/or far from those less likely to do so. Instead, the exact location of a mini-grid within a narrowly defined geographical area is likely determined by other (exogenous) factors, such as surface roughness, solar irradiance, climatic conditions and presence of a sufficiently ample flat terrain. Thus, each village's social characteristics, household, consumption, poverty, employment, amenities, and other characteristics should not be predictive of the village's treatment status. As an empirical test for this assumption, Table B3 examines whether different village-specific population characteristics can predict the mini-grid roll-out.[30] It shows that most of the village characteristics fail to predict whether the mini-grid would be installed. However, villages with a slightly higher number of households, higher village areas, and a larger number of primary schools are more likely to be treated. However, it is reassuring to see that taken jointly, predetermined characteristics of the villages cannot explain whether the village received a mini-grid.

---

[30]The village-specific baseline characteristics are computed based on Census 2011 data(year preceding the treatment).

5. Results and Discussion

1. Energy access

Main results. I begin by presenting descriptive evidence on the impact of mini-grid installation on maximum nighttime brightness in Figure 2. In the left panel of Figure 2, I illustrate the nighttime brightness trends in both the control and treatment groups over time, relative to the installation of the nearest mini-grid. Prior to the installation, no differential trends are observed. After year zero, the control group maintains a consistent level of 1.5 brightness units, while the treatment group experiences growth.[31]

Subsequently, I provide formal event-diagram-type estimation results in the right panel of Figure 2. The pattern shows no evidence of pre-trends: the estimates of the pre-treatment dummies are all close to zero and insignificant. The estimates for post-implementation years 4 and beyond are positive and statistically significant at the 5% level.[32]

The effects on brightness gradually emerge after the installation.[33] I find that, on average, the installation of mini-grids leads to an increase of approximately 0.23 brightness units, which is equivalent to a 21% growth in nighttime brightness compared to control villages.[34] When comparing these findings with previous studies such as Min & Gaba (2014), the estimated effect size is similar to installing 15 additional streetlights or providing electricity to 60 more homes in a village. For a more detailed

[31]This observation remains consistent when alternative brightness measures, such as mean and median brightness, are considered (see Figure A4 in the Appendix).

[32]Only a few observations are allocated to some of the dummy variables indicating each specific year of treatment duration. Thus, I do not have the power to identify significant effects for all the different years of duration of exposure.

[33]The lagged effects can be attributed to several factors. Firstly, it takes time for users to adopt new technology, learn about it through word of mouth, understand their energy requirements, and decide which appliances to acquire. Moreover, a significant amount of time is required for a sufficient number of people to connect to the mini-grid, enabling the detection of these changes. Also, the noise in satellite data makes it challenging to precisely measure the effects of early adopters if their numbers are limited. Secondly, the installation date is fuzzy. Some mini-grids are installed early in the year, while others are installed later. Additionally, the installation date is imperfectly measured. Since a considerable portion of mini-grid data is obtained from remote sensing, I record an installation year when solar panels are placed on the ground, but I may not observe the completion of wiring, infrastructure, and system testing, which can introduce additional delays. Finally, the increase in brightness may also reflect overall community development and the installation of streetlights. Therefore, it is plausible to expect that it would take time for the village to develop, and the increase in lights might signify the community's development, not just electrification.

[34]Intuitively, this result should be interpreted as a lower bound of the effect of mini-grid on energy access for several reasons. First, not all energy uses will generate electric light. Second, these effects will only reflect the effects attributable to systems that possess battery storage or where households are able to use rechargeable lights. In reality, the true effects may be larger.
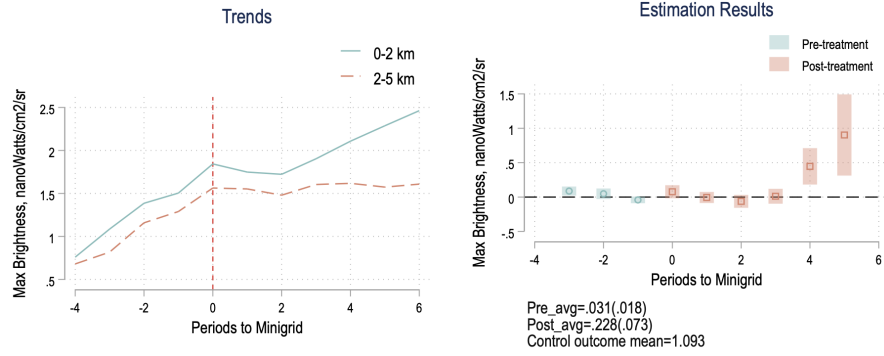
Figure 2. Effects of mini-grid on night-time brightness

Note: The figure illustrates the effects of mini-grid installation on nighttime brightness. The left panel presents descriptive evidence on the impact of mini-grid installation on nighttime brightness by plotting nighttime brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation. The right panel provides formal event-diagram-type estimation results. This panel plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval for night-time brightness. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

comparison to electrification effects found in the literature, please refer to Table 1. The key takeaway from this Table is that solar mini-grids indeed represent an effective means of providing energy access to remote communities, albeit with estimated effects somewhat smaller than those observed in central grid expansion programs in countries like India, Senegal, South Africa and others.

Table 1—Benchmarking of mini-grid effects on energy access

Study	Treatment	Effect size
This study	Stand-alone solar mini-grid, India	0.23-0.28 units ↑ at 2 km radius
Burlig & Preonas (2024)	Central grid (RGGVY), India	0.18–0.37 units ↑ 4–5 years later
Min et al. (2013)	Central grid, Senegal	0.36-unit ↑
Machemedze et al. (2017)	Central grid, South Africa	0.35-units ↑

Note: The table compares the primary estimates presented in this study and those documented in the existing literature pertaining to electrification effects. Column (1) identifies the specific studies referenced, while Column (2) outlines the different treatment types under consideration. These treatments encompass standalone mini-grid systems and central grid extensions. Column (3) presents the estimated effect sizes of each treatment as reported in the respective studies.

Heterogeneity by mini-grid system size and distance to mini-grid. I conduct a heterogeneity analysis of mini-grid effects. Previous research (e.g., Burlig & Preonas (2024)) has indicated that village characteristics and infrastructure features can influence the effectiveness of infrastructural projects. As shown in Figure A5, the results of the heterogeneity analysis based on mini-grid size indicate that the observed effects on brightness are primarily associated with medium and large-scale mini-grid installations. This result is consistent with the expectation that larger installations have the capacity to power more electric uses, including improved home and street electric lighting.

Additionally, I conduct a placebo exercise to measure the effects at varying distances from the mini-grid. The results, presented in Figure A6, reveal an expected pattern. Although the point estimates are not statistically different, the pattern of effects suggests that as distance to the mini-grid decreases, there is a more substantial increase in nighttime brightness. This observation aligns with the understanding that the cost of delivering electricity rises with the distance between the mini-grid and consumers (Odarno et al., 2017). Households located near a mini-grid are more likely to connect and benefit from a more reliable service compared to those farther away.

2. Education

Main results. Figure 3 displays the event-study estimation results for child enrollment outcomes, confirming no evidence against the parallel trend assumption. The estimates of the pre-treatment dummies are all close to zero and insignificant. On the other hand, all point estimates for post-treatment years are positive. Notably, the analysis reveals an approximate 8% increase in student enrollment at the village level in the post-treatment period, indicating a positive impact on children's educational outcomes.

These enrollment effects exhibit a cumulative pattern over time, which is in line with the requirement of sustained energy access to influence the way people live and, consequently, educational outcomes. To provide further context, Table 2 compares the impact sizes of mini-grid projects to those found in the literature on infrastructure projects, such as central grid electrification programs (Khandker et al., 2014; Van de
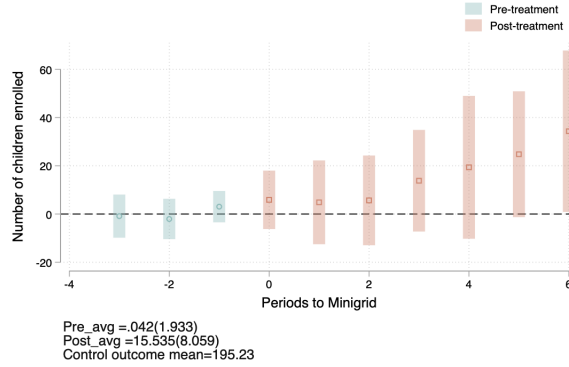
Figure 3. Effects of mini-grid on village-level enrollment

Note: The figure illustrates the effects of mini-grid installation on total village level school enrollment. It plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval for enrollment outcome. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

Walle et al., 2013; Khandker et al., 2013) and sanitation improvement programs (Adukia, 2017). The 8% increase in enrollment falls well within the range of school participation effects.

Table 2—Benchmarking of mini-grid effects on enrollment

Study	Treatment	Effect size
This study	Stand-alone solar mini-grid, India	8 %
Khandker et al. (2014)	Central grid (RGGVY program), India	6-7 %
Van de Walle et al. (2013)	Central grid expansion 1980-1990, India	10-14 %
Khandker et al. (2013)	Central grid, Vietnam	6-9 %
Adukia (2017)	Improving school sanitation, India	8-12 %

Note: The table compares the primary estimates presented in this study and those documented in the existing literature analyzing the effects of infrastructural projects on education. Column (1) identifies the specific studies referenced, while Column (2) outlines the different treatment types under consideration. These treatments encompass standalone mini-grid systems, central grid extensions and school sanitation improvement program. Column (3) presents the estimated effect sizes of each treatment as reported in the respective studies.

Heterogeneity. When analyzing effect sizes by gender, I observed similar magni-

tudes for both girls and boys. As shown in Figure 4, village-level enrollment increases by approximately 8 students, regardless of gender.
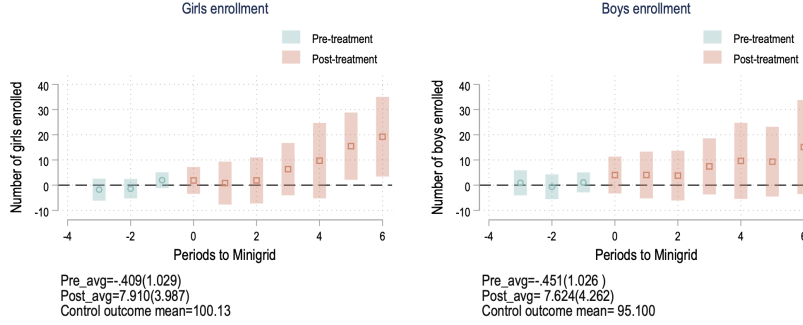

Figure 4. Heterogeneity analysis: Enrollment effects by gender

Note: The figure illustrates the effects of mini-grid installation on village level school enrollment by gender. Left panel plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval for girls enrollment. Right panel plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval for boys enrollment. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

Furthermore, Figure 5 examined enrollment effects based on school type, which includes primary, middle, and high school. This analysis is motivated by the fact that transitions from primary to middle school and from middle school to high school represent significant educational milestones. Additionally, younger children typically have fewer labor market opportunities. Given the near-universal enrollment in primary schools in India, it is unsurprising that we observe no substantial changes in the number of primary school students. The results indicate that the enrollment effects are primarily driven by high school enrollment.

6.   *Robustness*

To test the robustness of my baseline results, I conduct a variety of checks. The results are not sensitive to the inclusion of broad sets of controls, alternative sample restrictions, utilization of different measurements for treatment variables as well as utilization of alternative identification strategies.

First, I assess the sensitivity of the results to alternative definitions of control groups and distance thresholds. Table B5 explores the robustness of the estimated
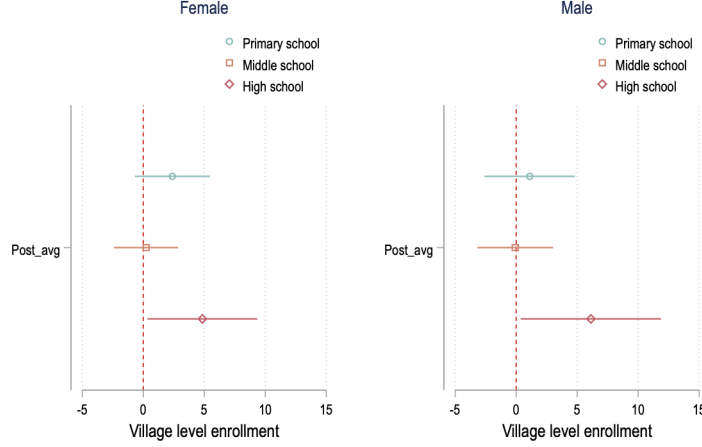
Figure 5. Heterogeneity analysis: Enrollment effects by school type and gender

Note: The figure presents the results of a heterogeneity analysis, specifically examining the effects of mini-grid installation on village-level school enrollment by gender and type of school. The types of schools have been categorized into three distinct groups: primary, middle, and high school. The depicted estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The treatment group includesvillages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

treatment effects to different control groups, while Table B6 conducts a placebo check analysis, examining the effects of minigrid installation on nighttime brightness at larger distances where no treatment effects are expected to occur. The results of these analyses provide evidence that the estimated results are robust and suggest that the effects are likely not driven by factors unrelated to the mini-grids.

Second, I address the sensitivity of the estimated results to the choice of brightness measures at the village level. In the Data section, I outlined the construction of a yearly brightness panel at the village level. The baseline measure assigns each village the maximum brightness value across all pixels within the village's shapefile polygon (Burlig & Preonas, 2024). This approach aligns with the typical organizational structure of South Asian villages, characterized by concentrated inhabited regions surrounded by fields. Using the maximum brightness effectively captures light emitted from village settlements while avoiding averaging over unlit agricultural land. To assess the robustness of the maximum brightness measure, I explore alternative

measures, such as the mean and median of village-level brightness. The results, presented in Table B7, demonstrate that while the significance of the findings remains consistent, the effect size is slightly smaller when using these alternative measures.

Third, I consider alternative sample restrictions beyond the baseline analysis, which is conducted on villages that were unelectrified as of Census 2011. To address concerns about data reliability, I introduce two alternative definitions for unelectrified villages. The first definition examines the presence of a central grid line within a village polygon, leveraging OpenStreetMap (OSM) data.[35] The second definition utilizes nighttime brightness from years preceding treatment (2014-2015) and restricts the sample to villages with a brightness level below 1 nanoWatts/cm2/sr, as measured by maximum brightness. Table B8 displays the results for the baseline and these additional definitions. While Definition (1) yields a larger sample but may be less precise due to potential missing minor central grid lines in OSM, Definition (2) broadly aligns with the baseline definition. Importantly, the results remain broadly consistent across all definitions.

Additionally, my baseline results are obtained using the Callaway & Sant'Anna (2021) approach, with the "never-treated" group as a control. As depicted in Figure A9, the results remain stable when employing the "not yet treated" group as an alternative control group. Additionally, I compare my baseline results with those obtained using the Two-Way Fixed Effects (TWFE) specification, as outlined in Equation 5. Specifically, Table B9 presents the results of this robustness analysis based on TWFE, which includes the use of different brightness measures and sample restrictions. The findings from this analysis are broadly consistent with the estimates obtained through the approach by Callaway & Sant'Anna (2021), although the effect sizes appear somewhat larger.[36] Furthermore, I test the robustness of my results using the alternative staggered treatment strategy proposed by De Chaisemartin & d'Haultfoeuille (2020). Figure A7 presents these results, which exhibit a consistent increasing trend, a finding that is mirrored across the different estimators I employed.

---

[35]Central grid infrastructure data from OSM has been previously used for the creation of India's geospatial energy map by NITI Aayog in collaboration with Indian Space Research Organization with the support of Energy Ministries (Jain, 2020).

[36]Given the presence of dynamic effects, the estimates derived through TWFE are potentially biased upwards. Thus, I use the results obtained with the Callaway & Sant'Anna (2021) approach as my baseline results.

Moreover, I demonstrate the robustness of my findings to different definitions of treatment variables. I report the results by grouping the years of exposure into pre-intervention, early post-intervention stage (0-2 years), and late post-intervention stage (3-5 years) in Figure A8. The idea is that if the effects are driven by income changes, we would only observe the changes after a certain amount of time. The results of this analysis reveal a pattern broadly consistent with the hypothesis that longer exposure generates larger impacts on energy access and child school enrollment. Indeed, most of the night-time brightness and education improvements occur in the later post-intervention stage, supporting the notion that the income channel could be at play.

In a final step, I conduct a robustness exercise to test an alternative timing for the treatment start year. This analysis is motivated by the potential imprecision in the recorded installation dates. Since a considerable portion of mini-grid data is obtained from remote sensing, my baseline results record the installation year when solar panels are placed on the ground. However, this method may not capture the completion of wiring, infrastructure, and system testing, which can introduce additional delays. For this robustness analysis, I record installation dates based on changes in night-time brightness. Specifically, I focus on locations that have experienced substantial changes in night-time brightness. These locations can be considered as ones where mini-grids are actually operational as opposed to merely installed.[37] Panel (a) of Figure A10 presents the results of this exercise graphically and shows that even in villages that experience changes in brightness, the effects on education still emerge over time, similar to the baseline results.[38][39] Finally, I show the robustness of the results to different threshold choices in Panel (b) of Figure A10. The results remain robust across different threshold levels.[40]

---

[37]In the pre-treatment periods, the villages in the sample have very low levels of light (almost near zero), so it is essential to establish an emitted light threshold to define the mini-grid installation date. This avoids setting a date based on noise in satellite data. I use a threshold of 0.25 nanoWatts/cm2/sr for this analysis (corresponds to 35% increase). A village is considered treated when the night-time brightness increases by at least 0.25 nanoWatts/cm2/sr for the first time after solar panels are recorded on the ground.

[38]Importantly, this sample is smaller than the baseline analysis because it only includes villages that experience a change in brightness.

[39]Intuitively, I expect the educational signal should improve if we refine the sample to only include mini-grids that are operational. However, the educational signal would decrease if other grids (excluded) were also operational but the sample was reduced by focusing only on grids that produce light.

[40]If I reduce the noise threshold, I expect the effect sizes will decrease because the start year will be more affected by noise in the data. The estimates may also become less precise if I increase the threshold too much,

7. Potential mechanisms

Given the observed changes in children's educational outcomes, it would be of interest to investigate the potential mechanisms underlying these changes. This study aims to elucidate two distinct channels contributing to these observed outcomes: the *supply of education* (educational infrastructure, teacher quality, and quantity, number of schools) and *demand for education* (time allocation, health, agricultural production, income, and social attitudes toward education). The findings reveal compelling evidence that mini-grids play a pivotal role in improving access to energy at home and enhancing ownership of electric appliances. The increased ownership of electric fans suggests potential health benefits and a reduction in exposure to extreme heat. Additionally, there are indications of improved ownership of productive assets, enhanced dwelling quality and improved agricultural yields, which, in turn, hint at possible improvements in household incomes. Finally, the increased ownership of cell phones, radios, and TVs suggests a potential increase in media exposure. This, in turn, could sensitize individuals to the importance of education, potentially stimulating parental investments in the education of their children.

1. Education supply and related mechanisms

I begin by examining the mechanisms related to education supply. In theory, electrification through mini-grids could grant schools access to electricity, enabling lighting, operation of electronic devices, and powering audio-visual equipment. Such access can significantly improve the learning environment, facilitating reading, studying, and participation in technology-based education. Moreover, electrification may make these areas more appealing for teachers, potentially encouraging inward migration from areas lacking electricity. Additionally, mini-grids have the potential to increase the number of schools in a community, as they can power electric tools and equipment, leading to enhanced precision and efficiency, resulting in faster construction processes.

Utilizing the DISE school data, I explore several channels, as summarized in Table 3. These channels encompass electricity access, teacher quantity and quality, school infrastructure, and the number of schools. Overall, I find no compelling evidence

as some treated villages with smaller brightness changes would be excluded from the sample.

of education supply factors playing a significant role, except for a small marginally significant increase in the number of schools.[41] This observation aligns with the notion that mini-grid systems are primarily targeted for residential use rather than school and municipal use in the setting of this study. It suggests that the primary driver of change is electricity at home, rather than in schools in this setting.

Table 3—Mechanisms: School energy access and infrastructure

	Any Electricity (1)	Electricity Functional (2)	Number of Schools (3)	Number of Teachers (4)	Teachers with ≥ BA (5)	Ramps (6)
Post Avg	0.022 (0.015)	0.016 (0.015)	0.048* (0.026)	0.062 (0.112)	-0.006 (0.018)	0.017 (0.016)
Observations	23,985	23,985	23,985	23,985	23,985	23,985
Control Outcome Mean	0.091	0.083	2.351	4.448	0.644	0.679
	Playground (7)	Boundary Wall (8)	Latrines Functional (9)	Medical Checks (10)	Road (11)	Any Computers Available (12)
Post Avg	0.002 (0.017)	-0.014 (0.016)	0.052 (0.070)	0.041 (0.033)	0.054 (0.036)	0.030 (0.045)
Observations	23,985	23,985	23,985	23,985	23,985	23,985
Control Outcome Mean	0.495	0.332	1.038	0.569	0.896	0.061

Note: The table presents the results for the effects of minigrid installation on school-level energy access and infrastructure. The estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Source: District Information System for Education, 2014-2022.

2. Education demand and related mechanisms

Agricultural outputs. The most compelling evidence arises from changes in agricultural production driven by the introduction of mini-grids. Mini-grids have the potential to support the use of electricity for pumps and irrigation systems, thereby contributing to mechanization of labor, increased agricultural production and family income.[42] To gauge this impact, I employ the Enhanced Vegetation Index (EVI) as

---

[41]While access to electricity may have facilitated school construction, leading to a marginal increase in the number of schools, the effect is small. The increase in schools could explain only about 7% of the observed enrollment effect, suggesting that the number of schools is not a substantial confounder.

[42]Previous literature demonstrates that the input of electricity and appliances such as pumps can significantly impact crop health and yields, which can be estimated through remotely sensed data (Best, 2014; Burke & Lobell, 2017; Gupta, 2019).

a proxy for agricultural output. EVI is a chlorophyll-sensitive measure of plant matter, generated at global coverage and 250 m resolution by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Earth Observing System-Terra satellite. Each image represents a 16-day composite, with each pixel value optimized for cloud cover obstruction, image quality, and viewing geometry via the MODIS VI algorithm (Huete et al., 2002).[43]

I utilize the Google Earth Engine to create composites of these data for the years 2014-2024 for nine 16-day periods from late May through mid-October, covering the major (Kharif) cropping season in India (Selvaraju, 2003). For each composite image, EVI pixels were spatially averaged to village polygons. After village aggregation within each 16-day composite, three proxies for agricultural production are calculated for each year's growing season: the difference between early-season EVI (the mean of the first three 16-day composites) and the max EVI value observed at the village level (Labus et al., 2002; Rasmussen, 1997), mean EVI (Mkhabela et al., 2005), and cumulative EVI (Rojas, 2007), which is the sum of EVI from each of the nine composites during the growing season. All EVI measures are then log-transformed for the regressions to allow for an interpretable effect.

The effects of mini-grid installation on the Enhanced Vegetation Index (EVI) are presented in Figure 6, with formal estimates provided in Table 4. I use the differenced measure for my baseline results as it effectively controls for non-crop vegetation (such as forest cover) by measuring the change in greenness from the planting period (when the land is fallow) to the point in the season when crops are the greenest.[44][45] Figure 6 suggests that following mini-grid installation, EVI increases by approximately 5-6%, with effects growing over time. The trajectory of these effects broadly aligns with trends observed in night-light and education outcomes.[46]

[43]Intuitively, EVI measures the 'greenness' and health of vegetation on the ground.

[44]Results for alternative measures of EVI are presented in Appendix A, Figure A11. The results are robust across alternative measures of EVI.

[45]Note that EVI data is available immediately, while there is a lag in the availability of night lights data, which is typically pre-processed by the data provider "Earth Observation Group". This allows for analysis over a longer time horizon to assess the effects of treatment on the vegetation index compared to night lights.

[46]To further validate the use of growing-season EVI measures as a proxy for agricultural output at the village level, I use additional likely correlates of agricultural production (Table B4). Cross-sectional regressions with state fixed effects were run using the log of year-over-year changes in growing season EVI (as described above) as the dependent variable. For this analysis, I utilize EVI measured in the pre-treatment period. To reduce noise, I define my baseline EVI measure as the average of the measures for 2011, 2012, and 2013. At the village level, these correlates include the potential production of cereal crops (with low input usage) from

Table 4—Mechanisms: Agricultural yields

| | Enhanced Vegetation Index | | |
	Difference between early season and max value (1)	Mean value of cropping season (2)	Cumulative value of cropping season (3)
Panel A: Logs			
Pre avg	0.006	0.002	0.002
	(0.005)	(0.001)	(0.001)
Post avg	0.056***	0.033***	0.033***
	(0.020)	(0.007)	(0.007)
Observations	23,985	23,985	23,985
Control mean	8.291	8.199	10.396
Panel B: Levels			
Pre avg	27.883	5.301	47.712
	(18.465)	(4.224)	(38.012)
Post avg	241.279**	118.304***	1064.738***
	(78.987)	(23.534)	(211.808)
Observations	23,985	23,985	23,985
Control mean	4164.103	3677.014	33093.12

Note: The table presents the results for the effects of minigrid installation on the agricultural outputs proxied by the Enhanced Vegetation Index (EVI). The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. Standard errors are clustered at village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Data source: satellite imagery collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Earth Observing System-Terra satellite from 2014 to 2024. Annual composites are generated from 16-day composites at a 250 m resolution by aggregating data within village polygons.

The use of electric water pumps facilitates labor-capital substitution, reducing the reliance on manual labor, particularly among older youth who were previously engaged in agricultural work. As a result, these children can return to school, leading to improvements in their educational outcomes (Self & Grabowski, 2008; Thévenon & Edmonds, 2019). Additionally, increased agricultural production can boost household incomes, enabling greater parental investment in their children's education.

Energy connections, asset ownership, and dwelling quality. As discussed in the previous subsection, increased agricultural production can boost household incomes, which may, in turn, drive the adoption of additional electric appliances and further enhance household welfare through multiple channels. In this subsection, I present

the FAO Global Agro-Ecological Zones (GAEZ) aggregated to the village level, the share of village land area under any type of irrigation, the share of village area used for agriculture, and per capita annual consumption. Table B4 shows that this measure is highly correlated with three other proxies for agricultural productivity and per capita consumption at the village level. Previous research, such as the work of Asher & Novosad (2020), has explored the use of this proxy. Researchers have shown that the district-level vegetation index is a good predictor of district-level agricultural output using data from the Planning Commission's series of district domestic product data.
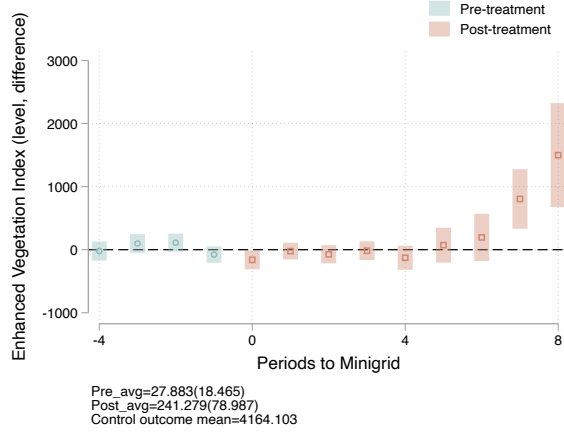
Figure 6. Mechanisms: Effects of mini-grids on agricultural productivity

Note: The figure plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval. Enhanced Vegetation Index (EVI) is represented as the difference between early-season EVI and the max EVI value observed at the village level. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.
Source: satellite imagery collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Earth Observing System-Terra satellite from 2014 to 2024. Annual composites are generated from 16-day composites at a 250 m resolution by aggregating data within village polygons.

findings on access to electricity and household assets using data from the 2015/16 and 2019/21 DHS waves. First, I present evidence on generalized outcomes in Table 5. To draw general conclusions about the mini-grids' effects, I present findings for summary indices that aggregate information over multiple treatment effect estimates. For example, I create an index of electric appliance ownership that averages together nine types of electric appliances. The aggregation improves statistical power to detect effects that go in the same direction within a domain.[47]

The results indicate increased at-home energy access and electric appliance ownership. However, it is essential to note that the increase does not yet seem sufficient to use electricity for cooking.[48] Further, I present the estimated effects on outcomes

---

[47]The summary index is defined to be the equally weighted average of z-scores of its components, with the sign of each measure oriented so that more beneficial outcomes have higher scores. The z-scores are calculated by subtracting the control group's mean and dividing by the control group's standard deviation. Thus, each component of the index has a mean of zero and a standard deviation of one for the control group. Consequently, the units of summary indices are standard deviations of control group outcomes.

[48]In principle this is conceivable as cooking appliances require larger power loads compared to simpler de-

Table 5—Mechanisms: Residential energy access and asset ownership

	Have Electricity		Electric Appliances Ownership Index		Electricity as Fuel for Cooking		Productive Asset Index		Dwelling Quality Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Within 2 km*After	0.096**	0.101**	0.078**	0.092**	0.031	0.030	0.049	0.065	0.033	0.040
	(0.046)	(0.046)	(0.035)	(0.037)	(0.025)	(0.025)	(0.051)	(0.048)	(0.040)	(0.040)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,239	10,239	10,239	10,239	10,239	10,239	10,239	10,239	10,239	10,239
Control Outcome Mean	0.037	0.037	0.000	0.000	0.024	0.024	0.000	0.000	0.000	0.000

Note: The table presents the results for the effects of minigrid installation on residential energy access, asset ownership, and associated outcomes. The estimates are based on a simple difference-in-differences approach that compares villages relatively close and relatively far from the minigrid before and after minigrid has been installed. The 'before' period is based on the 2015/16 wave DHS data, and the 'after' period uses the 2019/21 wave DHS data. The treatment group includes villages within 2 km of minigrid, while the control group includes villages from 2 to 5 km from minigrid. The electric appliance ownership, productive asset ownership, and dwelling quality are represented by summary indices. The summary indices are defined to be the equally weighted average of z-scores of its components, with the sign of each measure oriented so that more beneficial outcomes have higher scores. The z-scores are calculated by subtracting the control group's mean and dividing by the control group's standard deviation. Thus, each component of the index has a mean of zero and a standard deviation of one for the control group. Consequently, the units of summary indices are standard deviations of control group outcomes. Columns (1), (3), (5), (7), and (9) include state fixed effects and district fixed effects. Columns (2), (4), (6), (8), and (10) include village-level controls. Standard errors are clustered at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Source: The Demographic and Health Survey(DHS), waves 2015/16 and 2019/21

that can proxy for structural changes in households, such as productive asset ownership or household dwelling quality. While point estimates for these outcomes are not significant, it's worth noting the 0.065 SD increase in household productive asset ownership and 0.040 SD increase in the household quality index compared to the control group.[49]

In addition, I present evidence on specific electric asset ownership, as depicted in Figure 7. The results indicate that the effects are primarily driven by radios, TVs, and mobile phone ownership. This suggests the potential role of the media exposure channel. Prior studies (Cheung, 2012; Ferrara et al., 2012; Jensen & Oster, 2009; Keefer & Khemani, 2011) have shown that access to media can promote alternative

vices such as TVs, fans, phones and electric lights. Traditional cooking alternatives, such as wood, agricultural crop residues, shrubs, grass, coal, and animal dung, remain prevalent. Although the coefficient estimates are not significant, I cannot rule out the possibility of a doubling in cooking with electricity in treated communities in response to mini-grid installation.

[49]There are several key points to consider regarding these results. First, these findings are based on a smaller sample of villages from DHS data, rather than encompassing all villages in the Census data, which might result in reduced statistical power.

Secondly, it is important to acknowledge that for privacy reasons, DHS displaces respondents' village coordinates by up to 5 km for rural clusters. This displacement may potentially lead to contamination of the treated group with control units. As a result, I will mechanically understate the differences between control and treatment groups, and potentially obtain downward-biased estimates of the true effects. Finally, using DHS data, one can measure treatment effects at a maximum of 3 to 4 years after installation, which might not provide sufficient time to fully reflect changes in the outcomes of interest.

role models, teach life skills, and alter attitudes towards gender and education.
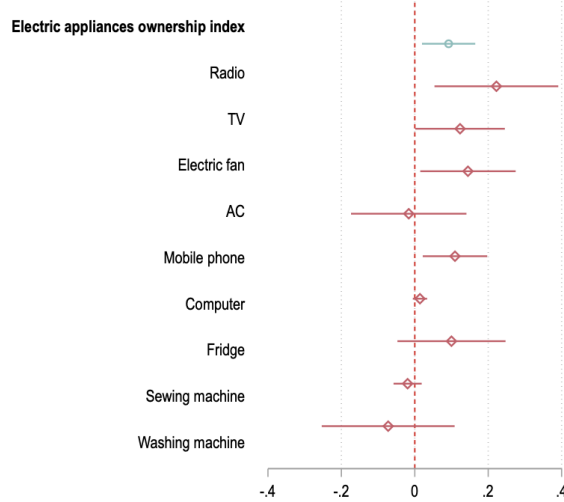

Figure 7. Mechanisms: Electric appliances ownership and index components

Note: The figure presents the results for the effects of mini-grid installation on the electric appliance ownership index and specific index components. The estimates are based on a simple difference-in-differences approach that compares villages relatively close and relatively far from the mini-grid before and after mini-grid has been installed. The 'before' period is based on the 2015/16 wave DHS data, and the 'after' period uses the 2019/21 wave DHS data. The treatment group includes villages within 2 km of mini-grid, while the control group includes villages from 2 to 5 km from mini-grid. The summary index of electric appliance ownership combines together nine types of electric appliances. The summary index is defined to be the equally weighted average of z-scores of its components, with the sign of each measure oriented so that more beneficial outcomes have higher scores. The z-scores are calculated by subtracting the control group's mean and dividing by the control group's standard deviation. Each component of the index has a mean of zero and a standard deviation of one for the control group. The units of summary indices are standard deviations of control group outcomes. *Source:* The Demographic and Health Survey (DHS), waves 2015/16 and 2019/21.

Notably, we observe that AC ownership remains unchanged, likely due to its lesser prevalence and affordability in rural Indian communities. However, the increase in fan ownership suggests a potential influence of the heat adaptation investment channel. Mini-grids offer energy for vital heating and cooling services, aiding communities in coping with extreme weather events, which is crucial given the documented detrimental impact of extreme temperatures on cognitive performance, educational attainment and productivity (Garg et al., 2020, 2022).

Demographic Changes and Migration. As discussed in the Background Section, the electrification of communities through mini-grids can make them more attractive, potentially leading to an influx of residents from unelectrified areas. Additionally, as

communities develop, they may experience population growth, including an increase in the number of children within a village. Given that I only have absolute enrollment numbers and cannot directly calculate enrollment and attendance rates, it is important to ensure that observed enrollment effects are not driven by changes in the demographic composition of the villages.

To assess whether there have been demographic changes following the installation of mini-grids, I utilize Census data from 2011 and a Mission Antyodaya Village Survey conducted in 2018/20.[50] I employ a simple difference-in-differences approach, where the 'before' period is based on the 2011 Census data, and the 'after' period uses the village survey. Control and treatment groups are defined based on distance, as discussed previously. The results are presented in Table 6 and provide suggestive evidence that there have been no significant changes in the number of children or adults present in a village. This indirect evidence sheds light on no observed changes in migration or fertility rates.

Table 6—Mechanisms: Demographic trends

| | Children aged 0-6 | | Total population | |
| | Female | Male | Female | Male |
	(1)	(2)	(3)	(4)
Within 2 km*After	-0.674	-6.224	9.383	2.698
	(8.536)	(8.793)	(72.098)	(66.774)
Observations	8,584	8,584	8,584	8,584
Control Outcome Mean	118.681	128.111	873.527	834.214

Note: The table presents the results for the effects of minigrid installation on the children counts and total village-level population counts. The estimates are based on a simple difference-in-differences approach that compares villages relatively close and relatively far from the minigrid before and after minigrid has been installed. The 'before' period is based on the Census 2011, and the 'after' period uses the Mission Antyodaya Survey(2018/20). The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. Standard errors are clustered at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Source: Census 2011 and Mission Antyodaya Survey(2018/20).

[50]This survey is used as the 2021 India Census data is still not available. This survey comprises a substantial subset of all census villages.

8. Cost Benefit Analysis

This section conducts back-of-the-envelope cost-benefit analysis of solar mini-grid technology for different scenarios. The analysis focuses on the average system in the sample (100 kWp capacity) and considers various costs, including wiring, solar panels, batteries, inverters, powerhouse construction, smart meters, and training on management and use. Costs are front-loaded, while benefits accumulate over time. Table B10 summarizes these results.

In the first scenario, I only include the household personal consumption benefits.[51] I compute village benefits by multiplying the change in consumption by per-capita consumption expenditure from Census 2011 by village population size, to measure these effects. Then, I calculate the present discounted sum of village-wide benefits over 20 years. Specifically, for a 1,900-person village, the computed internal rate of return (IRR) is 17%, which is above the 10–12% threshold for social discount rate commonly used to benchmark cost-effectiveness (Asian Development Bank, 2013; Bonzanigo & Kalra, 2014).[52] Initial expenditures are recouped within a 5-year period.

The second scenario adds the benefits of improved education to consumption benefits. The estimated 8% education improvement is converted to improved lifetime earning potential.[53] With this additional enrollment benefit, the mini-grid becomes even more cost-effective, with an IRR of 21% and costs recouped within 5 years. The third scenario incorporates the expected reduction in battery costs. According to IRENA (2017), battery storage costs are expected to fall by more than 50% by 2030. With this reduction, the mini-grid technology becomes even more cost-effective, with an IRR of 26% and costs recouped within 4 years.

This analysis shows that mini-grids bring comparable effects in increasing energy access (Burlig & Preonas, 2024; Machemedze et al., 2017; Min et al., 2013) and enrollment opportunities (Khandker et al., 2014; Van de Walle et al., 2013; Khandker

[51]I compute these benefits using the estimated effect of mini-grids on night lights. Specifically, there is an extensive literature that tries to connect night light to economic activity, local GDP, and consumption expenditure. I utilize the derived relationship from this literature, where an increase of 1 unit of light roughly means a 10% increase in household consumption (Chen & Nordhaus, 2011; Asher et al., 2021; Beyer et al., 2022).

[52]The internal rate of return (IRR) is the annual rate of growth that an investment is expected to generate. The IRR identifies the rate of discount, which makes the present value of the sum of annual nominal cash inflows equal to the initial net cash outlay for the investment.

[53]Earning potential figures are based on rural skilled salaries from the NSS survey 66th round.

et al., 2013) to central grid expansion projects. However, mini-grid installation costs are lower as compared to the central grid expansion costs in India.[54] Together, these findings potentially suggest that decentralized solar mini-grids offer a cost-effective solution for electrifying remote communities.

9. Conclusion

The global electrification frontier is evolving, with emerging green technologies like solar mini-grids helping to bridge the energy gap in remote rural areas. This paper investigates the impact of solar mini-grids on energy access and human capital accumulation in rural India.

By utilizing remote imagery data, conventional survey data, and a Difference-in-Differences estimation strategy, this study reveals significant positive effects of mini-grid electrification. The installation of mini-grids has led to a substantial 21% improvement in energy access, as measured by nighttime brightness. This increase in energy access, driven primarily by medium and large-scale mini-grid installations, has translated into tangible educational benefits for children in the affected communities. Enrollment in schools has seen an approximate 8% increase, with noteworthy effects observed for both boys and girls. Furthermore, this study delves into the mechanisms driving these observed outcomes, dispelling the notion that school electrification is the primary driver. Instead, it is the provision of electricity to homes that has had a more substantial impact on educational attainment, underscoring the importance of household access. Additionally, this research reveals evidence that aligns with shifts in the demand for education, encompassing changes in agricultural production, health, household income, and attitudes toward education.

This research contributes to the literature on the impact of electricity infrastructure projects on development by providing the first empirical evidence on the longer-term effects of solar mini-grid expansion at scale. It shows that such decentralized, renewable-based technologies can indeed drive positive changes and serve as cost-

---

[54]For this comparison, I utilize a conservative central grid expansion cost estimate based on the 2005-2012 RGGVY program costs (Burlig & Preonas, 2024; Banerjee & Duflo, 2014). Specifically, the RGGVY program costs include fixed cost of Rs 1.8 million per village, plus Rs 2,200 in variable costs per household. In reality, central grid expansion costs are likely even higher in my setting, as the sample of unelectrified villages is now more remote, and the costs only include extending distribution infrastructure, excluding maintenance or improvement in generating capacity costs.

effective alternatives for electrifying remote communities. These findings have implications not only for India but also for other developing countries facing similar energy access challenges. Policymakers could consider integrating mini-grids into the broader national energy mix while offering fiscal policy incentives, such as subsidies and tax benefits, to encourage widespread adoption and support upstream industries like solar cell and battery storage production.

As the world continues to grapple with the dual goals of sustainable development and environmental protection, the role of green technologies like solar mini-grids becomes increasingly significant. This research underscores the potential of such technologies to contribute to win-win outcomes, fostering development without compromising environmental quality.

While this study provides insights into the impact of solar mini-grids on energy access and educational outcomes in rural India, several avenues for future research remain. First, longitudinal studies that track the long-term impacts of mini-grid electrification on various socioeconomic outcomes, including health, income, employment opportunities, and firm creation, would offer a more comprehensive understanding of their benefits. Additionally, investigating the interplay between mini-grids and other renewable energy technologies, such as wind or biomass, could provide insights into optimal energy solutions for rural electrification. Finally, examining community engagement processes and local governance structures that support successful mini-grid projects could inform more effective implementation strategies. These future research directions can help refine policy approaches and maximize the development impact of solar mini-grids.

REFERENCES

Adukia, Anjali. 2017. "Sanitation and education." *American Economic Journal: Applied Economics*, 9(2): 23–59.

Aker, Jenny C., Christopher Ksoll, and Travis J. Lybbert. 2012. "Can mobile phones improve learning? Evidence from a field experiment in Niger." *American Economic Journal: Applied Economics*, 4(4): 94–120. Publisher: American Economic Association.

Aklin, Michaël, Patrick Bayer, S. P. Harish, and Johannes Urpelainen. 2017. "Does basic energy access generate socioeconomic benefits? A field experiment with off-grid solar power in India." *Science Advances*, 3(5): e1602153.

Aklin, M., P. Bayer, S. P. Harish, and J. Urpelainen. 2018. "Economics of household technology adoption in developing countries: Evidence from solar technology adoption in rural India." *Energy Economics*, 72: 35–46.

Alam, Majbaul, and Subhes Bhattacharyya. 2017. "Are the off-grid customers ready to pay for electricity from the decentralized renewable hybrid mini-grids? A study of willingness to pay in rural Bangladesh." *Energy*, 139: 433–446.

Alpert, William T., Kenneth A. Couch, and Oskar R. Harmon. 2016. "A randomized assessment of online learning." *American Economic Review*, 106(5): 378–382. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Andrabi, Tahir, Jishnu Das, Asim I. Khwaja, Selcuk Ozyurt, and Niharika Singh. 2020. "Upping the ante: The equilibrium effects of unconditional grants to private schools." *American Economic Review*, 110(10): 3315–3349. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Arderne, C., C. Zorn, C. Nicolas, and E. E. Koks. 2020. "Predictive mapping of the global power system using open data." *Scientific Data*, 7(1): 19.

Asher, Sam, and Paul Novosad. 2020. "Rural roads and local economic development." *American economic review*, 110(3): 797–823.

Asher, Sam, Tobias Lunt, Ryu Matsuura, and Paul Novosad. 2021. "Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India using the SHRUG Open Data Platform." *World Bank Policy Research Working Paper*.

Asian Development Bank. 2013. *Cost-benefit analysis for development: A practical guide.* Asian Development Bank.

Azimoh, Chukwuma Leonard, Patrik Klintenberg, Charles Mbohwa, and Fredrik Wallin. 2017. "Replicability and scalability of mini-grid solution to rural electrification programs in sub-Saharan Africa." *Renewable energy*, 106: 222–231.

Banares-Sanchez, Ignacio, Robin Burgess, David Laszlo, Pol Simpson, John Van Reenen, and Yifan Wang. 2024. "Chinese Innovation, Green Industrial Policy and the Rise of Solar Energy."

Banerjee, A., and Esther Duflo. 2014. "Economics education in the digital age: The implications of online technologies and MOOCS." Vol. 104, 514–518. Issue: 5.

Banerjee, Abhijit, Rukmini Banerji, James Berry, Esther Duflo, Harini Kannan, Shobhini Mukerji, Marc Shotland, and Michael Walton. 2017. "From proof of concept to scalable policies: Challenges and solutions, with an application." *Journal of Economic Perspectives*, 31(4): 73–102. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418.

Barrera-Osorio, Felipe, and Leigh L. Linden. 2009. "The use and misuse of computers in education: evidence from a randomized experiment in Colombia." *World Bank Policy Research Working Paper*, , (4836).

Barrett, Christopher B., Ariel Ortiz-Bobea, and Trinh Pham. 2023. "Structural Transformation, Agriculture, Climate, and the Environment." *Review of Environmental Economics and Policy*, 17(2): 195–216.

Barron, Manuel, and Maximo Torero. 2017. "Household electrification and indoor air pollution." *Journal of Environmental Economics and Management*, 86: 81–92.

Beg, Sabrin, Waqas Halim, Adrienne M. Lucas, and Umar Saif. 2022. "Engaging teachers with technology increased achievement, bypassing teachers did not." *American Economic Journal: Economic Policy*, 14(2): 61–90. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Best, Sarah. 2014. "Growing Power: Exploring energy needs in smallholder agriculture." *International Institute for Environment and Development (IIED) Discussion Paper. London, UK: IIED.*

Bettinger, Eric P., Lindsay Fox, Susanna Loeb, and Eric S. Taylor. 2017. "Virtual classrooms: How online college courses affect student success." *American Economic Review*, 107(9): 2855–2875. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Beyer, Robert CM, Yingyao Hu, and Jiaxiong Yao. 2022. *Measuring quarterly economic growth from outer space.* International Monetary Fund.

Bhatia, Mikul, and Niki Angelou. 2015. "Beyond Connections: Energy Access Redefined." Publisher: World Bank, Washington, DC.

Bianchi, Nicola, Yi Lu, and Hong Song. 2022. "The effect of computer-assisted learning on students' long-term development." *Journal of Development Economics*, 158: 102919. Publisher: Elsevier.

Blankenship, Brian, Jason Chun Yu Wong, and Johannes Urpelainen. 2019. "Explaining willingness to pay for pricing reforms that improve electricity service in India." *Energy Policy*, 128: 459–469.

Bold, Tessa, Mwangi Kimenyi, Germano Mwabu, and Justin Sandefur. 2018. "Experimental evidence on scaling up education reforms in Kenya." *Journal of Public Economics*, 168: 1–20. Publisher: Elsevier.

Bonzanigo, Laura, and Nidhi Kalra. 2014. "Making informed investment decisions in an uncertain world: a short demonstration." *World Bank Policy Research Working Paper*, , (6765).

Borghesan, Emilio, and Gabrielle Vasey. 2024. "The marginal returns to distance education: evidence from Mexico's telesecundarias." *American Economic Journal: Applied Economics*, 16(1): 253–285. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Bulman, George, and Robert W. Fairlie. 2016. "Technology and education: Computers, software, and the internet." In *Handbook of the Economics of Education.* Vol. 5, 239–280. Elsevier.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020. "Demand for electricity on the global electrification frontier." Cowles Foundation for Research in Economics, Yale University.

Burke, Marshall, and David B. Lobell. 2017. "Satellite-based assessment of yield variation and its determinants in smallholder African systems." *Proceedings of the National Academy of Sciences*, 114(9): 2189–2194.

Burlig, Fiona, and Louis Preonas. 2024. "Out of the Darkness and into the Light? Development Effects of Rural Electrification." *Journal of Political Economy*, 132(9): 2937–2971.

Byers, Logan, Johannes Friedrich, Roman Hennig, Aaron Kressig, Xinyue Li, COLIN McCormick, and Laura Malaguzzi Valeri. 2018. "A global database of power plants." *World Resources Institute*, 18.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of econometrics*, 225(2): 200–230.

Chen, Xi, and William D. Nordhaus. 2011. "Using luminosity data as a proxy for economic statistics." *Proceedings of the National Academy of Sciences*, 108(21): 8589–8594.

Cheung, Maria. 2012. "Edutainment radio, women's status and primary school participation: Evidence from cambodia." Stockholm University, Department of Economics.

Comello, Stephen D., Stefan J. Reichelstein, Anshuman Sahoo, and Tobias S. Schmidt. 2017. "Enabling mini-grid development in rural India." *World Development*, 93: 94–107.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964–2996.

Desai, Keyur. 2020. "Demand generation for solar mini-grid." Publisher: Rockefeller Foundation.

Dinkelman, Taryn. 2011. "The effects of rural electrification on employment: New evidence from South Africa." *American Economic Review*, 101(7): 3078–3108.

Dugoua, Eugenie, Ryan Kennedy, and Johannes Urpelainen. 2018. "Satellite data for the social sciences: measuring rural electrification with night-time lights." *International journal of remote sensing*, 39(9): 2690–2701.

Dunnett, Sebastian, Alessandro Sorichetta, Gail Taylor, and Felix Eigenbrod. 2020. "Harmonised global datasets of wind and solar farm locations and power." *Scientific data*, 7(1): 130.

Elvidge, Christopher D., Kimberly E. Baugh, Mikhail Zhizhin, and Feng-Chi Hsu. 2013. "Why VIIRS data are superior to DMSP for mapping nighttime lights." *Proceedings of the Asia-Pacific Advanced Network*, 35(0): 62.

Escueta, Maya, Vincent Quan, Andre Joshua Nickow, and Philip Oreopoulos. 2017. "Education technology: An evidence-based review." Publisher: National Bureau of Economic Research.

ESMAP. 2022. *Energy Sector Management Assistance Program Annual Report 2022.* World Bank.

Fabregas, Raissa, and Laia Navarro-Sola. 2024. "Broadcasting Education at Scale: Long-Term Labor Market Impacts of Television-Based Schools."

Ferrara, Eliana La, Alberto Chong, and Suzanne Duryea. 2012. "Soap Operas and Fertility: Evidence from Brazil." *American Economic Journal: Applied Economics*, 4(4): 1–31.

Fetter, T. Robert, and Faraz Usmani. 2020. *Fracking, farmers, and rural elec-*

trification in India. Ruhr Economic Papers.

Franz, Michael, Nico Peterschmidt, Michael Rohrer, and Bozhil Kondev. 2014. "Mini-grid policy toolkit." *Alliance for Rural Electrification, Eschborn, Tech. Rep.*

Garg, Teevrat, Maulik Jagnani, and Hemant K. Pullabhotla. 2022. "Structural transformation and environmental externalities." *arXiv preprint arXiv:2212.02664.*

Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2020. "Temperature and Human Capital in India." *Journal of the Association of Environmental and Resource Economists*, 7(6): 1113–1150.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Goodman, Joshua, Julia Melkers, and Amanda Pallais. 2019. "Can Online Delivery Increase Access to Education?" *Journal of Labor Economics*, 37(1): 1–34.

Graber, Sachiko, Tara Narayanan, Jose Alfaro, and Debajit Palit. 2018. "Solar microgrids in rural India: Consumers' willingness to pay for attributes of electricity." *Energy for Sustainable Development*, 42: 32–43.

Grantham, H. S., A. Duncan, T. D. Evans, K. R. Jones, H. L. Beyer, R. Schuster, J. Walston, J. C. Ray, J. G. Robinson, M. Callow, T. Clements, H. M. Costa, A. DeGemmis, P. R. Elsen, J. Ervin, P. Franco, E. Goldman, S. Goetz, A. Hansen, E. Hofsvang, P. Jantz, S. Jupiter, A. Kang, P. Langhammer, W. F. Laurance, S. Lieberman, M. Linkie, Y. Malhi, S. Maxwell, M. Mendez, R. Mittermeier, N. J. Murray, H. Possingham, J. Radachowsky, S. Saatchi, C. Samper, J. Silverman, A. Shapiro, B. Strassburg, T. Stevens, E. Stokes, R. Taylor, T. Tear, R. Tizard, O. Venter, P. Visconti, S. Wang, and J. E. M. Watson. 2020. "Anthropogenic modification of forests means only 40% of remaining forests have high ecosystem integrity." *Nature Communications*, 11: 5978.

Gupta, Eshita. 2019. "The impact of solar water pumps on energy-water-food nexus: Evidence from Rajasthan, India." *Energy Policy*, 129: 598–609.

Huete, Alfredo, Kamel Didan, Tomoaki Miura, E. Patricia Rodriguez, Xiang Gao, and Laerte G. Ferreira. 2002. "Overview of the radiometric and biophysical performance of the MODIS vegetation indices." *Remote sensing of environment*, 83(1-2): 195–213.

Ibisch, Pierre, Monika Hoffmann, and Stefan Kreft. 2016. "(PDF) A global map of roadless areas and their conservation status."

IEA. 2017. "Energy access outlook 2017: From poverty to prosperity." Publication Title: World Energy Outlook Special Report.

IRENA. 2017. "Electricity storage and renewables: Costs and markets to 2030."

Jain, Dr Gaurav V. 2020. "Geospatial Energy Map of India."

Jamison, Dean T., Barbara Searle, Klaus Galda, and Stephen P. Heyneman. 1981. "Improving elementary mathematics education in Nicaragua: An experimental study of the impact of textbooks and radio on achievement." *Journal of Educational psychology*, 73(4): 556. Publisher: American Psychological Association.

Jensen, Robert, and Emily Oster. 2009. "The power of TV: Cable television and women's status in India." *The Quarterly Journal of Economics*, 124(3): 1057–1094.

Johnston, Jamie, and Christopher Ksoll. 2022. "Effectiveness of interactive satellite-transmitted instruction: Experimental evidence from Ghanaian primary schools." *Economics of Education Review*, 91: 102315. Publisher: Elsevier.

Keefer, Philip, and Stuti Khemani. 2011. "Mass media and public services: The effects of radio access on public education in Benin." *World Bank policy research working paper*, , (5559).

Khandker, Shahidur R., Douglas F. Barnes, and Hussain A. Samad. 2013. "Welfare Impacts of Rural Electrification: A Panel Data Analysis from Vietnam." *Economic Development and Cultural Change*, 61(3): 659–692.

Khandker, Shahidur R., Hussain A. Samad, Rubaba Ali, and Douglas F. Barnes. 2014. "Who benefits most from rural electrification? Evidence in India." *The Energy Journal*, 35(2).

Kirubi, Charles, Arne Jacobson, Daniel M. Kammen, and Andrew Mills. 2009. "Community-based electric micro-grids can contribute to rural development: evidence from Kenya." *World development*, 37(7): 1208–1221.

Kruitwagen, L., K. T. Story, J. Friedrich, L. Byers, S. Skillman, and C. Hepburn. 2021. "A global inventory of photovoltaic solar energy generating units." *Nature*, 598(7882): 604–610.

Kumaranayake, Lilani. 2008. "The economics of scaling up: cost estimation for HIV/AIDS interventions." *Aids*, 22: S23–S33. Publisher: LWW.

Kurowski, Christoph, Kaspar Wyss, Salim Abdulla, and Anne Mills. 2007. "Scaling up priority health interventions in Tanzania: the human resources challenge." *Health policy and planning*, 22(3): 113–127. Publisher: Oxford University Press.

Labus, M. P., G. A. Nielsen, R. L. Lawrence, R. Engel, and D. S. Long. 2002. "Wheat yield estimates using multi-temporal NDVI satellite imagery." *International Journal of Remote Sensing*, 23(20): 4169–4180.

Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham. 2013. "Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil." *American Economic Journal: Applied Economics*, 5(2): 200–231.

List, John A. 2022. *The voltage effect: How to make good ideas great and great ideas scale.* Crown Currency Publisher.

Machemedze, Takwanisa, Taryn Dinkelman, Mark Collinson, Wayne Twine, and Martin Wittenberg. 2017. "Throwing light on rural development: using nightlight data to map rural electrification in South Africa." *DataFirst Technical Paper*, 38.

Masuda, Yuta J., Teevrat Garg, Ike Anggraeni, Kristie Ebi, Jennifer Krenz, Edward T. Game, Nicholas H. Wolff, and June T. Spector. 2021. "Warming from tropical deforestation reduces worker productivity in rural communities." *Nature Communications*, 12(1): 1601.

Min, Brian, and Kwawu Mensan Gaba. 2014. "Tracking electrification in Vietnam using nighttime lights." *Remote Sensing*, 6(10): 9511–9529.

Min, Brian, Kwawu Mensan Gaba, Ousmane Fall Sarr, and Alassane Agalassou. 2013. "Detection of rural electrification in Africa using DMSP-OLS night lights imagery." *International Journal of Remote Sensing*, 34(22): 8118–8141.

Mini-Grids Partnership. 2020. "State of the Global Mini-grids Market Report

2020."

Mishra, Pulak, and Bhagirath Behera. 2016. "Socio-economic and environmental implications of solar electrification: Experience of rural Odisha." *Renewable and Sustainable Energy Reviews*, 56: 953–964.

Mkhabela, Manasah S., Milton S. Mkhabela, and Nkosazana N. Mashinini. 2005. "Early maize yield forecasting in the four agro-ecological regions of Swaziland using NDVI data derived from NOAA's-AVHRR." *Agricultural and Forest Meteorology*, 129(1-2): 1–9.

Mobarak, Ahmed Mushfiq. 2022. "Assessing social aid: the scale-up process needs evidence, too." *Nature*, 609(7929): 892–894. Publisher: Nature Publishing Group UK London.

Moneke, Niclas. 2020. "Can big push infrastructure unlock development? evidence from Ethiopia." *STEG Theme*, 3: 14–15.

Monroe-DeVita, Maria, Gary Morse, and Gary R. Bond. 2012. "Program Fidelity and Beyond: Multiple Strategies and Criteria for Ensuring Quality of Assertive Community Treatment." *Psychiatric Services*, 63(8): 743–750.

Muchunku, Charles, Kirsten Ulsrud, Debajit Palit, and Wim Jonker-Klunne. 2018. "Diffusion of solar PV in East Africa: What can be learned from private sector delivery models?" *WIREs Energy and Environment*, 7(3): e282.

Odarno, Lily, Estomih Sawe, Mary Swai, Maneno JJ Katyega, and Allison Lee. 2017. "Accelerating mini-grid deployment in sub-Saharan Africa: Lessons from Tanzania."

Ortiz, Anthony, Dhaval Negandhi, Sagar R. Mysorekar, Shivaprakash K. Nagaraju, Joseph Kiesecker, Caleb Robinson, Priyal Bhatia, Aditi Khurana, Jane Wang, and Felipe Oviedo. 2022. "An artificial intelligence dataset for solar energy locations in India." *Scientific Data*, 9(1): 497.

Peskett, Leo. 2011. "The history of mini-grid development in developing countries." *Policy brief. Global Village Energy Partnership, London, UK*.

Rasmussen, M. S. 1997. "Operational yield forecast using AVHRR NDVI data: Reduction of environmental and inter-annual variability." *International Journal of Remote Sensing*, 18(5): 1059–1077.

Rojas, O. 2007. "Operational maize yield model development and validation based on remote sensing and agro-meteorological data in Kenya." *International Journal of Remote Sensing*, 28(17): 3775–3793.

Rud, Juan Pablo. 2012. "Electricity provision and industrial development: Evidence from India." *Journal of development Economics*, 97(2): 352–367.

Self, Sharmistha, and Richard Grabowski. 2008. "EXAMINING THE LINK BETWEEN JAPAN'S DEVELOPMENT AND EDUCATION OF FEMALES." *Pacific Economic Review*, 13(3): 279–288.

Selvaraju, R. 2003. "Impact of El Niño–southern oscillation on Indian foodgrain production." *International Journal of Climatology*, 23(2): 187–206.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

Tenenbaum, Bernard, Chris Greacen, and Dipti Vaghela. 2018. "Mini-grids and arrival of the main grid." Publisher: World Bank, Washington, DC.

Thévenon, Olivier, and Eric Edmonds. 2019. "Child labour: Causes, conse-

quences and policies to tackle it." Publisher: OECD.

Twerefou, Daniel Kwabena. 2014. "Willingness to pay for improved electricity supply in Ghana." *Modern Economy*, 2014.

Van de Walle, Dominique P., Martin Ravallion, Vibhuti Mendiratta, and Gayatri B. Koolwal. 2013. "Long-term impacts of household electrification in rural India." *World Bank Policy Research Working Paper*, , (6527).

Yadav, Prabhakar, Peter J. Davies, and Samuel Asumadu Sarkodie. 2019. "The prospects of decentralised solar energy home systems in rural communities: User experience, determinants, and impact of free solar power on the energy poverty cycle." *Energy Strategy Reviews*, 26: 100424.

Zubi, Ghassan, Rodolfo Dufo-López, Guzay Pasaoglu, and Nicolás Pardo. 2016. "Techno-economic assessment of an off-grid PV system for developing regions to provide electricity for basic domestic needs: A 2020–2040 scenario." *Applied Energy*, 176: 309–319.
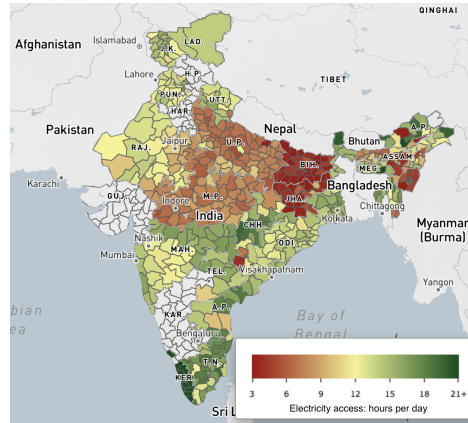
Appendix A. Additional figures

Figure A1. Electricity reliability

Note: The figure illustrates the reliability of electricity in terms of hours per day, along with the corresponding scale. Greener regions on the plot represent a higher number of electricity hours, while redder areas indicate a lower number of electricity hours. The data is aggregated at the sub-district level.
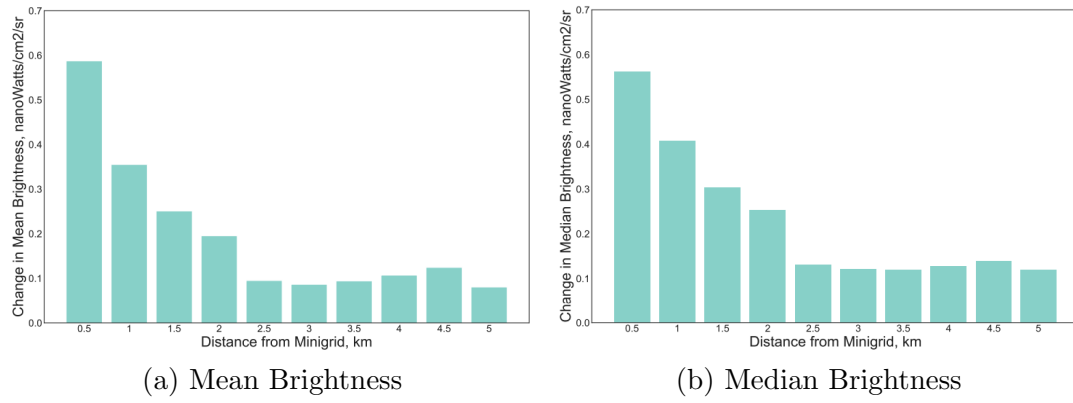*Source:* SHRUG Atlas based on 2011 Population Census.

(a) Mean Brightness   (b) Median Brightness

Figure A2. Data-driven control and treatment groups: Alternative brightness measures

Note: The figure displays the difference in nighttime brightness levels (measured in nanoWatts/cm^2/sr) before and after mini-grid installation at varying distances from all mini-grids within my study sample. In Panel (a), each bar represents the mean recorded brightness value within concentric circles (or rings) at 0.5 km intervals. In Panel (b), each bar represents the median recorded brightness value within concentric circles (or rings) at 0.5 km intervals.
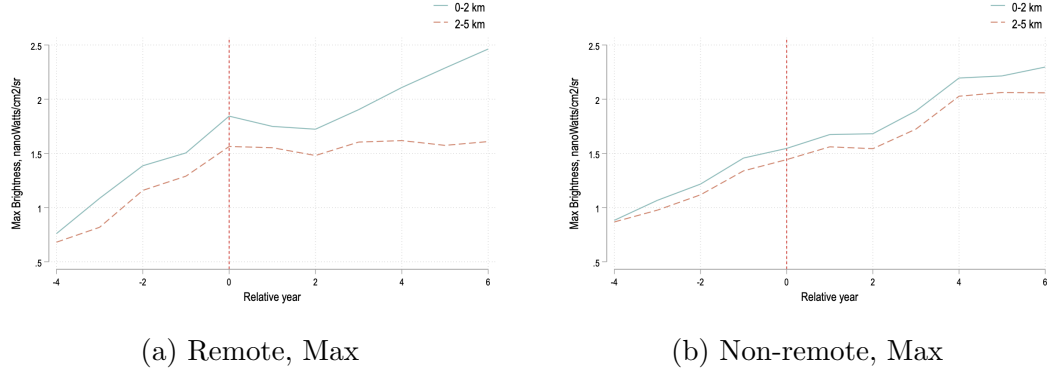
(a) Remote, Max   (b) Non-remote, Max

Figure A3. Brightness trends: Comparing remote and non-remote mini-grids

Note: The figure provides a comparative analysis of the influence of mini-grid installations on nighttime brightness based on the remote mini-grid installation status. "Remote status" is defined as a location situated at least 7 kilometers away from the nearest mini-grid. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. Panel (a) presents descriptive evidence on the impact of mini-grid installation on nighttime brightness by plotting maximum nighttime brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation for remote mini-grids. Panel (b) presents descriptive evidence on the impact of mini-grid installation on nighttime brightness by plotting maximum nighttime brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation for non-remote mini-grids.
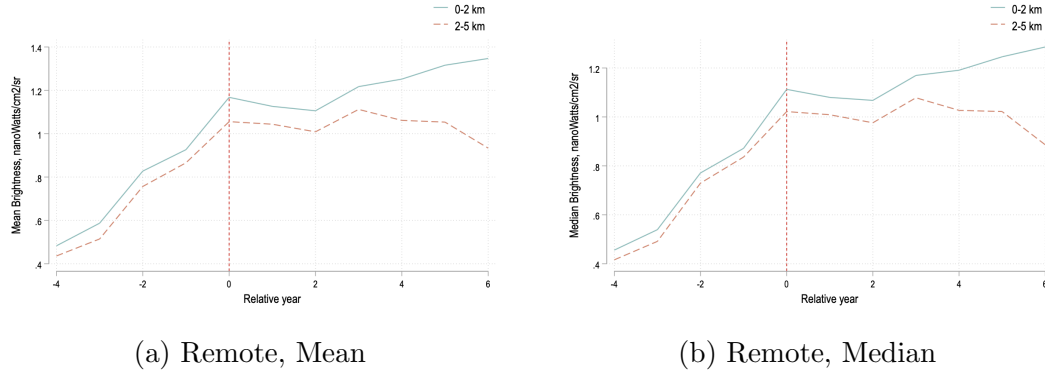
(a) Remote, Mean (b) Remote, Median

Figure A4. Brightness trends: Robustness to alternative brightness measures

Note: The figure compares the effects of mini-grid installation on nighttime brightness by type of brightness measure used. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. Panel (a) presents descriptive evidence on the impact of mini-grid installation on nighttime brightness by plotting mean nighttime brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation. Panel (b) presents descriptive evidence on the impact of mini-grid installation on nighttime brightness by plotting median night-time brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation.

Figure A5. Heterogeneity analysis: Effects by mini-grid capacity

Note: The figure presents the results of a heterogeneity analysis, specifically examining the effects of mini-grid installation with respect to mini-grid capacity sizes. These capacities have been categorized into three distinct groups: top, medium, and bottom terciles. The depicted estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.
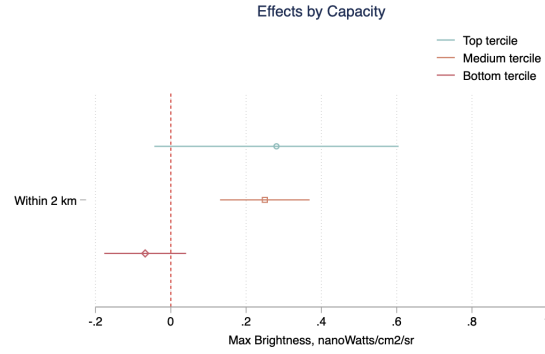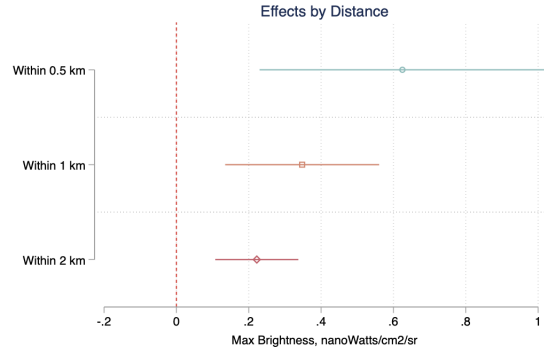
Figure A6. Heterogeneity analysis: Effects by distance to mini-grid

Note: The figure presents the results of a heterogeneity analysis, specifically examining the effects of mini-grid installation at different distances from the mini-grid. Specifically, the control group remains the same, comprising villages situated between 2 to 5 kilometers from the mini-grid. In contrast, the treatment group undergoes changes, encompassing villages within 2 kilometers from the mini-grid and, subsequently, villages located within 1 kilometer and 0.5 kilometers from the mini-grid. The depicted estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.
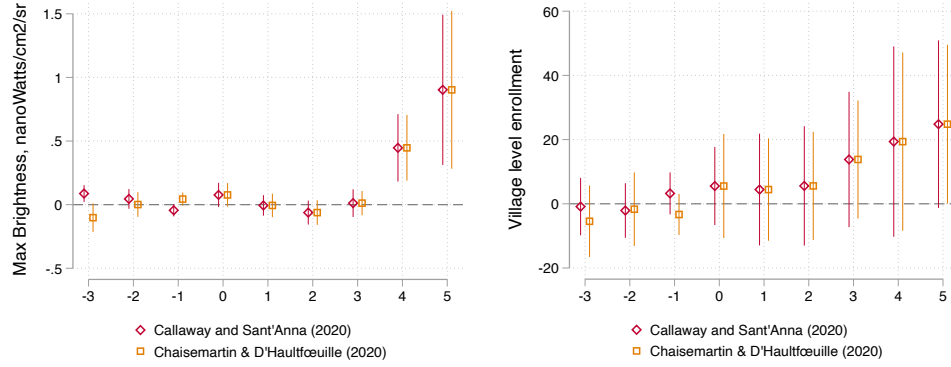
Figure A7. Robustness: Alternative staggered estimation strategy

Note: The figure compares the post-treatment and anticipatory effects using the event-study specification from Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages 2 to 5 km away from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.
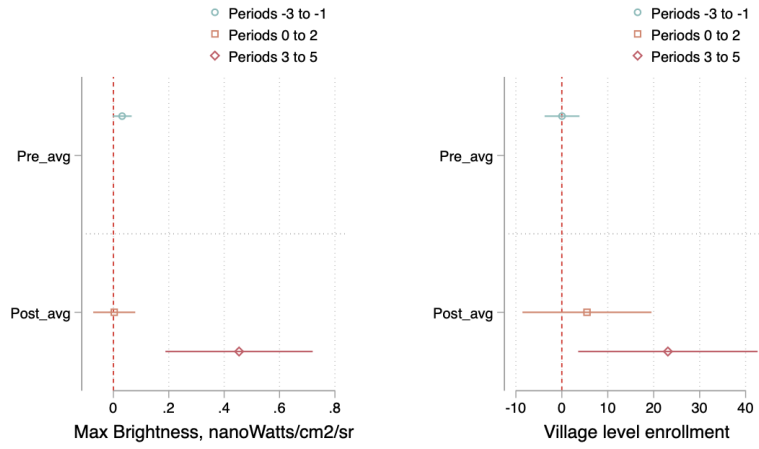
Figure A8. Robustness: Effects by stage

Note: The figure presents the results on the effects of mini-grid installation on energy access and education outcomes at different stages relative to the installation. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

(a) Control group: never treated   (b) Control group: not yet treated

Figure A9. Differential treatment timing: Callaway & Sant'Anna (2021)

Note: The figure illustrates the effects of mini-grid installation on night-time brightness by utilizing different control group definitions. Panel (a) plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval using "Never treated" villages as control group. Panel (b) plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval using "Not yet treated" villages as control group. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

(a) Event-study: Enrollment   (b) Effects by threshold: Enrollment

Figure A10. Robustness: Alternative treatment start time based on night time brightness and effects by threshold

Note: The figure presents the results on the effects of mini-grid installation on education outcome using an alternative approach to treatment start timing based on nighttime brightness. Panel (a) plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval. This plot uses an alternative start timing compared to the baseline specification. The baseline specification uses the start year (year zero) when solar panels first appear on the ground. The new start year for the current results is the year after the mini-grid installation, when nighttime brightness increases by at least 35%. This indicates that the mini-grid is functional and actively providing light. This high threshold is chosen to mitigate the effects of noise in satellite data. Panel (b) shows the robustness of the results to alternative thresholds. The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.
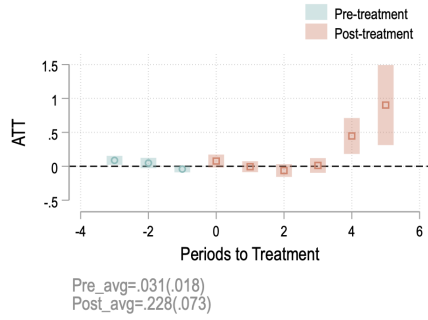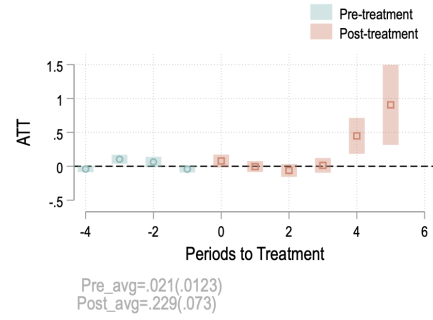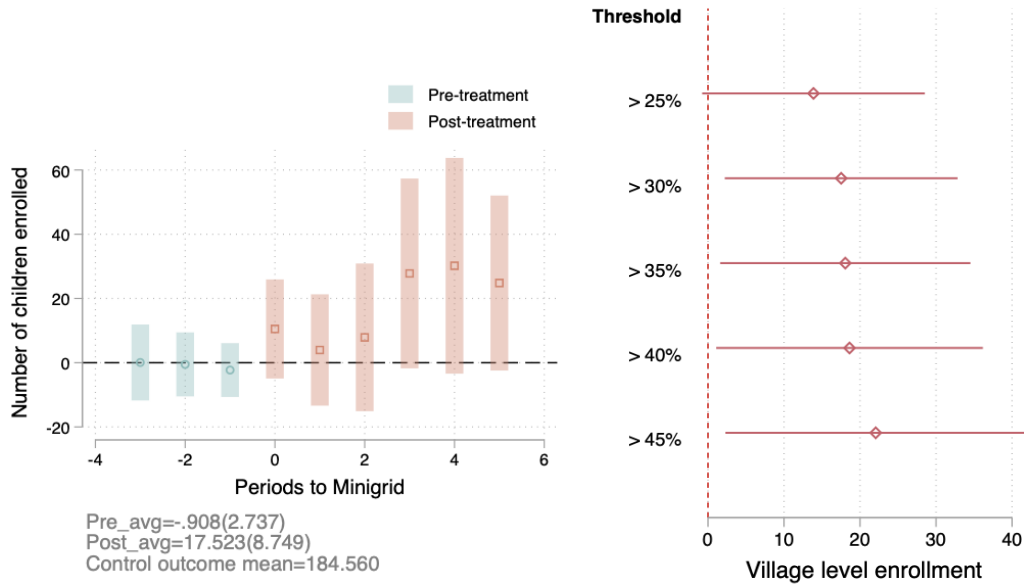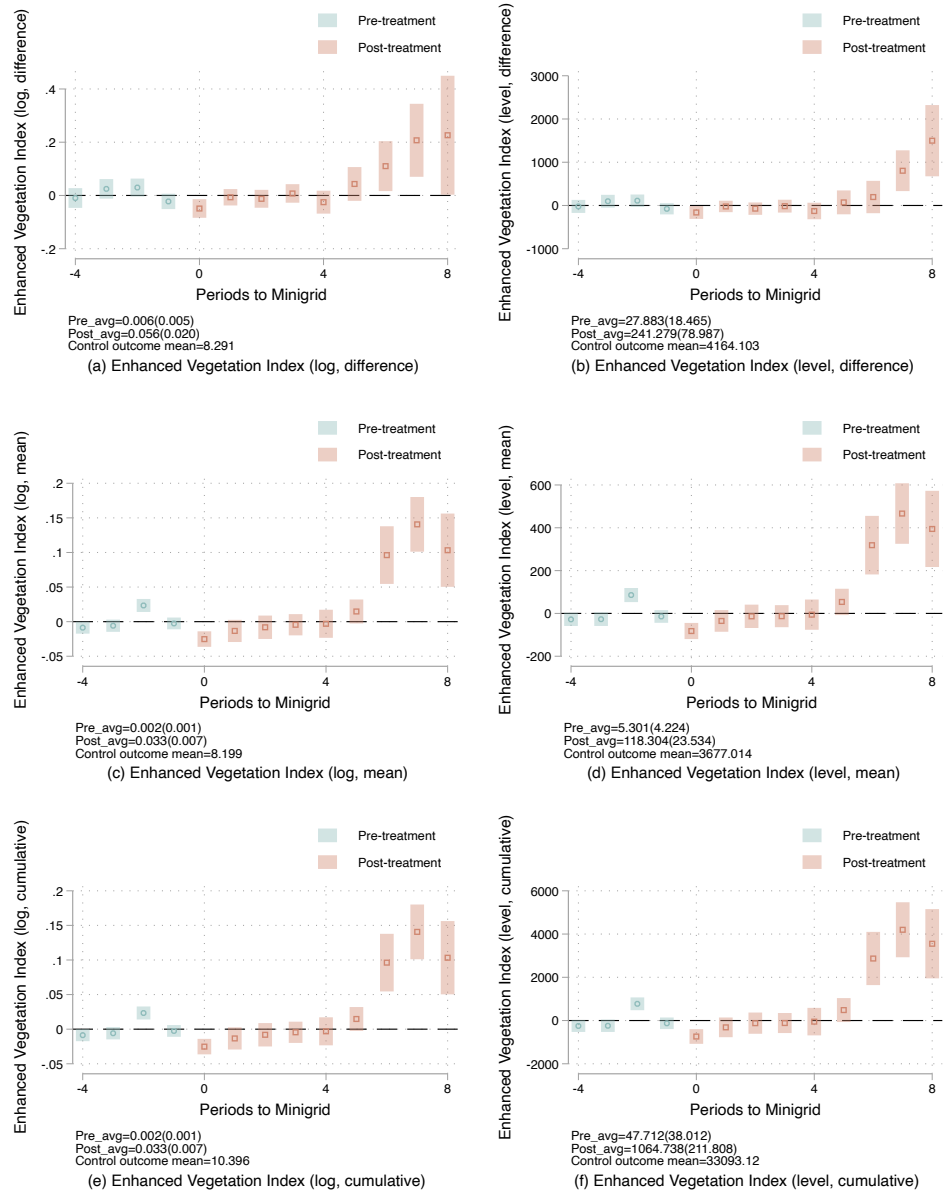
Figure A11. Mechanisms: Alternative measures for EVI as proxy of agricultural yields

Note: The figure plots the post-treatment and anticipatory effects from the event-study specification corresponding to Equation 6 as well as the 95% confidence interval. The Enhanced Vegetation Index (EVI) is presented in logarithmic terms in panels (a), (c), and (e), and in levels in panels (b), (d), and (f). The treatment group includes villages within 2 km of the mini-grid, while the control group includes villages from 2 to 5 km from the mini-grid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level.

Source: satellite imagery collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Earth Observing System-Terra satellite from 2014 to 2024. Annual composites are generated from 16-day composites at a 250 m resolution by aggregating data within village polygons.
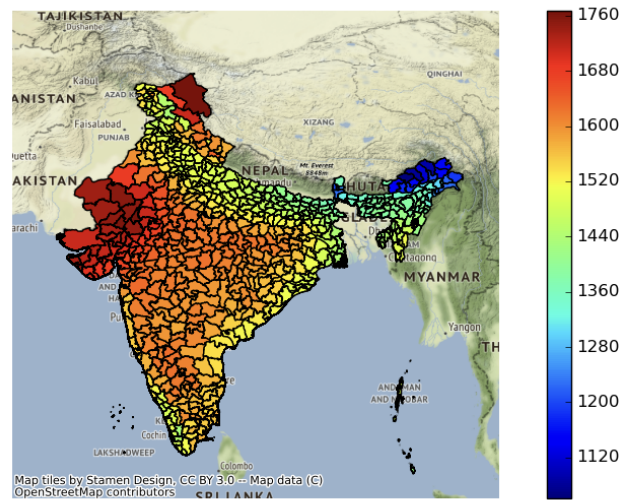
Figure A12. Photovoltaic power potential of India

Note: The figure depicts the map showing the average Photovoltaic power potential (PVOUT), which represents the potential for solar energy generation. PVOUT is measured in kWh/kWp and data is aggregated at the district level.
Source: Data is generated by SOLARGIS (https://solargis.com) and made available through the Global Solar Atlas, World Bank.

Table B1—Comparison of rural energy alternatives

Category	Central Grid Extension	Mini-grid	Solar Home System(SHS)	Diesel Generator
Electricity Cost	Low, economies of scale and sub-sidies	Medium, cheaper than SHS, economies of scale	High	High, increasing cost of diesel
Reliability	Low, load shed-ding, tail-end voltage drops	Reliable for load within system's initial capacity	Reliable for load within system's initial capacity	Reliable
Pollution	At generation point	Low	Low	Very high

Note: The table compares rural energy generation options, including the Central Grid, Mini-grid, Solar Home Systems (SHS), and Diesel Extension System. It evaluates these alternatives based on key parameters such as electricity cost, reliability, and environmental impact.
Source: Psaltakis (2019), the Smart Power India Report (2020).

Table B2—Comparison of night-time brightness data sources

Characteristic	DMSP-OLS	JPSS(VIIRS)
Spatial Resolution	5000*5000 meters	742*742 meters
Radiometric Resolution	Low, 6-bit pixel data, values range 0-63	High, 14-bit pixel data
Calibration	No	On-board calibration
Saturation	Common in urban cores	No
Time Span (ready-to-use)	1992-2012	2014-2021
Measurement units	Digital number	nanoWatts/cm2/sr

Note: The table offers a comprehensive comparison of nighttime brightness data sources, specifically contrasting the VIIRS Day/Night Band data, provided by the Earth Observation Group, with its predecessor, the DMSP-OLS series. The comparison encompasses several key parameters, including Spatial Resolution, Radiometric Resolution, Calibration, Saturation, Time Span, and Measurement Units

Table B3—Balance table: How do treated villages compare to control villages?

	Control (2-5 km) Mean/SE (1)	Treat (0-2 km) Mean/SE (2)	T-test for Difference In Means (1)-(2)		Control (2-5 km) Mean/SE (1)	Treat (0-2 km) Mean/SE (2)	T-test for Difference In Means (1)-(2)
Household characteristics				**Schools**			
Number of households	332.558	368.920	-36.362*	Number of primary schools	1.368	1.556	-0.188**
	(12.758)	(31.590)			(0.036)	(0.096)	
Average household size	6.714	6.649	0.065	Number of middle schools	0.653	0.716	-0.063
	(0.023)	(0.043)			(0.025)	(0.062)	
Consumption and poverty				Number of secondary schools	0.145	0.188	-0.043
Per capita consumption	15170.153	14987.722	182.431		(0.013)	(0.028)	
	(127.511)	(222.272)		Number of senior secondary schools	0.088	0.112	-0.024
Poverty rate	0.386	0.397	-0.011		(0.009)	(0.023)	
	(0.005)	(0.010)		Number of colleges	0.023	0.012	0.011
Area and proximity					(0.005)	(0.007)	
Village area	216.636	282.199	-65.563*	**Employment**			
	(8.375)	(21.126)		Manufacturing employment per adult population	0.012	0.012	0.000
Agricultural land as a % of village area	0.756	0.700	0.056		(0.003)	(0.002)	
	(0.007)	(0.017)		Services employment per adult population	0.036	0.041	-0.005
Agricultural productivity	8.379	8.357	0.021		(0.002)	(0.004)	
	(0.004)	(0.009)		% of agroprocessing employment	0.715	0.638	0.077
Accessible by road	0.797	0.836	-0.039		(0.044)	(0.076)	
	(0.012)	(0.023)		% of storage and warehousing employment	0.090	0.117	-0.028
Min distance place population > 10k	7.365	8.221	-0.856		(0.030)	(0.054)	
	(0.172)	(0.399)		% of households with cultivation as main income source	0.321	0.384	-0.062
Min distance place population > 50k	26.645	25.538	1.107		(0.010)	(0.022)	
	(0.286)	(0.605)		% of workers employed in agriculture	0.304	0.347	-0.043
Min distance place population > 100k	35.005	40.673	-5.668		(0.009)	(0.019)	
	(0.601)	(1.497)					
Min distance place population > 500k	79.617	78.803	0.814				
	(0.606)	(1.177)					
Min distance to canal	1.882	2.594	-0.712				
	(0.106)	(0.275)					
Min distance to river	15.523	14.389	1.134				
	(0.336)	(0.612)					
Observations	3541	751			3541	751	
Joint significance test (p-value)							0.849

Note: The table examines whether different social and cultural village-specific population characteristics can predict village treatment status. The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. The value displayed for t-tests are the differences in the means across the groups. The bottom line indicates p-value of joint significance test. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Source: 2011 Population Census.

Table B4—Correlates of EVI proxy for agricultural yields

	Enhanced Vegetation Index, log difference				
	(1)	(2)	(3)	(4)	(5)
Crop suitability (log)	0.247***				0.248***
	(0.038)				(0.039)
Irrigation (share)		0.148***			0.139***
		(0.024)			(0.023)
Agricultural land (share)			0.044		0.072**
			(0.032)		(0.033)
Consumption (log)				0.051**	0.065**
				(0.026)	(0.029)
Observations	4,292	4,292	4,292	4,292	4,292

Note: Enhanced Vegetation Index (EVI) is expressed in logarithmic terms and is represented as the difference between early-season EVI and the max EVI value observed at the village level. For validation purposes, agricultural production proxy is regressed on other likely correlates of yields. Village level EVI is regressed on log crop suitability, share of village land irrigated, and log consumption per capita, all with district fixed effects. Heteroskedasticity robust standard errors are reported below point estimates. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B5—Robustness to Utilizing Alternative Control Groups: Night Time Brightness

	Specification type							
	Treat: 0-2 km Control: 2-5 km		Treat: 0-2 km Control: 3-5 km		Treat: 0-2 km Control: 5-8 km		Treat: 0-2 km Control: 8-10 km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Avg	0.228***	0.228***	0.222***	0.225***	0.210***	0.212***	0.232***	0.233***
	(0.074)	(0.073)	(0.074)	(0.074)	(0.071)	(0.069)	(0.075)	(0.074)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Control Outcome Mean	1.093	1.093	1.017	1.017	0.934	0.934	0.923	0.923
Observations	23,985	23,985	19,188	19,188	25,328	25,328	26,354	26,354

Note: The table displays the findings of a robustness analysis that assesses the impact of minigrid installation on nighttime brightness utilizing alternative control groups. The treatment group consists of villages within 2 km of the minigrid, while the control groups are defined as villages located 2-5 km, 3-5 km, 5-8 km, and 8-10 km from the minigrid, respectively. The estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The estimates are presented with and without controls, and robust standard errors are adjusted for clustering at the village level. The set of control variables includes village controls. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B6—Placebo Check: Effects on Night Time Brightness at Larger Distances

	Specification type							
	Treat: 0-2 km Control: 2-5 km		Treat: 2-5 km Control: 5-8 km		Treat: 5-8 km Control: 8-10 km		Treat: 8-10 km Control: 10-12 km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Avg	0.228***	0.228***	0.040	0.042	0.020	0.019	-0.003	-0.003
	(0.074)	(0.073)	(0.075)	(0.075)	(0.074)	(0.074)	(0.075)	(0.075)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Control Outcome Mean	1.093	1.093	0.934	0.934	0.923	0.923	0.907	0.907
Observations	23,985	23,985	27,040	27,040	26,728	26,728	28,352	28,352

Note: The table presents the results of a placebo check analysis, which examines the effects of minigrid installation on nighttime brightness at larger distances where no treatment effects are expected to occur. In this analysis, the treatment and control groups are redefined to include villages at varying distances from the minigrid. The table reports the average post-treatment effects on nighttime brightness for each of these redefined groups. The estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The estimates are presented with and without controls, and robust standard errors are adjusted for clustering at the village level. The set of control variables includes village controls. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B7—Robustness: Effect of Minigrid on Night Time Brightness Using Alternative Brightness Measures

	Max (1)	Mean (2)	Median (3)
Post Avg	0.228***	0.195***	0.213***
	(0.073)	(0.038)	(0.036)
Observations	23,985	23,985	23,985
Control Outcome Mean	1.093	0.684	0.654

Note: The table displays the findings of a robustness analysis that assesses the impact of minigrid installation on nighttime brightness at the village level. This evaluation employs various measures of nighttime brightness. In Column (1), the dependent variable is the maximum brightness, which is calculated as the highest level of brightness aggregated over a village polygon and composited on an annual basis. In Column (2), the analysis employs mean brightness as the dependent variable, calculated as the average brightness level aggregated over the same polygon of villages and composited annually. Column (3) employs median brightness as the dependent variable, calculated as the median value of brightness within the same polygon of villages and also composited annually. The estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B8—Robustness: Effect of minigrid on night-time brightness using alternative electrification definitions

	Max (1)	Mean (2)	Median (3)
Panel A: unelectrifed as of Census 2011			
Post Avg	0.228***	0.195***	0.213***
	(0.073)	(0.038)	(0.036)
Observations	23,985	23,985	23,985
Panel B: no central grid line			
Post Avg	0.200**	0.071	0.074
	(0.066)	(0.037)	(0.039)
Observations	28,172	28,172	28,172
Panel C: baseline brightness ≤ 1			
Post Avg	0.253***	0.151**	0.170**
	(0.070)	(0.047)	(0.041)
Observations	23,399	23,399	23,399

Note: The table presents the results of a robustness analysis, which involves assessing nighttime brightness under varying sample criteria based on electrification definitions. Panel A provides estimates from the baseline analysis, where only villages lacking electricity access for domestic and agricultural purposes, as of the 2011 Census, are included. Panel B focuses on villages that do not have a central grid line within their respective village polygons. In Panel C, the sample is restricted to include only villages with a brightness level below 1 nanoWatt/cm²/sr, as determined by the maximum brightness levels observed in the years prior to the treatment period (2014-2015). The estimates correspond to the average post-treatment effects, which were computed utilizing the approach proposed by Callaway & Sant'Anna (2021). The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. The set of control variables includes village controls. Robust standard errors are adjusted for clustering at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B9—Robustness: TWFE estimates by remote minigrid status

	All	Max Remote Only	Non Remote	All	Mean Remote Only	Non Remote	All	Median Remote Only	Non Remote
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Within 2 km*Post	0.186***	0.275***	0.069	0.108***	0.205***	0.025	0.113***	0.223***	0.020
	(0.057)	(0.085)	(0.075)	(0.029)	(0.038)	(0.044)	(0.028)	(0.036)	(0.043)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,798	23,985	11,813	35,798	23,985	11,813	35,798	23,985	11,813
Control Outcome Mean	1.089	1.093	1.083	0.692	0.684	0.703	0.664	0.654	0.676

Note: The table presents the robustness analysis results on the effects of mini-grid installation on nighttime brightness. The estimates are based on the TWFE specification corresponding to Equation 5. The table facilitates a comparative evaluation of these results across three categories: the overall sample, remote mini-grids, and non-remote mini-grids. For this analysis, a remote mini-grid is defined as one located at a minimum distance of 7 kilometers from the nearest mini-grid. Further, this evaluation employs various measures of nighttime brightness. In Columns (1) to (3), the dependent variable is the maximum brightness. In Columns (4) to (6), the analysis employs mean brightness as the dependent variable. Columns (7) to (9) employ median brightness as the dependent variable. The treatment group includes villages within 2 km of the minigrid, while the control group includes villages from 2 to 5 km from the minigrid. The set of control variables includes state fixed effects, district fixed effects, village controls. Robust standard errors are adjusted for clustering at the village level. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B10—Cost-benefit analysis for mini-grid system

Solar mini-grid	IRR	Break even time
(1) With benefits from increased consumption	17 %	5 years
(2) With benefits from improved education	21 %	5 years
(3) With battery cost reduction	26 %	4 years

Note: The table presents the results of cost-benefit analysis of solar mini-grid technology for three scenarios. Scenarios are as follows: (1) household consumption benefits, (2) consumption benefits + education benefits, and (3) consumption benefits + education benefits + reduced battery costs. The analysis focuses on the average system in the sample (100 kWp capacity). The Internal Rate of Return (IRR) is calculated over 20 years for each scenario. Mini-grid costs include wiring, solar panels, batteries, inverters, powerhouse construction, smart meters, and training on management and use. Household consumption benefits are estimated using the relationship between night lights and consumption, where a 1-unit increase in night lights corresponds to a 10% increase in household consumption. Estimated education benefits are converted to improved lifetime earning potential using rural skilled salaries from the NSS survey 66th round. Scenario 3 assumes a reduction in battery costs by more than 50% by 2030, based on projections by IRENA (2017).

Appendix C. Data

1. Sample construction details

A key feature that datasets in this study share is their detailed spatial coverage, enabling a granular analysis of the local effects of mini-grids by establishing precise linkages between datasets. The final sample, covering the years 2014-2022, is constructed by intersecting the data sources and creating a village panel dataset using precise geocoordinates. Several important aspects of the DISE data merit attention.

Firstly, DISE school data experienced a change in school identification codes, with distinct sets of numerical codes used for 2010-2017 and 2018-2022.[55] I apply a multistep string matching algorithm to merge the 2010-2017 DISE school data with the 2018-2022 DISE data. First, I create a concordance between school codes and village names as reported in the DISE dataset. Often, a single school is associated with multiple village names in different years due to variant spellings or administrative village splits. Second, I search for exact string matches between villages in earlier and later school data based on state, district, zip code, and village name. Third, for the remaining unmatched villages, I use Stata's reclink fuzzy string matching function.[56] Fourth, for any remaining unmatched villages, I apply the Masala merge fuzzy match routine developed by Asher & Novosad (2020). This algorithm computes the Levenshtein distance between strings, accounting for letter substitutions and interpolations common to Hindi transliterations.[57] After establishing a rough new DISE-old DISE village concordance, I use school codes to resolve duplicate village matches.[58]

Secondly, DISE school data lacks geocoordinates. To address this, I link DISE data to Census village geocoordinates using location names and then integrate it with other datasets. Specifically, I use a procedure similar to the one outlined above to match DISE schools to Census villages through a fuzzy matching process. First, for each village in the school data, I construct a list of all observed village name transliterations. Next, I search for string matches between village names already linked to Census codes and DISE village names, following the exact string match, reclink, and Masala merge progression described above. Overall, about 96% of villages from the DISE school data match the 2011 Census. The matching status of the village does not appear to be related to observable characteristics of the villages, as shown in Table C1.

---

[55]Within these two sets of data, I separately link schools across years based on unique numerical school codes.

[56]I utilize a cutoff of 0.8 for the reclink command.

[57]Masala merge has been shown to be more accurate and flexible than standard fuzzy merging routines like reclink. However, I utilize reclink to remove close matches before applying the more computationally intensive Masala merge algorithm.

[58]I keep the most frequent match for each school.

Table C1—Balance table: How do matched villages compare to unmatched villages?

	Matched Villages Mean/SE (1)	Unmatched Villages Mean/SE (2)	T-test for Difference In Means (1)-(2)		Matched Villages Mean/SE (1)	Unmatched Villages Mean/SE (2)	T-test for Difference In Means (1)-(2)
Household characteristics				**Schools**			
Number of households	388.374	367.282	21.092	Number of primary schools	1.607	1.718	-0.111
	(23.673)	(54.759)			(0.061)	(0.160)	
Average household size	6.625	6.555	0.070	Number of middle schools	0.732	0.709	0.023
	(0.035)	(0.059)			(0.041)	(0.086)	
Consumption and poverty				Number of secondary schools	0.121	0.137	-0.016
Per capita consumption	15229.648	14712.302	517.346		(0.020)	(0.036)	
	(174.711)	(306.780)		Number of senior secondary schools	0.065	0.043	0.022
Poverty rate	0.391	0.419	-0.028		(0.014)	(0.025)	
	(0.008)	(0.016)		Number of colleges	0.011	0.009	0.002
Area and proximity					(0.005)	(0.009)	
Village area	297.625	345.653	-48.028	**Employment**			
	(16.043)	(30.321)		Manufacturing employment per adult population	0.009	0.011	-0.002
Agricultural land as % of total village area	0.676	0.600	0.075		(0.001)	(0.002)	
	(0.013)	(0.027)		Services employment per adult population	0.029	0.030	-0.001
Agricultural productivity	8.359	8.326	0.033		(0.002)	(0.003)	
	(0.006)	(0.011)		% of agroprocessing employment	8.113	6.715	1.398
Accessible by road	0.842	0.812	0.030*		(0.783)	(1.336)	
	(0.017)	(0.036)		% of storage and warehousing employment	0.114	0.125	-0.012
Min distance place population > 10k	8.964	10.338	-1.374		(0.060)	(0.094)	
	(0.331)	(0.677)		% of households with main income from cultivation	0.362	0.467	-0.105
Min distance place population > 50k	24.223	22.988	1.235		(0.017)	(0.038)	
	(0.449)	(0.921)		% of workers employed in agriculture	0.311	0.384	-0.073
Min distance place population > 100k	38.940	47.740	-8.800		(0.016)	(0.033)	
	(1.158)	(2.578)					
Min distance place population > 500k	80.694	80.106	0.588				
	(1.094)	(2.080)					
Min distance to canal	2.989	4.311	-1.322				
	(0.200)	(0.500)					
Min distance to river	12.651	10.355	2.296				
	(0.449)	(0.777)					
Observations	4292	155			4292	155	
Joint significance test (p-value)							0.746

Note: The table examines whether different social and cultural village-specific population characteristics can predict village matching status. The value displayed for t-tests are the differences in the means across the groups. The bottom line indicates p-value of joint significance test. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Source: 2011 Population Census and DISE data.

2. Mini-grids data sources

Since no comprehensive data on the locations of mini-grids exists, I use a combination of satellite-derived data sources, Open Street maps data, Bloomberg data, and World Resource Institute data. This multi-source approach enables me to overcome the limitations of previous research and broaden the project's scope.

Specifically, I utilize a union of solar installation data from all these sources, recognizing that each has its strengths and weaknesses. Satellite data, for instance, offers objectivity and extensive geographical coverage but may miss smaller installations (those below 10 kW) due to its coarse imagery resolution. In contrast, incorporating data sources based on survey data, government agency information, and crowdsourced data helps pinpoint the locations of smaller capacity installations. I provide detailed description of each data source in this section.

BloombergNEF data: mini-grid asset data survey (Mini-Grids Partnership, 2020).

This dataset was compiled using information from various sources, including GIZ, Carbon Trust, CLUB-ER, surveyed mini-grid developers, donor agencies, research institutes, non-profit organizations, and technology vendors. It offers the advantage of including only genuine mini-grid solar installations.[59] However, it primarily focuses on third-generation renewable mini-grids, potentially limiting its coverage and missing other types of installations. To address potential coverage limitations in BloombergNEF's data, I supplement it with additional data sources that encompass a wider range of solar installations.

World Resource Institute Global Power Plant Database (Byers et al., 2018)

This is a dataset typically used for energy research. This database is based on aggregating information through primary sources (such as national government agencies, plant developers, public utilities, power plant construction companies, intergovernmental organizations), secondary sources with quality assurance processes (Global Energy Observatory, CARMA among others) and Crowdsourced data (Wikipedia, KTH Royal Institute of Technology in Stockholm crowd sourcing). Importantly though, at this point there is no formal process for contributing data provided by any private citizen or submitting corrections for these data.

Sources that are directly linked to power plant operations or have the legal authority to gather power plant statistics are considered the most reliable. The database uses the most reliable data available for each power plant observation. Although official data is preferred because it is most authoritative, the complete accuracy cannot be guaranteed. However, to conduct a data quality check authors verify plants' geolocation through satellite imagery and conduct random sampling, which lets them estimate how reliably data is geolocated.

---

[59]The authors conducted structured interviews with 68 organizations to collect information and data. The data collection for the report focused primarily on renewable mini-grids that are predominant among projects installed in the recent years in order to analyze recent market trends. In general, first- and second-generation mini-grid systems are often small and not well publicized systems that have been developed by local communities or entrepreneurs. Third-generation systems, by contrast, are far better documented as they often involve non-local investors or others.

Harmonized global dataset of solar farm locations (Dunnett et al., 2020)

It is based on Open Street Maps which is an open-source, collaborative global mapping project generated by a community of millions of users that can provide a unique insight into energy infrastructure locations.[60] Users may collect data using manual ground surveys, GPS devices, aerial photography, street-level imagery, and other free sources, or use their own local knowledge of the area. Where available, data includes data from the national governments, satellite imagery from NOAA and others. OpenStreetMap data has been utilized in various scientific studies. For instance, it has been used for research on identifying remaining roadless areas (Ibisch et al., 2016), calculating the Forest Landscape Modification Index (Grantham et al., 2020), global mapping for power infrastructure (Arderne et al., 2020) as well as creating geospatial energy map of India by NITI Aayog in collaboration with Indian Space Research Organisation with the support of Energy Ministries (Jain, 2020).

Since (2) and (3) datasets might not capture the full range of development given sampling biases inherent to crowd sourcing approaches[61] I further incorporate solar installations datasets derived though applying machine learning techniques to freely available high-resolution remotely sensed imagery that allow to objectively map utility-scale projects.

Global inventory of PV generating units (Kruitwagen et al., 2021)

Solar cell locations in this dataset have been identified using a machine learning algorithm, which has been trained on remote sensing images from a global inventory of solar installations. Specifically, Solar PV installations were identified using Sentinel-2 and SPOT-6/7 multispectral remote sensing images. Sentinel-2, an Earth observation mission by the European Space Agency and SPOT-6/7 satellites from Airbus were utilized. Training data for prediction models came from OpenStreetMap (OSM). The polygon labels are precise (i.e. do not contain false positives) but are noisy due to the crowd-sourced nature of OSM data.

A validation dataset was created from hand-labeled polygons using latitude and longitude coordinates from the World Resources Institute Global Power Plant Database. PV solar energy facilities in the validation and test set were both labeled according to the 'direct area' land use convention. The test set can be used to determine the error between the predicted and true 'direct area' of the PV solar energy facility, allowing the areas to be corrected in the calculation of nominal generating capacity.

There are two important considerations related to these data. The training and validation datasets, drawn from OSM and the Global Power Plant Database respectively, are also geographically biased to the Global North - predominantly the United States and Europe - which can potentially undermine the quality of performance of the algorithm to identify the installations in India (South). Secondly, the coarse resolution of the remote sensing imagery causes weaker performance of the machine learning pipeline on smaller facilities, so we expect diminished ability of algorithm to identify installations below 10 kW capacity.

---

[60]More information on the structure of OSM data can be found on the OSM Wiki https://wiki.openstreetmap.org/wiki/Elements

[61]Specifically, the caveat of this data is that the solar installation will only appear in this data, if it has been labeled by a person, government official or appears in official government agency data.

Similar to (4), this database was constructed using machine learning techniques applied to remotely sensed imagery. However, in contrast to (4), which relies on data sources with global coverage, this database employs an algorithm specifically fine-tuned to identify solar installations in India. The training dataset comprises georeferenced point labels representing the central points of various solar installations in the states of Madhya Pradesh, Maharashtra, Kerala, Telangana, Karnataka, and Andhra Pradesh. These labels were derived from previously mapped solar farms available through OpenStreetMap (OSM) and collaborations with other Nature of Conservancy (TNC) partners. Much like (4), the analysis utilized Sentinel-2 satellite imagery from the European Space Agency.

3. Mini-grid sample construction

I utilize all installations from data source (1) since they are all mini-grids. However, for data sources (2) to (5), I refine the sample of solar installations to include only those that meet typical mini-grid criteria, which are as follows:

a Capacity ranging from 10 kW to 10 MW

b Not connected to the central grid[62][63]

c Ground-mounted (as opposed to roof or water-mounted)

d Located in rural areas (not urban)

In cases where an installation consists of multiple solar cell polygons within 500 meters of each other, I merge them and calculate the total power-generating capacity as the sum of individual capacities. The final list of mini-grid locations includes precise location data and the area of the solar installations. Most installation also include information on installation dates and power capacities. In cases where capacity information is unavailable, I estimate it based on the area of solar installations and location-specific photovoltaic generating potential (pvout). Similarly, when installation dates are missing, I supplement the data by manually collecting installation dates from satellite imagery.

Furthermore, I limit my baseline analysis to remote mini-grids, ensuring that each mini-grid is at least 7 km away from the closest mini-grid. This decision is made because my empirical strategy relies on comparing villages close to and further away from the mini-grid. Including mini-grids within 7 km could lead to contamination of

---

[62]Determining whether a mini-grid or village is connected to the central grid can be done in various ways. In my primary analysis, I rely on village-level central grid connectedness from the 2011 Census, where only villages lacking electricity access for domestic and agricultural purposes, as of the 2011 Census, are included. Additionally, I explore alternative definitions of grid connectivity. The first alternative definition relies on OpenStreetMap (OSM) data pertaining to central grid lines. Specifically, a village is considered electrified if any part of a central grid line intersects or is contained within the village's geographical polygon. It is worth noting that OSM central grid infrastructure data has previously been utilized in creating India's geospatial energy map through a collaborative effort involving NITI Aayog and the Indian Space Research Organisation, with support from Energy Ministries (Jain, 2020). The second definition utilizes nighttime brightness from years preceding treatment (2014-2015) and restricts the sample to villages with a brightness level below 1 nanoWatts/cm2/sr, as measured by maximum brightness.

[63]I include only off-grid mini-grids, which are not connected to the central grid.

the control group of one mini-grid with treated villages from another mini-grid. Over 65% of the total sample consists of remote mini-grids.

In the Appendix, Figure A3 and Table B9 present a comparison of results between remote and non-remote mini-grids. The findings reveal that, in the case of non-remote grids, there is no discernible divergence in the nighttime brightness trend between control and treatment groups during the post-treatment periods. Conversely, both control and treatment villages exhibit an increase in raw brightness levels. This observation lends further support to the notion that contamination of the control group of one mini-grid by treated villages from another mini-grid is indeed occurring, resulting in diminished disparities in brightness between treated and control villages.

4. Comparison of data sources

Table C2—To what extent do data sources intersect?

X/Y	Bloomberg	Nature	Scientific Data 1: Satellite	Scientific Data 2: OSM	WRI
Bloomberg	1	0	0	0	0
Nature	0	1	0.05	0.35	0.68
Scientific Data 1	0	0.01	1	0.22	0.02
Scientific Data 2	0	0.03	0.12	1	0.05
WRI	0	0.11	0.02	0.09	1

Note: The table displays the outcomes of a comparative analysis of mini-grid data sources, where each numerical value denotes the proportion of observations from dataset X (found in the table rows) that are also present in dataset Y (found in the table columns). The data sources under examination encompass the following: BloombergNEF data, as described in the mini-grid asset data survey by Mini-Grids Partnership (2020) (hereafter referred to as Bloomberg); the Global inventory of PV generating units by Kruitwagen et al. (2021) (referred to as Nature); the Database of solar photovoltaic farms in India by Ortiz et al. (2022) (referred to as Scientific Data 1: Satellite); a harmonized global dataset of solar farm locations by Dunnett et al. (2020) (referred to as Scientific Data 2: OSM); and the World Resource Institute Global Power Plant Database by Byers et al. (2018) (referred to as WRI).