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

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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.

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

JEL Codes: I25, J24, O13, Q42

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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, where 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).

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

To assess the effectiveness of mini-grids, I employ the Difference-in-Differences approach that exploits the phased rollout of mini-grids in Indian villages between 2016 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. To establish causality, the key assumption of this approach is that the distance to the mini-grid is exogenous within narrowly defined geographical zones. This assumption is plausible given that villages in close proximity to a mini-grid are more likely to connect to it and benefit from it compared to those that are further away. This strategy is suitable considering the localized nature of mini-grids' impacts.

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 project. To analyze the effect of mini-grids on electricity access outcomes, I use changes in nighttime brightness as a proxy for electricity access. 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 on electrification (Machemedze et al., 2017; Burlig & Preonas, 2016).

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 primary and middle schools in India. As compared to other education data in India, DISE data have the most detailed temporal and spatial coverage. 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 SHRUG village-level data, which offers detailed spatial coverage of all Census villages. This is beneficial for the project 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. 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. Comparing these findings with previous studies in developing county context such as Min & Gaba (2014), the estimated effect size is equivalent to installing 15 additional streetlights or providing electricity to 60 more homes in a village. 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 stark heterogeneity of effects by school type. Specifically, the results indicate that the enrollment effects are primarily driven by high school students.

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 and ownership of low-load electric appliances (including cell phones, radios, TV, and electric fans). 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 increased 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. These results are not sensitive to a 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.

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 from traditional electrification infrastructure, such as centralized grids based on fossil fuel, nuclear or hydroelectric sources, due to their relatively low-cost, 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, 2016), 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 affected communities. Specifically, I find that mini-grids can provide more energy and contribute to higher levels of school enrollment in villages they serve. While the impact of mini-grids on energy access may be somewhat smaller compared to large-scale central grid expansions programs observed in countries like India, Senegal, and South Africa (Burlig & Preonas, 2016; Machemedze et al., 2017; Min et al., 2013), they still deliver comparable improvements in enrollment rates seen in the literature on infrastructure projects, such as central grid electrification programs (Khandker et al., 2014; Van de Walle et al., 2013; Khandker et al., 2013). The observed 8% increase in enrollment falls within the range of school participation effects found in studies of central grid electrification programs.

Second, this study expands on prior work on electrification via renewable technologies by carrying out a large-scale causal evaluation of mini-grids. Prior work has primarily focused on case study evidence from a relatively small number of mini-grids. The existing evidence 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).[1] There are only a few causal investigations of mini-grids' effects, primarily from a small number of randomized

[1] 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 on local communities in rural Cambodia.

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 RCT projects, 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 utilizes 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. People require time to learn about the benefits of 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.

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 of solar mini-grids on educational outcomes (for reviews, see Bulman & Fairlie (2016); Escueta et al. (2017)). 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 infrastructure, specifically solar mini-grids, in enabling the adoption of these technologies. The findings reveal increased ownership of electric appliances—including TVs, radios, and cell phones—in villages with mini-grids, underscoring their role as a prerequisite for technology penetration. By expanding access to electricity, mini-grids facilitate broader access to educational technologies, potentially leading to sustainable improvements in human capital development in underserved regions. These findings are particularly relevant for developing countries, where limited access to reliable energy sources often restricts the potential benefits of educational technologies.

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.

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.[2] Figure A1 shows that this issue was particularly pronounced for Indian states in Central and Eastern zones where the average hours of electricity

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

per day varied from 3 to 12 hours depending on specific location.[3]

To support the second point, Figure A13 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.[4]

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.[5]

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 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

[3] 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.

[4] 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.

[5] 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).

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).[6]

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. [7]

Mini-grid construction and placement

Construction of mini-grids conducted by private firms is financed through grants, debt, and equity investment. Notably, the three largest private mini-grid developers

[6] 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.

[7] 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 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.

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.[8]

(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 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.

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

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.[9]

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. This allows children to engage in homework and household tasks during the evening. Second, children can perform chores in the evening, thus they can have more time for attending school during the day. Finally, mini-grids allow other household members to work more efficiently (including use electrified solutions), relaxing the household task burden on children.

[9] 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).

(2) Health Channel: Transitioning from coal and wood for cooking to cleaner electricity reduces indoor pollution and disease incidence, indirectly boosting education.[10] 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 human capital accumulation and productivity (Garg et al., 2022; Masuda et al., 2021).
(3) 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. In addition, electrification can make communities more attractive, potentially motivating inward migration from unelectrified areas.
(4) 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. 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.

2. Supply of education and related channels:

(1) Improved 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 increases: 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.

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

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 nightlights 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).[11] The data has undergone filtering to exclude information affected by stray light, lightning, lunar illumination, and cloud cover. Monthly VIIRS nighttime lights data were further preprocessed and composited annually.

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, 2016). 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 averaging 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

[11] Please, refer to Table B2 for more detailed comparison of VIIRS and DMSP-OLS series.

use of three consecutive Indian Population Censuses from 1991, 2001, and 2011. This data serves 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

A key feature of the datasets used in this study is their detailed spatial coverage, which allows for 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. 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. It generates geographic and temporal variations in energy access and, consequently, human capital outcomes. To study the effectiveness of mini-grids, I use the Difference-in-Differences (DID) approach. It is based on comparing 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. This strategy is appropriate given the localized nature of the effects of the mini-grids.

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.[12]

Secondly, even if there is no dynamic effect, TWFE can still introduce bias when there are heterogeneous treatment effects across groups.[13] It is reasonable to expect heterogeneous treatment effects across groups because reasons such as 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":

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

Where $g \in (2016, 2022)$ 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:

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

[12] 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.

[13] 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).

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:

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

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

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

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

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. ϵ_{vt} errors 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) approach states that there is limited treatment anticipation.[14] The second assumption is that the conditional parallel trends assumption. Specifically, in this setting I utilize conditional parallel trends assumption based on a "Never-Treated" group. More specifically, it states 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.[15]

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

[15]In addition, the following set-up specific assumptions of Callaway & Sant'Anna (2021) DiD need to be

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:

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

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[16]:

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

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. This specification is useful in this context since

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.

[16]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.

it also allows us to capture the dynamics of the effect on treated villages. 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/cm^2/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.

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 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.[17] Thus, each village's social characteristics, household, consumption, poverty, employment, amenities, and

[17]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, presence of a sufficiently ample flat terrain and close connection to a road.

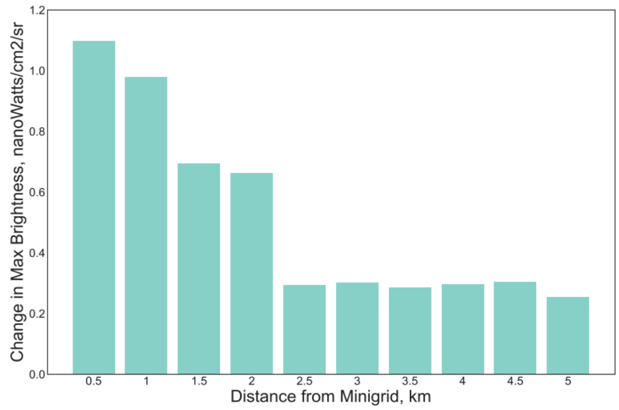

Figure 1. Data-driven control and treatment groups: Maximum brightness

Note: The figure displays the difference in 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. In this Figure, each bar represents the maximum recorded brightness value within concentric circles (or rings) at 0.5 km intervals.

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.[18] 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.

5. *Results and Discussion*

The installation of mini-grids leads to a measurable increase in energy access. More specifically, nighttime brightness increases by approximately 21% in the treated communities. This, in turn, leads to improved educational outcomes among children, as reflected in village-level student enrollment, which experiences an approximately 8% growth. Notably, the increase in enrollment is primarily seen at the high school level. The subsequent subsections provide detailed discussions of specific outcomes.

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

1. Energy access

Main results. I begin by presenting descriptive evidence on the impact of mini-grid installation on 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.[19]

Subsequently, I provide formal event-diagram-type estimation results in the right panel of Figure 2. The plotted pattern shows no evidence of clear pre-trends: the estimates of the pre-treatment dummies are all close to zero and insignificant. On the other hand, most point estimates for post-implementation years are positive, and some are significant at a 5% level.[20]

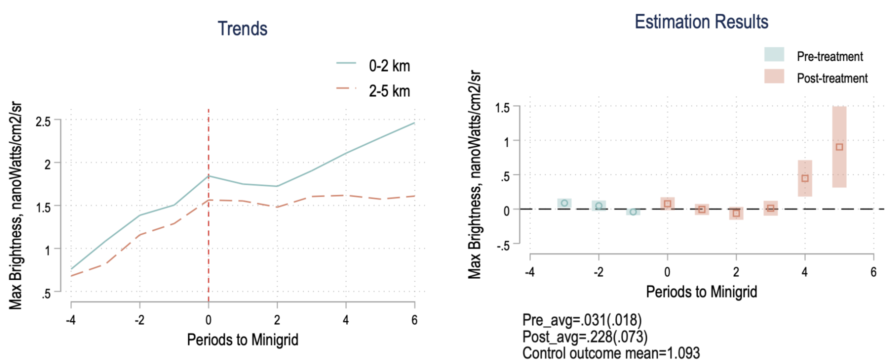

Figure 2. Effects of mini-grid on night-time brightness

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.

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

[20]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.

The effects on brightness gradually emerge after the installation.[21] 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. 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 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 (2016)	Central grid (RGGVY), India	0.18–0.37 units ↑ after 4–5 years
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

[21]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.

(2016)) 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.

Additionally, I conduct a placebo exercise to measure the effect at varying distances from the mini-grid. The results, presented in Figure A6, reveal an expected pattern. As we move closer to the mini-grid, 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-diagram-type 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 indicates an approximate 8% increase in student enrollment at the village level due to improved energy access, demonstrating 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 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.

Heterogeneity. When analyzing effect sizes by gender, I observed similar magnitudes for both girls and boys. As shown in Figure 4, village-level enrollment increases

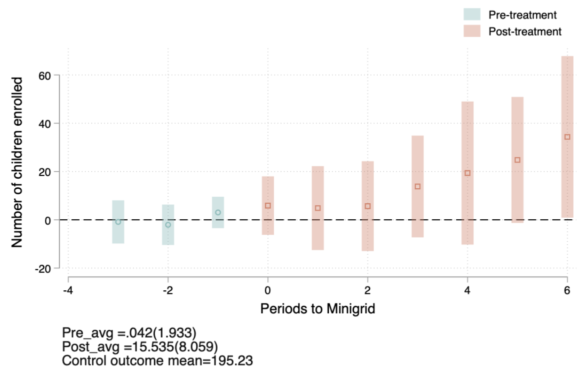

Figure 3. Effects of mini-grid on village-level enrollment

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.

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.

by approximately 8 students, regardless of gender.

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

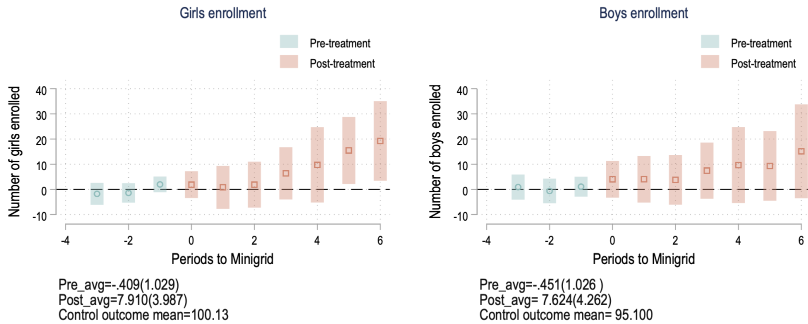

Figure 4. Heterogeneity analysis: Enrollment effects by gender

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.

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 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, 2016). 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

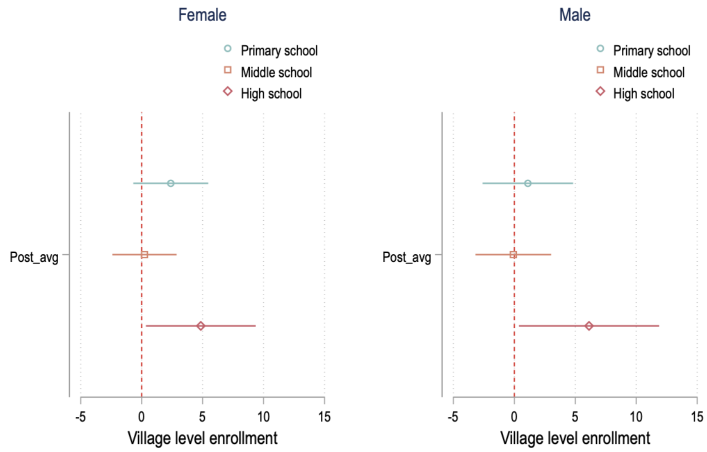

Figure 5. Heterogeneity analysis: Enrollment effects by school type and gender

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.

measures, such as the mean and median of village-level brightness. The results, presented in Table B5, demonstrate that while the significance of the findings remains consistent, the effect size is slightly smaller when using these alternative measures.

Secondly, 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.[22] 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 B6 displays the results for the baseline and these additional definitions. While Definition (1) yields a larger sample but may be

[22]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, n.d.).

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.

Thirdly, 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 B7 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.[23] 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.

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

[23] 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.

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 installed and are actually operational.[24]

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. 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. Figure A10 presents the results of this exercise graphically.[25][26]

Since the installation date is based on brightness, we mechanically begin to observe the effects on brightness in the first year of exposure. However, even in villages that experience changes in brightness, the effects on education still emerge over time, similar to the baseline results. Finally, I show the robustness of the results to different threshold choices in Figure A11. The results remain robust across different threshold levels.[27]

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

[24]The limitation of this analysis is that it will only capture locations where villages use mini-grid energy for lighting houses or streetlights. It won't capture locations where energy is used for purposes that don't emit light, such as pumping water for agriculture.

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

[26]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.

[27]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, as some treated villages with smaller brightness changes would be excluded from the sample.

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). 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 of education supply factors playing a significant role, except for a marginally significant increase in the number of schools. 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.

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	0.016	0.048*	0.062	-0.006	0.017
	(0.015)	(0.015)	(0.026)	(0.112)	(0.018)	(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	-0.014	0.052	0.041	0.054	0.030
	(0.017)	(0.016)	(0.070)	(0.033)	(0.036)	(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*

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.[28] 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

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

discussed previously. The results are presented in Table 4 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 4—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).

Energy connections, asset ownership, and dwelling quality. In this subsection, I present findings related to access to electricity and household assets based on 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.[29]

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

[29]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.

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

to use electricity for cooking.[30] Further, I present the estimated effects on outcomes 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.[31]

In addition, I present evidence on specific electric asset ownership, as depicted in Figure 6. 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;

[30] In principle this is conceivable as cooking appliances require larger power loads compared to simpler devices such as TVs, fans, and phones. 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.

[31] 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.

Keefer & Khemani, 2011) have shown that access to media can promote alternative role models, teach life skills, and alter attitudes towards gender and education.

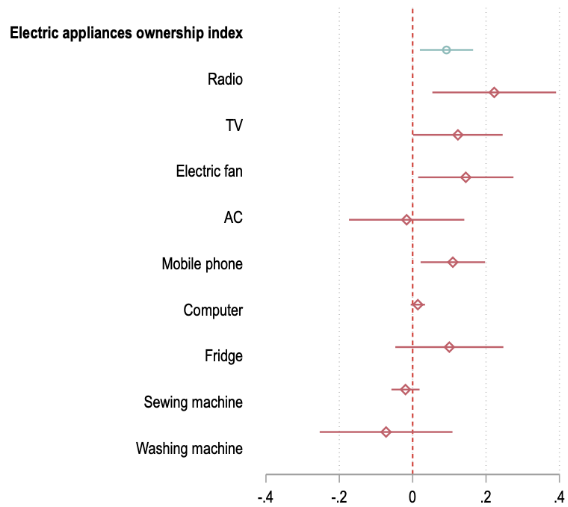

Figure 6. Mechanisms: Electric appliances ownership and index components

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 human capital and productivity (Garg et al., 2020, 2022).

Agricultural outputs. Mini-grids have the potential to support the use of electricity for pumps and irrigation systems, thereby contributing to increased agricultural production and family income.[32] To gauge this impact, I employ the Enhanced Vegetation Index (EVI) as 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).[33]

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 7, with formal estimates provided in Table 6. 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.[34][35] Figure 7 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.

[32] 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).

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

[34] Results for alternative measures of EVI are presented in Appendix A, Figure A12. The results are robust across alternative measures of EVI.

[35] 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.

Table 6—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.

I use additional likely correlates of agricultural production to validate the use of growing-season EVI measures as a proxy for agricultural output at the village level (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.[36]At the village level, these correlates include the potential production of cereal crops (with low input usage) from 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. [37]

[36]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.

[37]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.

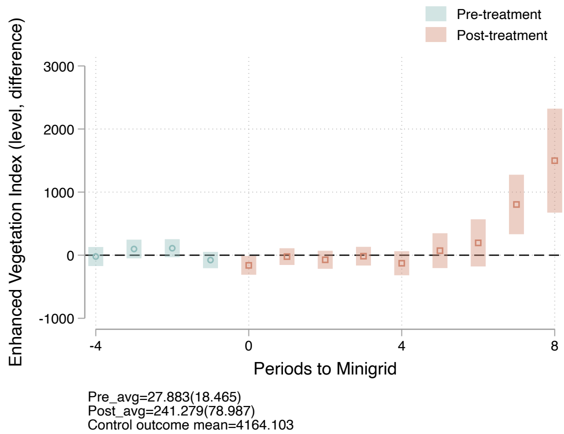

Figure 7. Mechanisms: Effects of mini-grids on agricultural productivity

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.

8. 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 health, household income, and attitudes toward education.

This research contributes to the literature on the impact of electricity infrastructure projects on development. In a broader context, this study addresses a critical gap in knowledge regarding the effectiveness of solar mini-grids in promoting energy access and rural community development. It provides empirical evidence supporting the notion that such decentralized and renewable-based technologies can indeed drive positive changes, albeit gradually. These findings hold implications not only for India but also for other developing countries facing similar energy access challenges. 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.

The findings of this study highlight the potential of solar mini-grids to enhance energy access and educational outcomes in rural India over time. Policymakers could focus on investments in these decentralized, renewable energy solutions, offering financial incentives and support to ensure widespread adoption. Emphasizing household electrification is crucial, as it has shown substantial benefits for educational attainment, albeit with effects that take time to emerge. Additionally, integrating mini-grid initiatives with broader rural development programs can create synergistic impacts on health, income, and community attitudes toward education.

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 local economic growth, would offer a more comprehensive understanding of their benefits. Second, research exploring the scalability and sustainability of mini-grids in different geographical and socio-economic contexts could help identify best practices for broader application. 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. Further studies should also analyze the effects of mini-grids on productive activities, such as small businesses and agricultural operations, to understand how enhanced energy access can drive economic development. 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.

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Appendix A. Additional figures

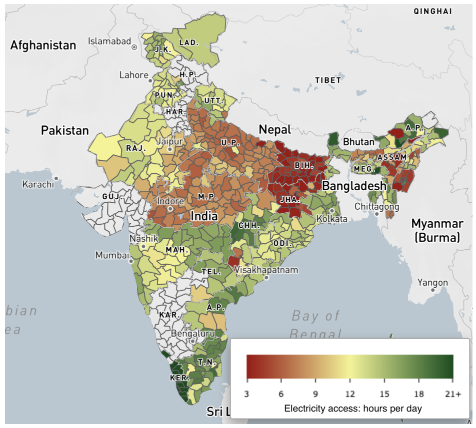
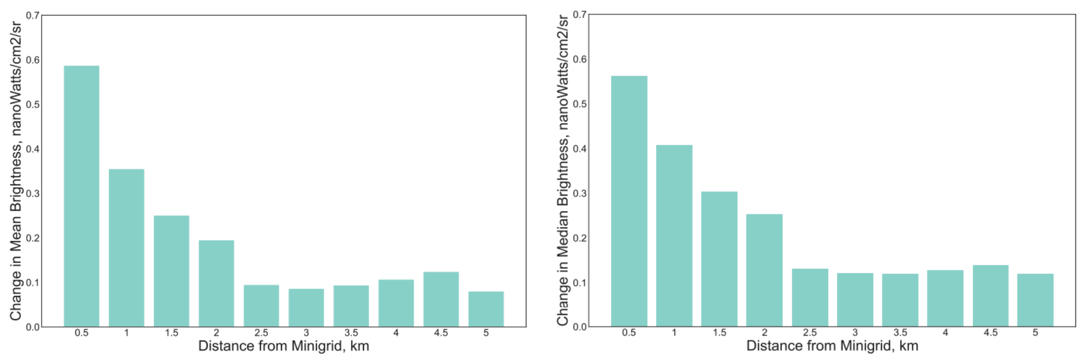


Figure A1. Electricity reliability

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.

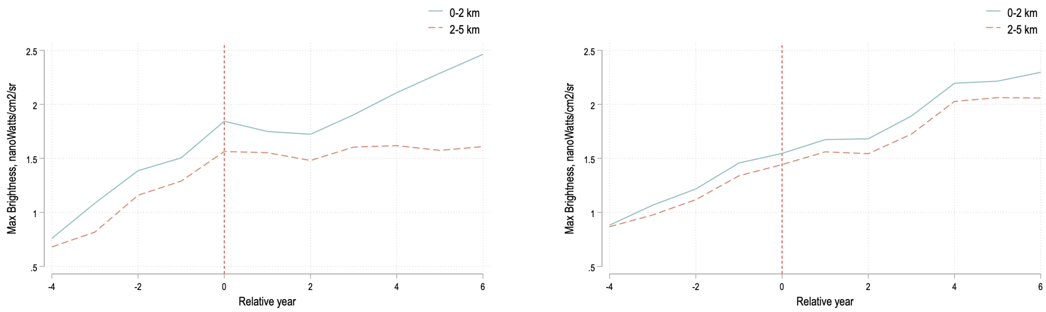


(a) Mean Brightness

(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.

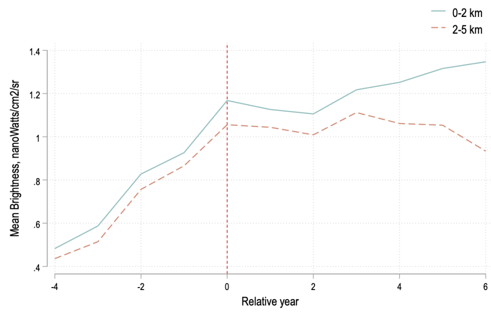


(a) Remote, Max

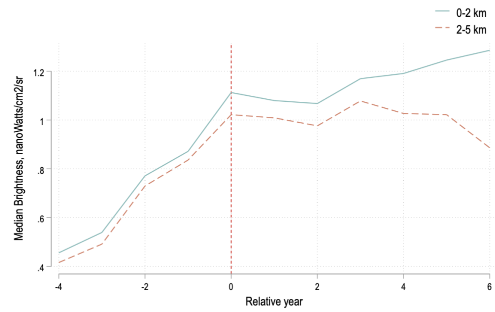
(b) Non-remote, Max

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 nighttime brightness trends in both the control and treatment groups over time, relative to the period of mini-grid installation.

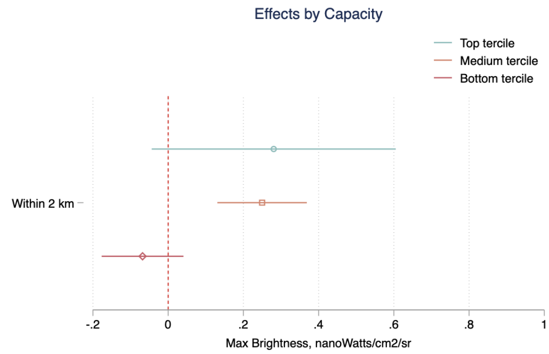


Figure A5. Heterogeneity analysis: Effects by mini-grid capacity

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.

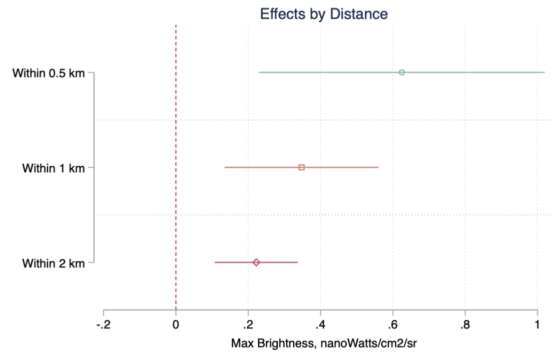


Figure A6. Heterogeneity analysis: Effects by distance to mini-grid

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.

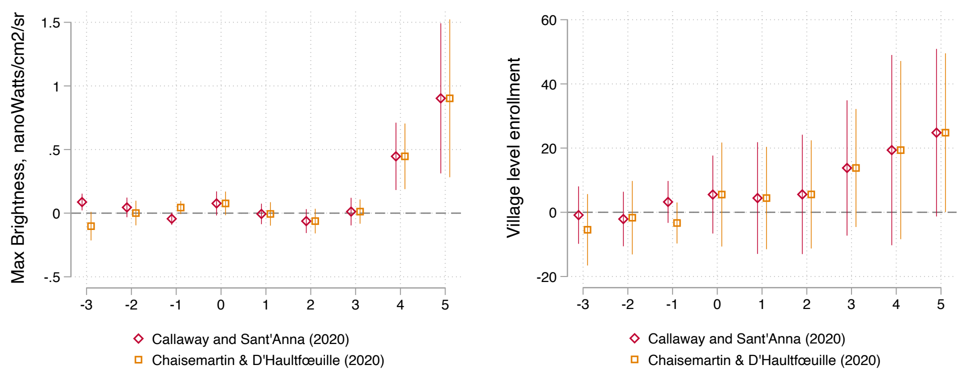


Figure A7. Robustness: Alternative staggered estimation strategy

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.

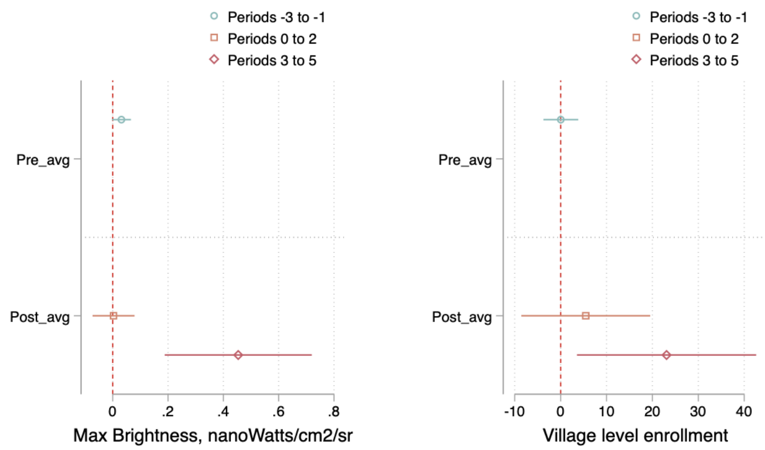
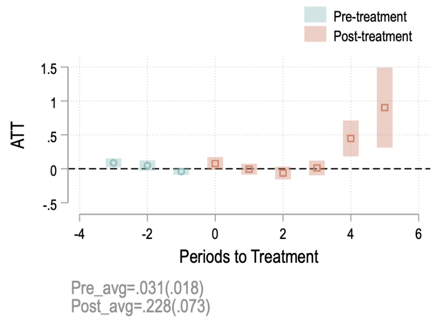
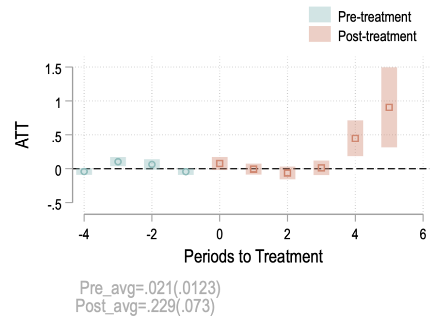


Figure A8. Robustness: Effects by stage

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.

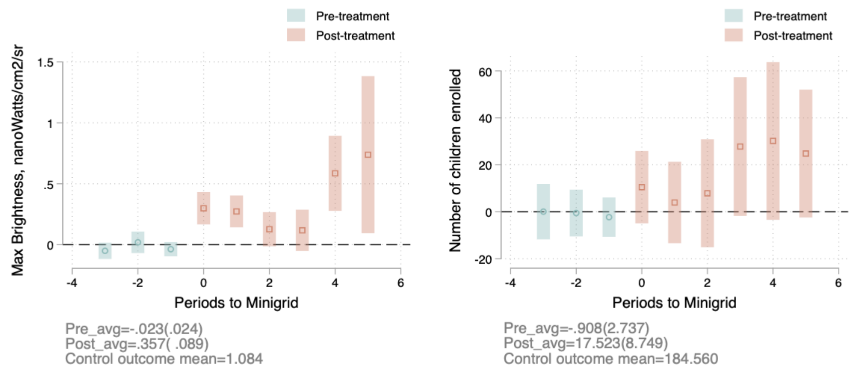


Figure A10. Robustness: Alternative treatment start time based on night time brightness

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. 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. 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.

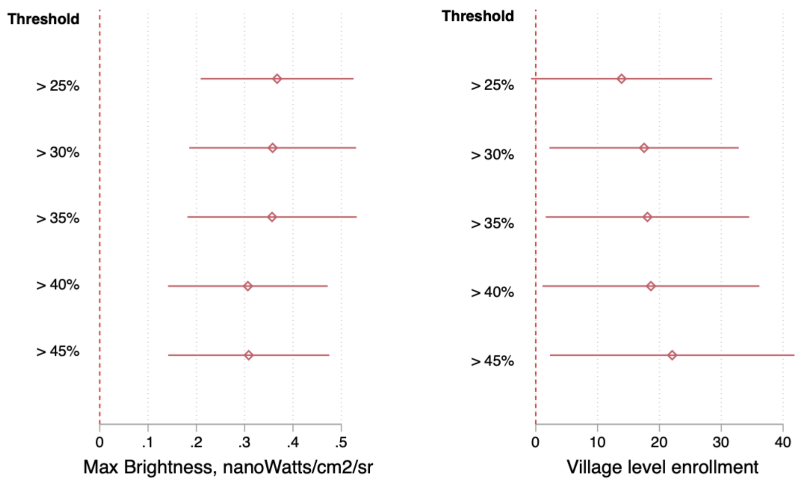


Figure A11. Robustness: Alternative treatment start time and effects by threshold

Note: The figure presents the results on the effects of mini-grid installation on energy access and education outcomes using an alternative approach to treatment start timing based on nighttime brightness. Specifically, the new start year of treatment is defined as the year after the mini-grid installation, when nighttime brightness increases substantially. The baseline results use a threshold of 35%. The figure 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.

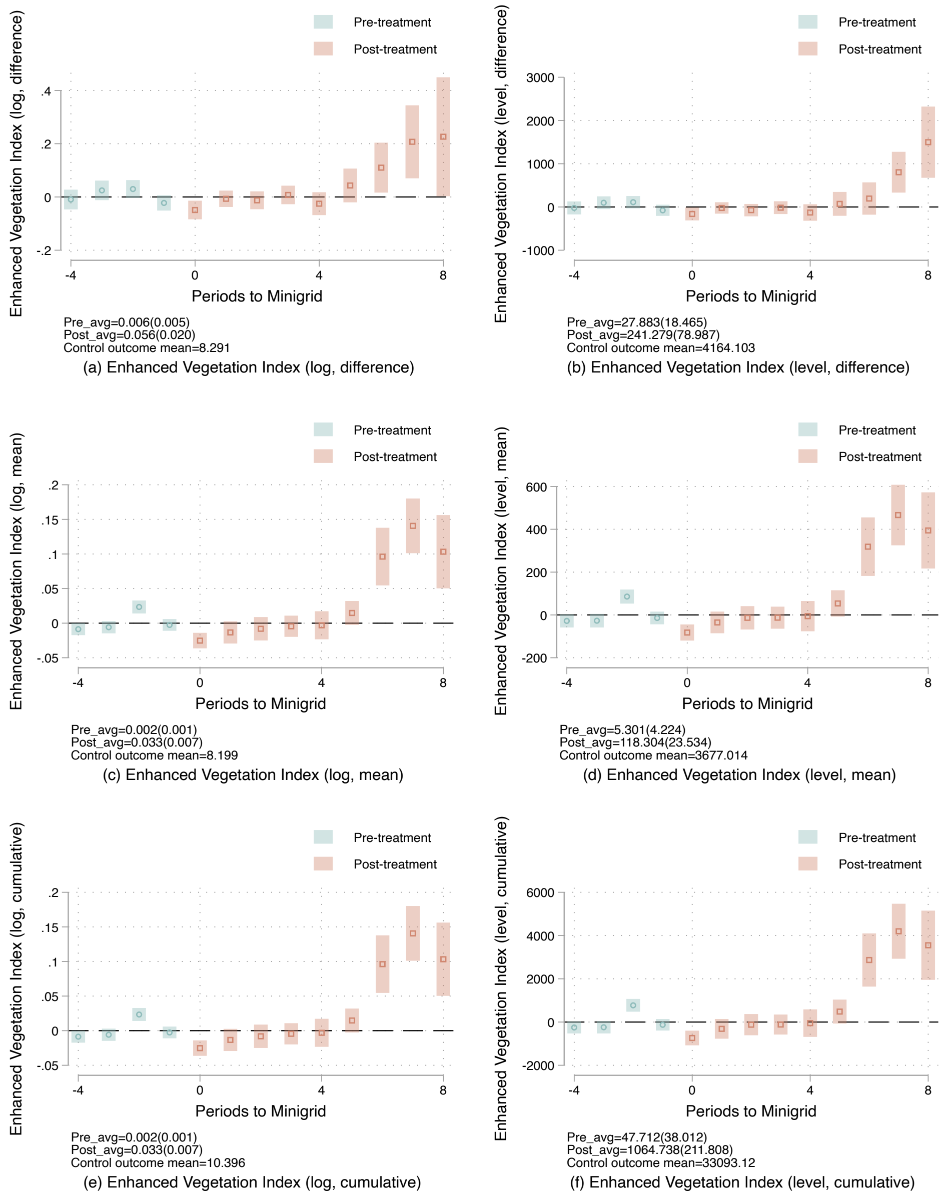


Figure A12. Mechanisms: Alternative measures for EVI as proxy of agricultural yields

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.

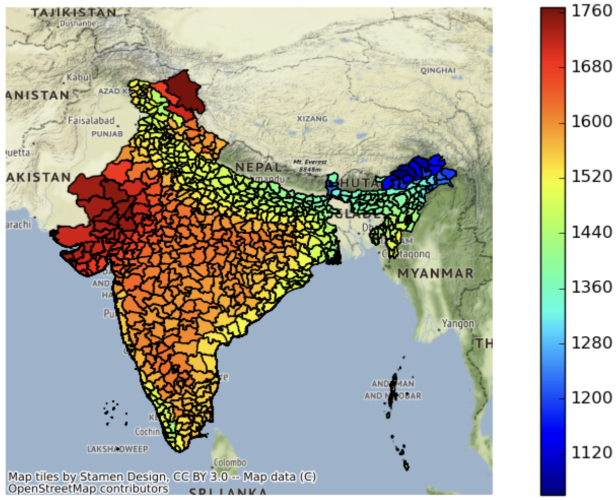


Figure A13. Photovoltaic power potential of India

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.

Appendix B. Additional tables

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 subsidies	Medium, cheaper than SHS, economies of scale	High	High, increasing cost of diesel
Reliability	Low, load shedding, 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)
Household characteristics			
Number of households	332.558	368.920	-36.362*
	(12.758)	(31.590)	
Average household size	6.714	6.649	0.065
	(0.023)	(0.043)	
Consumption and poverty			
Per capita consumption	15170.153	14987.722	182.431
	(127.511)	(222.272)	
Poverty rate	0.386	0.397	-0.011
	(0.005)	(0.010)	
Area and proximity			
Village area	216.636	282.199	-65.563*
	(8.375)	(21.126)	
Agricultural land as a % of village area	0.756	0.700	0.056
	(0.007)	(0.017)	
Agricultural productivity	8.379	8.357	0.021
	(0.004)	(0.009)	
Accessible by road	0.797	0.836	-0.039
	(0.012)	(0.023)	
Min distance place population > 10k	7.365	8.221	-0.856
	(0.172)	(0.399)	
Min distance place population > 50k	26.645	25.538	1.107
	(0.286)	(0.605)	
Min distance place population > 100k	35.005	40.673	-5.668
	(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	
Joint significance test (p-value)			

	Control (2-5 km) Mean/SE (1)	Treat (0-2 km) Mean/SE (2)	T-test for Difference In Means (1)-(2)
Schools			
Number of primary schools	1.368	1.556	-0.188**
	(0.036)	(0.096)	
Number of middle schools	0.653	0.716	-0.063
	(0.025)	(0.062)	
Number of secondary schools	0.145	0.188	-0.043
	(0.013)	(0.028)	
Number of senior secondary schools	0.088	0.112	-0.024
	(0.009)	(0.023)	
Number of colleges	0.023	0.012	0.011
	(0.005)	(0.007)	
Employment			
Manufacturing employment per adult population	0.012	0.012	0.000
	(0.003)	(0.002)	
Services employment per adult population	0.036	0.041	-0.005
	(0.002)	(0.004)	
% of agroprocessing employment	0.715	0.638	0.077
	(0.044)	(0.076)	
% of storage and warehousing employment	0.090	0.117	-0.028
	(0.030)	(0.054)	
% of households with cultivation as main income source	0.321	0.384	-0.062
	(0.010)	(0.022)	
% of workers employed in agriculture	0.304	0.347	-0.043
	(0.009)	(0.019)	
Observations	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: 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 B6—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 $\leq$ 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/cm^2/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 B7—Robustness: TWFE estimates by remote minigrid status

	Max			Mean			Median		
	All	Remote Only	Non Remote	All	Remote Only	Non Remote	All	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.

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.[38] 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.[39] 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.[40] After establishing a rough new DISE-old DISE village concordance, I use school codes to resolve duplicate village matches.[41]

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.

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

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

[40] 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.

[41] 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 crowd-sourced 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.[42] 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.

[42] 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.[43] 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, n.d.).

Since (2) and (3) datasets might not capture the full range of development given sampling biases inherent to crowd sourcing approaches[44] 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.

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

[44] 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.

Database of solar photovoltaic farms in India (Ortiz et al., 2022)

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 [45][46]

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

[45] 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, n.d.). 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.

[46] 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 B7 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 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).