Sunny Days, Bright Nights:
How Solar Power Affects Electricity Reliability in India

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Conventional wisdom suggests that solar generation reduces emissions by displacing fossil fuels but, because of its variability, might undermine electricity reliability. Using plausibly exogenous spatial and temporal variation in solar plants' exposure to the sun's energy, I find that while this holds for the US, where solar displaces fossil fuel generation one-for-one, in India, solar generation instead expands energy supply and eases shortages that cause power outages. Solar does not contemporaneously displace nonsolar generation one-for-one in India, and solar generation over the past week *increases* current nonsolar generation and, in turn, total generation. This result is driven by the accumulation of coal stocks at power plants in India, where coal shortages drive power outages. When solar fulfills a greater share of demand, power plants need less coal, which allows residual stocks to build up. These stocks are drawn down in subsequent days to increase generation. I test whether this increase in generation translates to improvements in reliability by applying machine learning techniques: I predict power outages using daily satellite night-time lights data and find that solar generation reduces the share of pixels under outage by 9%. Hence, in India, solar delivers a low-carbon energy expansion, not an energy transition: it improves reliability but does not necessarily cut emissions from existing fossil fuel sources.

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1. Introduction

Solar power has grown rapidly over the past decade in both developed and developing countries. With a global annual rate of growth in installed capacity of 23%, it plays a key role in decarbonizing the power sector — the largest contributor to global emissions. In developed countries, solar reduces emissions by displacing fossil fuels but may also reduce electricity reliability. Since solar generates electricity only when the sun shines, backup sources must quickly adjust to fluctuations in supply to prevent power outages. Thus, the rapid growth of solar power has also come with concerns about its impacts on electricity reliability.

However, in developing countries such as India, solar power may not displace fossil fuels and may instead expand energy supply and ease the shortages that cause power outages. Indian households face an average of 3.4 hours of outages *per day*; the corresponding figure for American households is 5.5 hours *per year* (Agrawal et al. 2022; US Energy Information Administration 2024). These outages stem from conditions specific to developing countries, where supply shortages persist and large electricity subsidies undermine infrastructure investment (McRae 2015). While electricity utilities in developed countries must meet all retail demand, utilities in India may ration supply and induce power outages during supply shortages or when fuel procurement costs are too high (Burlig and Preonas 2024; Burgess et al. 2020). By providing additional electricity supply, solar power might buffer against these shortages and improve reliability.

This paper studies how solar generation affects electricity reliability in India through its short-run effects on nonsolar generation.[1] The effect of solar generation on nonsolar generation determines both emissions and reliability. If solar displaces nonsolar generation, emissions fall because nonsolar sources are primarily fossil-fuel based, but total supply remains unchanged. When this is true, and I find it is in the US — where outages are rare — solar power advances the energy transition. Conversely, in India — where outages are frequent — I find that solar generation does not displace nonsolar generation. Emissions from existing fossil fuel sources therefore remain unchanged, but total supply increases, reducing shortages. Solar power thus has distinct implications for the energy transition in developed and developing countries. In India, it delivers a low-carbon energy expansion, not an energy transition: it improves reliability but does not necessarily reduce emissions from existing fossil-fuel generation.

I estimate utility-scale solar generation at power plants as a function of their installed capacity and solar irradiance to examine how variation in solar generation affects nonso-

[1]Throughout this paper, I use "electricity reliability" to refer to the continuous availability of power without supply interruptions.

lar generation, coal stocks and deliveries, and night-time lights (NTL). Solar irradiance measures the amount of solar radiation that reaches the earth's surface. Changes in solar generation arise from spatial and temporal variation in solar plants' exposure to irradiance, interacted with variation in installed solar plant capacity. Using the interaction between capacity and irradiance allows me to isolate the variation that is driven by plausibly exogenous solar irradiance and examine its contemporaneous and intertemporal effects: The contemporaneous effects capture how solar displaces nonsolar generation in meeting electricity demand, whereas the lagged effects capture intertemporal responses of fuel shortages to solar generation.

Conventional wisdom suggests that solar generation displaces nonsolar generation; I begin my analysis by showing this to be true for the US. In New England, a setting with almost no outages and ample solar variation, solar generation affects nonsolar generation only contemporaneously: Current solar displaces nonsolar generation one-for-one, whereas solar generation over the previous week has no significant effects on current nonsolar generation. This result supports two observations. First, it confirms the assumption that in markets without unmet demand, solar generation substitutes (predominantly fossil fuel–based) nonsolar generation, implying a decrease in emissions. Second, the result provides a benchmark for the effects of solar in a developed-country setting where outages almost never happen. Distinct effects of solar generation in developing-country settings would then reflect determinants unique to those settings.

In India, solar generation does not contemporaneously displace nonsolar generation, and lagged solar generation *increases* current nonsolar generation. I find that the lagged effects of solar follow a clear decaying pattern: Solar generation on the previous day has the strongest impact on current nonsolar generation — an increase of one megawatt-hour (MWh) in solar generation on the previous day increases current nonsolar generation by approximately 0.2 MWhs. This effect weakens over time — a one MWh of increase in solar generation four days ago increases current nonsolar generation by approximately 0.04 MWhs. This pattern suggests positive effects of past solar generation on current nonsolar generation in the short-run in India. Past solar generation therefore increases total electricity generation.

What explains the contrast between the contemporaneous and lagged impacts of solar generation in the US and India? A key distinction is reliability. Solar generation over the last few days affects current nonsolar generation because India is prone to shortages of coal, which powers 73% of India's electricity generation.[2] Solar power provides a buffer for coal stocks to build up at fuel-constrained power plants. Indian power plants typically maintain

[2] Based on electricity generation data for 2024-2025 reported by NITI Aayog.

only a few days' worth of coal reserves. On average, power plants in India hold approximately 16 days of coal stock vs. 116 days of stock at US power plants.[3] Several factors contribute to these shortages: India's state-owned non-profit-maximizing coal production monopoly has struggled to meet rising electricity demand, plants have limited financial ability to stockpile reserves, and transport bottlenecks limit timely coal deliveries.

I show that coal stock accumulation is the key mechanism behind the lagged effects of solar generation. I find that by reducing contemporaneous coal consumption, solar power increases the net stocks of coal available over the following day, which are drawn down on subsequent days through increased coal generation. While coal consumption responds to solar generation, coal deliveries do not change significantly, reinforcing that there is intertemporal reallocation of coal.

As another piece of evidence supporting this mechanism, I show that the effects are driven by coal-constrained power plants. If easing the pressure on coal is the mechanism driving the lagged results, then we would expect plants whose coal constraint is more binding to respond more strongly than the less constrained. I classify plants based on how often they declare coal shortages, either through plant outages because of insufficient coal or critical stock flags raised in daily reports. I find that shortage-prone plants — which are more coal-constrained — exhibit stronger effects in response to solar generation.

To test whether the solar induced increase in total generation translates to improvements in reliability, I construct a measure of reliability using satellite NTL data, the most direct available measure of power outages. To detect outages, I train a random forest algorithm on outage readings from electricity supply monitors matched to the corresponding NTL pixels. I then apply this algorithm to classify outages in daily NTL data for the full period of analysis. I find that solar generation leads to a 9% decline in the share of pixels under outage at the state level in India. This reflects an energy expansion: the improvement in reliability is consistent in magnitude with increases in solar generation. This effect confirms the causal chain that goes from increased solar production to increased total generation to reduced outages.

My findings suggest that solar power improves electricity reliability in India but does not necessarily cut emissions from existing fossil fuel sources. While the physical constraints tied to the variability of solar power apply universally and may undermine electricity reliability in both developed and developing country settings, the economics of solar power differs. An

[3] India's days of stock estimated from daily stock levels and coal consumption data from the Central Electricity Authority's *Daily Coal Reports*. US' days of stock for the same period estimated from the Energy Information Administration's Days of Burn by Coal Rank data.

additional reliability concern from increases in solar power in developed countries is that as solar fulfills an increasing share of electricity demand, it might lead to the retirement of less competitive fossil fuel generators. This in turn might lead to power shortages on days with insufficient solar resource. However, fossil fuel generators are not yet being retired with increasing solar power in India where there are supply shortages, and hence the reliability concerns from insufficient power generation on low solar resource days do not factor into the economics of solar power in this setting. When solar leads to an energy expansion — not an energy transition — in developing countries such as India, it ameliorates the issue of power shortages by solving a more immediate problem: insufficient power supply to meet electricity demand.

Related Literature. This paper's main contribution is to show that in India, solar power leads to an energy expansion, easing constraints and improving reliability. This raises an important distinction relative to the impacts of solar power in developed countries such as the US, where it reduces emissions but has raised concerns around maintaining grid reliability as incremental variable solar power is integrated.

Prior work shows that the distinctive features of developing countries' electricity markets affect infrastructure, investment, and reliability. Widespread electricity theft and large, politically sensitive electricity subsidies strain the finances of electricity utilities, incentivize rationing, and foster corruption (Gertler et al. 2017; Burgess et al. 2020; Jha et al. 2023; Mahadevan 2024). Such a policy environment undermines electricity reliability, discourages infrastructure investment, and distorts power procurement (McRae 2015; Pathak 2020; Ryan 2022; Jha et al. 2023). I show that solar power can ease some of these constraints and improve reliability. These reliability improvements have important economic implications: Several studies show that poor reliability hurts firm revenue and productivity, undermines economic growth, and lowers household welfare (Chakravorty et al. 2014; Allcott et al. 2016; Cole et al. 2018; Fried and Lagakos 2023; Cisse 2025).

In addition, I contribute to the literature on the economic and environmental impacts of solar power and its intermittency. This is the first paper to show that the net effects of solar power on emissions and reliability depend on the market structure and underlying grid operations in a developing-country context. Baker et al. (2013) note that economic analyses of solar power, particularly for the US, must consider three things: first, that the fuel (sunlight) is free; second, that increases in solar capacity displace fossil-fuel generation, thereby reducing both costs and emissions; and third, that the intermittency of solar power makes supply unreliable. This paper shows that economic analyses of solar power in India must also account for energy expansion and the resulting reliability gains. Other studies have sought to quantify the effects of intermittency by estimating the costs of building backup generation (Gowrisankaran et al. 2016; Joskow 2019; Butters et al. 2025). This paper shows that in India, solar solves a more immediate generation issue: inadequate supply to meet existing — much less rising — electricity demand.

Finally, I contribute by developing a novel, high-frequency reliability measure from publicly available NTL data. The standard reliability metrics that track grid interruptions typically reported by utilities — namely, the system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI) — are of limited reach, incomplete, and of low frequency (Klugman et al. 2023). Alternative attempts to develop measures through self-reports, surveys, or smartphone data (Klugman et al. 2014), although reasonable, have proved expensive and require systematic data collection. In contrast, NTL data provide a low-cost, frequent, and globally available proxy. Starting with Henderson et al. (2012), several papers have used NTL as a proxy for economic outcomes, including economic growth and electrification (Min et al. 2024; Walter and Moneke 2024; Mahadevan 2024; Burlig and Preonas 2024). However, this paper is one of the first to use NTL data to measure electricity reliability. Min et al. (2017) identify outage-prone areas by detecting excess fluctuations in radiance annually and Dugoua et al. (2022) detect outages by applying ML methods to monthly NTL data. Mann et al. (2016) is the only other paper to analyze NTL data at a daily level to predict outages. I further develop this measure, producing the first local, daily estimate of outages that's national and multi-year.

The rest of this paper is organized as follows. I describe the context of coal shortages and electricity reliability that shapes the effects of solar generation in India in Section 2. Section 3 presents a conceptual framework for how the impacts of solar on nonsolar generation determine emissions and reliability. Section 4 describes the data. Section 5 presents the empirical strategy using solar irradiance as a source of plausibly exogenous variation. Section 6 presents the estimates of the causal impacts of solar on nonsolar generation, coal stocks, and electricity reliability. Section 7 describes the external validity and policy implications of my findings. Section 8 concludes.

2. Background

2.1. Electricity Generation and Blackouts in India

There are three main causes of blackouts in India: technical failures, electricity rationing, and fuel shortages. Technical failures occur when the power system fails to balance supply and demand, often because of faults in transmission and distribution. Electricity rationing is specific to developing countries, where utilities limit supply to reduce financial losses from subsidized electricity tariffs and theft. (Burgess et al. 2020; Jha et al. 2023). Shortages occur when there is not enough fuel to meet electricity demand.

This paper focuses on the third cause: fuel shortages that prevent power plants from meeting electricity demand. India's electricity generation is coal intensive, with coal supplying about 75% of all generation in 2024-2025 (NITI Aayog 2025). When coal stocks run low, power plants are forced to ration fuel, which may lead to blackouts. For example, in October 2021, about 86% power plants reported critically low stocks, leading to widespread outages across India. Some states experienced up to 14 hours of outages per day (John Kemp 2021; Ellis-Petersen 2021). On average, about 10% of power plants have critically low coal stocks each day, and about 2% declare outages due to fuel shortages.[4]

2.2. Coal Shortages in India

The chronic coal shortages at Indian power plants stem from three inefficiencies in the coal market: The state monopoly does not produce enough coal, power plants have neither the incentives nor the financial resources to stockpile excess reserves, and transportation bottlenecks limit timely deliveries.

The output of the state's coal monopoly has failed to keep pace with growing demand in India's coal-intensive electricity sector. Coal India Limited (CIL), a publicly owned, non-profit-maximizing enterprise, produces approximately 75% of domestic coal, while other public sector companies account for another 20%.[5] The power sector consumes 90% of all domestically produced coal. To keep electricity affordable for retail customers, state producers keep domestic coal prices inefficiently low (Tongia et al. 2020). As a result, the non-profit-maximizing state monopoly has had consistently low output and suffered from legacy issues such as obsolete mining practices and technology and lengthy permitting processes (Tongia and Sehgal 2019). On average, domestic production has fallen below target by at least 50 MT each year.[6] Although imported coal does bridge some of this gap, it is an order of magnitude more expensive than domestic coal and incurs high transportation costs (Tongia and Sehgal 2019).[7]

[4] Estimated from *Daily Coal Reports* and *Daily Generation Reports* data by the Central Electricity Authority (CEA) following the methodology described in the *Daily Coal Reports*.

[5] Based on calculations from data reported on the NITI Aayog India Climate and Energy Dashboard. In 2023–2024, CIL produced 774 million tonnes (MT) of coal,the other public sector companies 219 MTs, and the private sector 48 MT. Out of 964 MT of consumption, the power sector consumed 860 MT.

[6] Shortfall estimated from targets and actual production figures in the Ministry of Coal's Annual Reports.

[7] Vanamali (2022) estimates imported coal to be five times more expensive than domestic coal on average, whereas Tongia et al. (2020) estimate that on energy equivalence basis, domestic coal prices have been lower by up to 90% than international coal prices.

Past attempts to increase private participation in the coal sector have failed because of corruption and judicial intervention. In 1993, the Indian government tried to increase private participation by allocating individual coal mines to power generators and industrial users with specific use cases (Pathak 2020; Tongia et al. 2020). However, the Supreme Court struck down these allocations in 2014, citing a lack of transparency in the allocation structure. While subsequent auctions followed, only a fraction of the initial set of mines have been successfully reallocated, and there has been limited private sector expansion. As of 2018, CIL operated approximately 400 mines, while other public and private firms operated fewer than 20, such that the state monopoly on coal production persists today (Tongia et al. 2020).

Power plants thus face chronic coal shortages and operate on limited stock. They are required to maintain 12–26 days' worth of coal, depending on their distance from mines, but many fall short of even these minimum thresholds. On average, power plants in India hold approximately 16 days of stock. For comparison, US coal plants hold 116 days' average stock.[8] Jha (2023) notes that coal-fired plants very rarely run out of coal in the US; in contrast, approximately 10% of Indian plants face critically low coal stocks each day.[9]

Plants' ability to stockpile large amounts of coal is limited because they are financially constrained. Plants sign fuel supply agreements (FSAs) with coal producers, CIL, to purchase a fixed quantity of coal. FSAs impose penalties if the plants fail to purchase or CIL fails to deliver the contracted quantity of coal (Tongia et al. 2020).[10] However, many plants are financially constrained by payment delays from perennially bankrupt state-owned utilities (Ryan 2022). These utilities often face liquidity shortages because they sell electricity at subsidized rates but government reimbursements are frequently delayed. CIL, in turn, often requires advance payment.

The length and congestion of coal supply chains worsens shortages. Roughly 70% of all coal consumed in India is transported by train, and coal accounts for about 40% of all freight traffic on Indian Railways (Tongia et al. 2020). Figure 1 shows the location of mines in the east and power plants throughout India. Coal must travel about 500 kilometers (310 miles) on average, mostly by rail, from mines located predominantly in eastern India to plants throughout the country.[11] These rail corridors tend to be heavily congested, creating bottlenecks that prevent timely coal deliveries. Gupta et al. (2020) estimate that by 2030,

[8] Estimated days of stock for India calculated using daily stock and consumption reported in the Central Electricity Authority's *Daily Coal Reports*. Days of stock data for the US are reported by the US Energy Information Administration (EIA).

[9] Estimated based on critical coal stock triggers reported in Ministry of Coal's *Daily Coal Reports*.

[10] There have been proposals to reduce the penalties on CIL for nondelivery. In addition, *force majeure* provisions allow CIL to avoid penalties in case of contingencies.

[11] National Rail Plan, India, 2020.

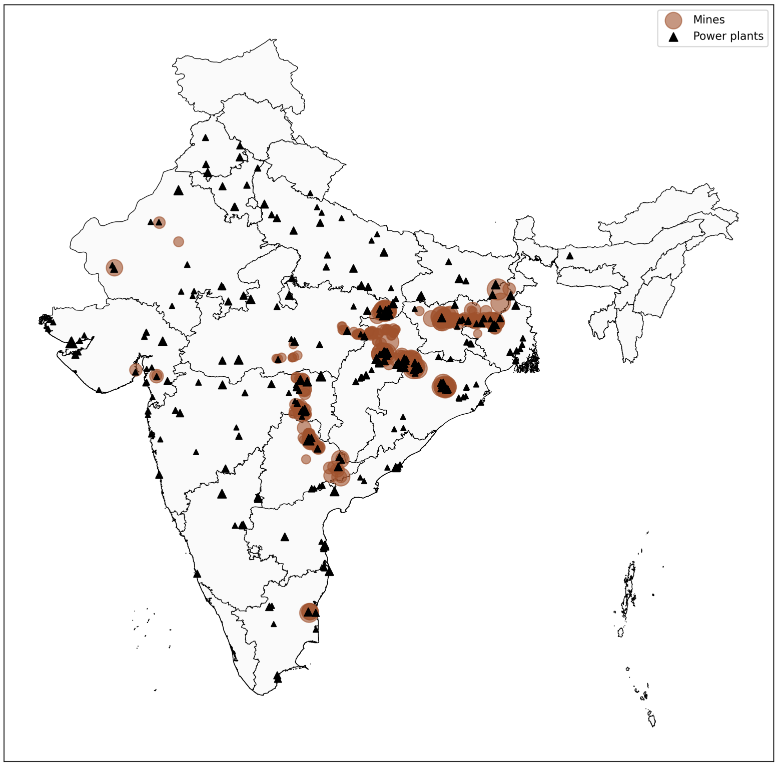


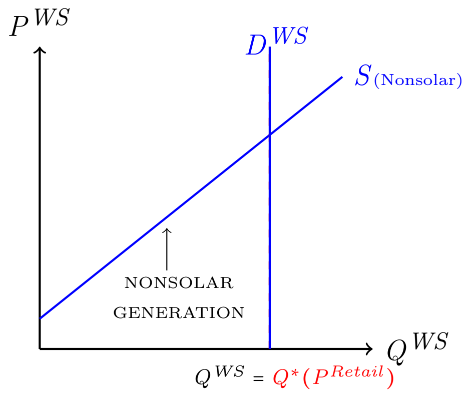
FIGURE 1. Coal Mines and Plants in India, Scaled by Capacity

Data from Global Energy Monitor. This map includes all operational mines and power plants as of May 2025, scaled by their capacity.

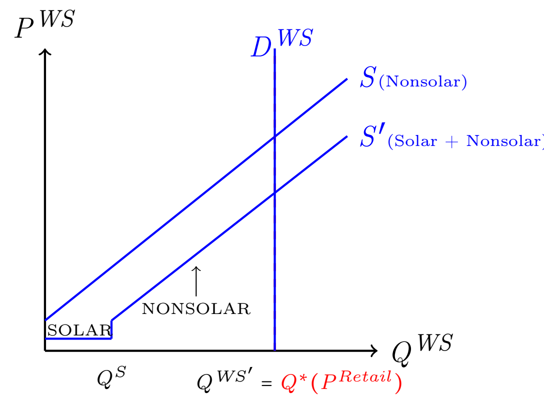
railway bottlenecks will be responsible for 15% of the coal shortages in India.

3. Conceptual Framework

In developed countries, all electricity demand is met, and utilities' wholesale demand curve is inelastic. Increases in solar generation in such a setting displace nonsolar generation and reduce emissions, but there is no change in how much electricity demand is met. In contrast, utilities' wholesale demand curve in developing countries such as India is downward sloping (Jha et al. 2023), and high costs lead to unmet demand. In such a setting, the effect of solar on total demand met, emissions, and reliability is ambiguous and depends on how nonsolar generation responds to changes in solar generation.



(a) Before solar



(b) After solar

FIGURE 2. Wholesale Electricity Supply and Demand in the US

3.1. Developed Countries: Inelastic Wholesale Demand Curve

Utilities purchase electricity from power generators and sell it to retail customers. Power outages are rare in developed countries such as the US, where regulatory mandates require electricity utilities to meet all retail demand, such that their wholesale demand curve is inelastic at the quantity of retail demand they must fulfill.[12] Figure 2(a) depicts utilities' inelastic wholesale demand curve D^{WS} and the supply curve of power generators S. Retail demand from downstream consumers, which utilities are required to serve, is denoted by Q^*. Since retail consumers typically face fixed electricity tariffs in the short run, their demand is determined by retail prices (P^{Retail}) and is exogenous to the wholesale prices faced by electricity utilities (P^{WS}). Utilities therefore take retail demand as given and purchase power from generators to meet retail demand Q^*.[13]

When zero-marginal-cost solar generation is added to the power mix, it shifts out the supply curve from S to S' as in Figure 2(b). Since the wholesale demand curve is inelastic, total demand met remains fixed at $Q^{WS} = Q^*$. Solar displaces Q^S units of nonsolar generation in the power supply, most of which is fossil-fuel based. As a result, less fossil fuel is burned, and emissions decline, with no change in how much electricity demand is met ($Q^{WS'} = Q^*$).

[12]Note the distinction between the wholesale demand curve and the retail demand curve. In this section, I focus on the wholesale demand curve of *electricity utilities* when they purchase electricity from power generators. This is different from what we typically think of as retail demand curves when retail consumers purchase electricity from utilities.

[13]The representation of the wholesale power markets in Figures 2 and 3 is stylized and abstracts from several features of the respective electricity markets, including differing renewables subsidies, capacity markets, power purchase contracts, and other details of modern grid optimization.

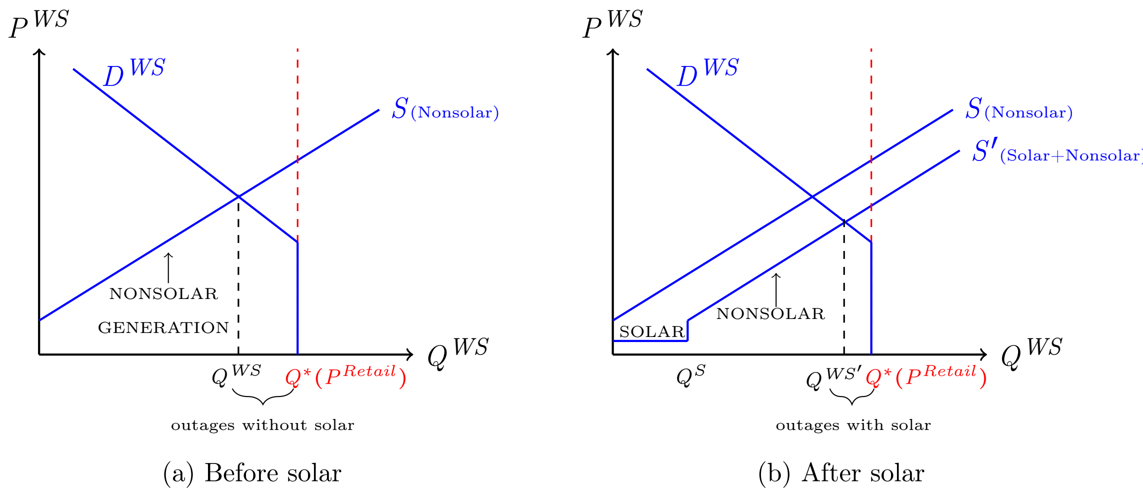


FIGURE 3. Wholesale Electricity Supply and Demand in India

3.2. India: Downward-Sloping Wholesale Demand Curve

In contrast with the inelastic wholesale demand curve so far, utilities' wholesale demand curve in developing countries such as India is elastic and downward sloping (Jha et al. 2023). Indian utilities are not required to meet all demand at all times, and power outages are common because of the factors outlined in Section 2, such as theft and high electricity subsidies. Q^* in Figure 3 denotes the hypothetical retail demand that would be met if there were no outages. Q^* is determined by the price in the retail sector (P^{Retail}), which is heavily subsidized relative to the wholesale price (P^{WS}) for maintaining electricity affordability (Burgess et al. 2020). In the presence of outages, actual electricity demand fulfilled by utilities Q^{WS} is less that the total demand Q^*. This gap between the potential demand and demand actually met is illustrated in Figure 3 by $Q^* - Q^{WS}$, in contrast to Figure 2, where all retail demand is met, or $Q^* - Q^{WS} = 0$.

When solar power increases electricity supply in this setting by shifting the supply curve from S to S', it does not necessarily displace nonsolar. The net effect depends on how nonsolar generation responds to incremental solar supply. If solar simply displaces nonsolar generation, as it does in Figure 2, the demand met will remain constant at Q^{WS}, there would be no change in outages ($Q^* - Q^{WS}$), and emissions will decline because nonsolar generation is predominantly coal-based in India. On the other hand, if solar power adds to total supply instead of displacing it as illustrated in Figure 3, the electricity demand met by utilities increases from Q^{WS} to $Q^{WS'}$, and outages decrease from $Q^* - Q^{WS}$ to $Q^* - Q^{WS'}$. However, emissions remain unchanged.

I study how solar affects nonsolar generation and the corresponding impacts on electricity reliability, as reflected by the difference between retail demand Q^* and demand met Q^{WS} in Figure 3. The prediction from Figure 2 is clear for the developed-country setting. However, this simple framework has demonstrated how solar power might not displace fossil-fuel based power in developing countries, where shortages are common.

4. Data

I estimate solar generation at utility-scale power plants using data on their location, capacity and daily solar irradiance received. To compile data on nonsolar generation and mechanisms driving the effects through coal stocks in India, I web-scrape and digitize daily electricity reports published by Indian electricity authorities. I compile comparable data for ISO New England in the US to benchmark my results. Finally, I compile daily NTL data to examine downstream effects on electricity reliability.

4.1. Indian Electricity Data

I compile a rich daily dataset covering electricity generation by fuel type and total electricity consumption in each state, generation at all nonrenewable powerplants in India, and stock levels at each coal plant for 2019–2025. I web-scrape and digitize data from four sources: the *Daily Grid Reports* published by the Grid Controller of India and the *Daily Generation Reports*, *Daily Coal Reports*, and *Daily Renewable Reports* published by the Central Electricity Authority (CEA).

The *Daily Generation Reports* include data on coal, natural gas, hydro, and nuclear power plants. As of 2025, India had 472 gigawatts (GW) of installed power capacity, approximately one-third of the total installed capacity in the US.[14] At the same time, India generated approximately 2000 terrawatt-hours (TWh) of electricity in 2024, about half as much as the US.[15] These ratios suggests that India has less idle capacity than the US.

Table 1 displays summary statistics for electricity generation in India. The top panel reports statistics in levels, and the bottom panel reports shares. Installed capacity and Solar farm capacity refer to total and utility-scale solar power generating capacity, respectively. Approximately 7% of all installed capacity is solar on average over the whole time period. When power plants are temporarily taken out of operation, they are declared as being under outage in the *Daily Generation Reports*.[16] Generation refers to how much electricity

[14]India had 472,468 MW of installed electricity capacity according to the CEA's April 2025 *Monthly Installed Capacity Report*; the US had 1,189,492 MW of installed electricity capacity as of the July 16, 2024, according to the *Electricity Explained* update by the US EIA.

[15]Source: Ember Energy Yearly Electricity Data.

[16]Plant outages may occur because of maintenance, fuel shortages, technical failures, or rationing.

TABLE 1. Summary Statistics at State-Day Level

	mean	sd	min	max	count
Installed Capacity (MW)	11676	9352	48	65240	59580
Solar Farm Capacity (MW)	2091	3465	0	47329	59580
Outage Capacity (MW)	3255	3427	0	26461	59580
Generation (MWh)	6363	5531	0	38799	59580
Solar Generation (MWh)	456	807	0	7908	59580
Solar Irradiance (kwh/m^2)	4.93	1.38	0	8.34	59580
Generation/Capacity	0.50	0.21	0	1.22	59580
Outage Capacity/Capacity	0.28	0.20	0	1.00	59580
Solar Farms/Capacity	0.07	0.07	0	0.54	59580
Solar Generation/Generation	0.10	0.21	0	1.00	59573

Summary statistics at the state–day level for India from 2019 to 2025. Installed capacity denotes total nonsolar power plant capacity. Solar farm capacity denotes utility-scale solar power plants. Outage capacity refers to the plant capacity under outage on any given day. Generation denotes electricity generation per hour. Solar irradiance is the total solar radiation received on the given day.

is generated at plants. On average, approximately a quarter of the power plants in a given state are under outage, and half of capacity is utilized for generation, leaving little idle capacity to manage shocks to demand.

4.2. US (ISO-New England) Electricity Generation Data

I use results for New England to benchmark for the impacts of solar generation in a developed-country setting with no outages. In India, grid operations are managed at state level, whereas in the US, balancing authorities oversee power dispatch and transmission across control areas, which may span multiple states (Cicala 2022). To establish a benchmark comparable to Indian states, I focus on the ISO New England (ISO-NE) power control area, which has a balanced mix of renewable and nonrenewable sources of energy and considerable variation in solar irradiance. ISO-NE manages electricity markets in Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and most of Maine. I use the US EIA-930 reports and operations reports released by ISO-NE to compile data on daily electricity generation by fuel type. As of January 2024, ISO-NE had approximately 8 GW of solar power capacity, and solar accounted for about 4% of its electricity generation (ISO New England 2025).

4.3. Solar Farms

I compile data on the location and capacity of utility-scale solar farms in India and the US to estimate daily solar generation at these plants. The *Global Energy Monitor* (GEM) maintains an annual dataset of utility-scale solar farms with capacities of 1 MW or more.[17] It compiles information from government sources, power companies, news reports, and other databases to build a comprehensive record. I use the GEM dataset to obtain the start date, operating status, and installed capacity of solar farms in India and the US for 2018–2025. As of 2025, GEM reported that India had 83.36 GW of installed solar farm capacity, closely matching the 82.39 GW reported by the Ministry of New and Renewable Energy.[18] Installed solar capacity has expanded rapidly in India, increasing nearly threefold from 29 GW in 2018 to 84 GW in 2025.[19]Figure 4 maps solar farms across India in 2025, with each dot representing a farm and scaled by its installed capacity. India has a rich solar resource, and solar farms are distributed throughout the country, particularly in the west, which receives high solar irradiance.

4.4. Weather Data

Solar irradiance measures the amount of solar radiation that reaches a horizontal plane at the surface of the earth.[20] I use the ERA5 reanalysis dataset from the European Centre for Medium-Range Weather Forecasts to compile total daily solar irradiance received at the grid point nearest to each solar farm. I then use these values to estimate daily electricity generation at each farm. Figure 5 shows daily solar irradiance across all solar farms in India for a random day. By capturing solar irradiance at the precise location of each farm, I leverage within-state local variation in solar irradiance. This also allows me to disentangle the supply and demand-side impacts of solar irradiance. Solar generation is driven by the local irradiance at power plants, whereas I use population-weighted average solar irradiance in a state to control for its demand-side impacts.

To control for weather-related impacts on electricity consumption, I compile state-level data on temperature and solar irradiance for 2018 to 2025, again using the ERA5 reanalysis dataset. These data cover both India and the U.S. (New England region) at an hourly resolution and 31 km spatial scale (0.28 degrees). I aggregate the data to the daily level by adding up the total solar irradiance received on each date and calculating the average daily wet-bulb temperature.[21] I apply district-level population weights using population data from the Indian Census to account for population exposure to the weather when I

[17]The 1 MW threshold for generation capacity is consistent with what would be considered utility-scale solar. For example, the US EIA defines utility-scale generation as that from power plants with at least 1 MW of electricity-generating capacity.

[18]Data from the Ministry of New and Renewable Energy's April 2025 Physical Achievements Report.

[19]Author calculations based on the GEM dataset.

[20]This is the mean surface downward short-wave radiation flux variable in the ERA5 reanalysis dataset. This includes both direct and diffuse radiation.

[21]I estimate the approximate wet-bulb temperature by $T_{wetbulb} = \frac{2}{3}T_{dry bulb} + \frac{1}{3}T_{dew point}$. I then take the daily average as $T_{d,avg} = \frac{T_{d,max} + T_{d,min}}{2}$ for each day d.

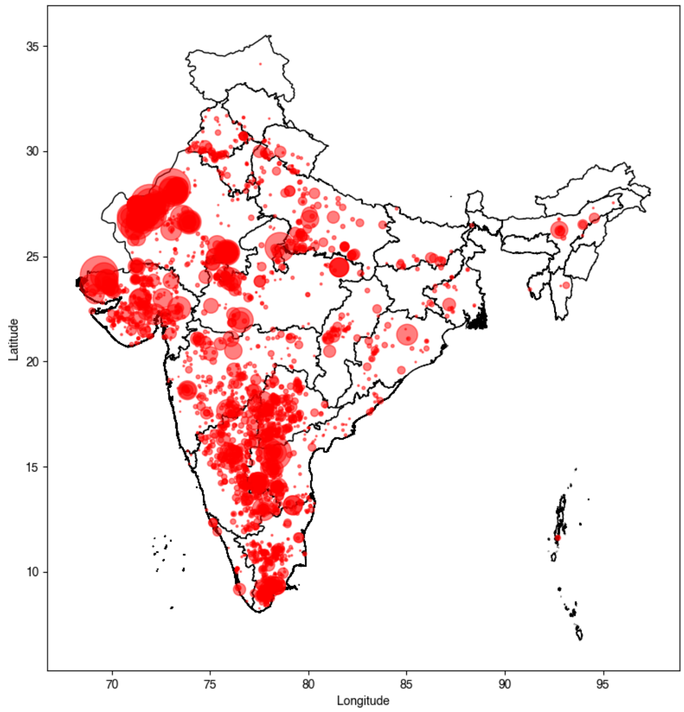


FIGURE 4. Utility-Scale Solar Farms in India, 2025

Source for plant locations and sizes: Global Energy Monitor. Source for the shapefile: Database of Global Administrative Areas (GADM). Each dot represents a utility-scale solar farm and is scaled by the installed capacity size of the solar farm.

aggregate to state level.

4.5. Night-time Lights Data

While total electricity generation provides an indirect proxy for electricity reliability, satellite NTL data offer a more direct measure of electricity reliability. I compile daily luminosity data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensors onboard the Suomi National Polar-orbiting Partnership (SNPP) satellite. These data are publicly available through Google Earth Engine and sourced from the National Aeronautics and Space Administration (NASA).[22] The series is corrected for biases from moonlight, aerosols, surface reflectance, and seasonal variation. It reports daily radiance values captured around

[22] I use the VNP46A2 product, which is the short-name for the VIIRS/NPP Gap-Filled Lunar BRDF-Adjusted Nighttime Lights Daily L3 Global 500m Linear Lat Lon Grid product.

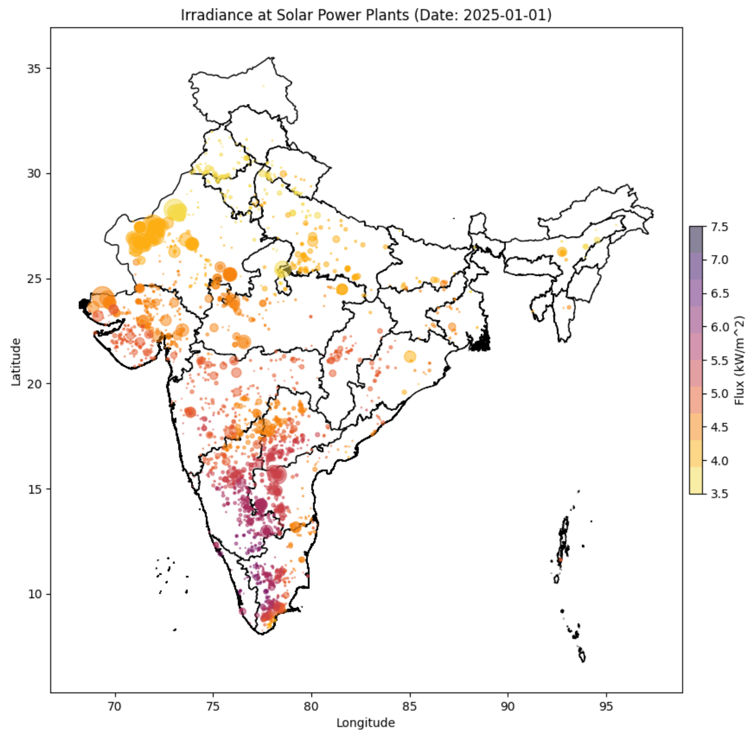


FIGURE 5. Irradiance at Solar Power Plants in India on January 1, 2025

Source for power plant locations and sizes: Global Energy Monitor. Source for irradiance: ERA5 Reanalysis Dataset. Source for the shapefile: GADM. Each dot represents a solar power plant and is scaled by its installed capacity; dot colors represent the total solar irradiance received at the point closest to the respective power plants on January 1, 2025.

1:30 a.m. local time at a 500-meter spatial resolution, allowing high-frequency tracking of light activity across regions.

NTL can capture outages through two mechanisms. First, if the outages coincide with SNPP satellite overpass time, then night lights directly capture outages through lights being turned off. Second, outages earlier in the day might affect lights at night through persistence in lighting behavior. For example, if blackouts occur in the evening, consumers may not turn on lights before going to sleep that would otherwise remain on overnight, resulting in lower observed radiance during the overpass of the satellite. Mann et al. (2016) show that there may be persistence in lighting behavior during the day. Using household voltage meters to validate NTL-based outage detection in Maharashtra, India, the authors find that reliability estimates using NTL data are representative of daytime reliability.

To construct and validate my NTL measure of daily power outages, I use high-frequency electricity monitor readings of outages from the Electricity Supply Monitoring Initiative (ESMI) by the Prayas Energy Group (2021). This dataset includes minute-level voltage readings from 2014-2018 for 528 monitors installed in domestic and commercial locations across 22 states in India. Figure A6 shows the location of all the monitors and Table A5 reports summary statistics on the outages captured by the monitors and corresponding NTL values. The monitors in villages capture approximately 5 hours of outages per day and the urban monitors capture about 24 minutes of outages per day, on average. Appendix C describes the construction of the NTL and monitor readings data.

5. Empirical Strategy

I estimate solar generation at power plants as a function of their installed capacity and irradiance received to examine how variation in solar generation — driven by plausibly exogenous changes in solar irradiance — affects nonsolar generation. I examine contemporaneous impacts to assess whether solar displaces fossil-fuel generation in meeting electricity demand and lagged effects to capture intertemporal responses through coal stock accumulation.

5.1. Estimating Electricity Generation at Solar Plants

I estimate electricity generation at a solar farm f on date t using Equation (1), as a function of its installed capacity (capacity_f) and the solar irradiance received at the grid point closest to the power plant ($irradiance_{ft}$).[23,24] Next, I aggregate solar generation to the state level for India and the ISO-NE region level for the US because electricity operations and reporting occur at these levels. I estimate electricity generation at the solar farms only after they start operating (their start year). $\text{Solar Generation}_{st}$ in Equation (2) represents daily solar electricity generation in state s on date t. This is the unit of analysis for most of the empirical analysis that follows.

$$\text{Solar Generation}_{ft} = \text{Capacity}_f \times \text{irradiance}_{ft} \tag{1}$$

[23] Installed capacity represents the maximum electricity a plant can generate per hour under ideal conditions, typically measured using a "peak-sun hour" (Lozanova 2025). A peak-sun hour corresponds to 1000 watt-hours of solar irradiance per square meter (Wh/m^2) (Hyder 2024). Given this, the total daily flux or irradiance (in Wh/m^2, divided by 1,000) received per day yields the total number of peak-sun hours. With this definition, electricity generation at solar farm f on day t is calculated as shown in Equation (1), where $capacity_f$ denotes the plant's installed capacity and $irradiance_{ft}$ represents total peak-sun hours.

[24] Unobserved, time-invariant factors, such as the tilt angle of solar panels or their maintenance, affect how efficiently solar panels convert irradiance into electricity output. However, these time-invariant factors do not affect the daily variation in solar generation, which this paper leverages. Further, because these inefficiencies reduce output, my estimates solar generation represent an upper bound, which implies that the estimated effects of solar power may be biased toward zero and the true impacts larger than estimated.

$$\text{(2)} \qquad \text{Solar Generation}_{st} = \sum_{f \in F_s}^{F_s} \mathbf{1}\{\text{start\_year}_f < t\} \text{ Solar Generation}_{ft}$$

Figure A1 shows that the estimated solar generation closely aligns with the reported generation for both ISO New England and India: The correlation between estimated and actual solar generation is 0.9 for New England and 0.93 for India. While I have data on actual solar generation, I choose to use the estimated generation because its construction allows me to credibly identify and isolate variation in solar generation driven by plausibly exogenous variation in solar irradiance. Further, reported values may be affected by solar curtailment or may be incomplete.[25] Relying on estimated generation mitigates these concerns about the reported data and yields comparable values for India and the US to allow a valid assessment. However, my use of estimated solar generation might introduce attenuation bias. In Appendices B and D, I show that this bias is minimal and the results are similar whether I use actual or estimated generation. Appendix B shows the results with actual solar generation and Appendix D the results when I instrument actual with estimated solar generation.

5.2. Effects of Solar Generation

Regression (3) estimates how daily variation in solar generation, driven by changes in solar irradiance, affects nonsolar electricity generation Y_{st} in state s on date t.[26] Solar generation may influence nonsolar electricity generation contemporaneously by displacing it in electricity supply or intertemporally by affecting coal stocks and fuel availability. The coefficient β_0 captures the marginal contemporaneous effect of a 1 MWh increase in solar generation. If solar entirely displaces nonsolar generation, total generation remains unchanged, and $\beta_0 = -1$. β_j for each $j \in (1, 7)$ captures how daily solar generation over each day $(t - j)$ within the last week affects current nonsolar generation. If there are no fuel shortages and the only channel through which solar affects nonsolar generation is contemporaneous displacement as in Figure 2, then $\beta_j \approx 0$ for each $j \in (1, 7)$. On the other hand, nonzero values of β_j indicate that solar affects nonsolar generation in ways beyond contemporaneous displacement in electricity supply.

$$\text{(3)} \;\; Y_{st} = \alpha + \beta_0 \text{ solar generation}_{st} + \sum_{j=1}^{7} \beta_j \text{ solar generation}_{st-j} + \kappa' \mathbf{X}_{st} + \rho_{sy} + \delta_{ym} + \varepsilon_{st}$$

[25] Lowe (2024) discusses the range of solar photovoltaic generation sources in ISO-NE and how the visibility of these sources to ISO-NE varies with size and function.

[26] Note that the date t here represents the calendar date and is informative of the corresponding month and year.

Solar generation depends on the stock of installed solar capacity and the flow of irradiance received by the installed solar panels as in Equation (1). While how much solar capacity is installed may be endogenous to income or electricity demand, solar irradiance is naturally occurring and plausibly exogenous. Installed capacity varies annually across states, and solar irradiance varies daily across solar plants within a state (in my data). The state–year fixed effects (ρ_{sy}) hold the stock of installed capacity constant. Then, any changes in daily solar generation are driven by changes in plausibly exogenous solar irradiance.

The thought experiment is analogous to a differences-in-differences strategy: Differences in solar irradiance affect nonsolar generation differently depending on the installed solar capacity in the state. The comparison analyzes how high and low solar irradiance affects nonsolar generation for states with high and low levels of solar capacity. Figure 5 shows the spatial variation in solar irradiance across power plants on a single day; the temporal variation comes from variation in solar irradiance across days. Combining these together, identification comes from a comparison of how changes in solar generation, driven by changes in plausibly exogenous solar irradiance and weighted by installed solar capacity, affect nonsolar generation.

This strategy assumes that all capacity additions occur on the first day of the year of installation. While capacity is added throughout the year, the share of new additions within a year is limited. Nonetheless, solar generation from some power plants may be counted before they begin operating, overstating solar generation earlier in the year. This would bias the coefficients toward zero, making any estimated effects a lower bound on the true effect of solar generation.

Year–month fixed effects (δ_{ym}) control for seasonal variation in both solar generation and electricity demand, and the vector $\mathbf{X}_{st}$ includes controls for demand-side determinants of electricity, including temperature, average solar irradiance, and a dummy for whether date t is a weekend. The temperature and irradiance variables are constructed as population-weighted state–day averages to capture population exposure to weather changes. Population-weighted temperature variables help control for cooling and heating effects on electricity consumption. The population-weighted irradiance variable controls for any demand-side impacts of daily irradiance, which might affect how warm people feel (beyond temperature effects), and for hours of sunlight, which in turn affects when people turn on their lights and consume electricity.

To capture nonlinear temperature effects, I include both cooling degree days (CDDs) and heating degree days (HDDs), along with a dummy for whether each day qualifies as a CDD or an HDD. This specification allows both intercepts and slopes to vary by temperature regime. CDDs, HDDs, and the associated dummies are included for the current day and the last seven days. I also include both contemporaneous and lagged values for the weather variables for a given past week. The contemporaneous weather variables account for real-time demand impacts, whereas the lags control for any persistence in consumption or changes in residual coal stocks from lagged consumption. I cluster the standard errors at the state–year level because solar capacity varies at this level, which also defines the level of treatment.

6. Results

In the US, solar generation almost completely displaces non-solar generation in the current period but has no lasting effects on future nonsolar generation. In India, by contrast, solar generation does not fully displace nonsolar generation, and solar output over a given past week increases current nonsolar generation.

6.1. Impacts of Solar Generation in the US (ISO-NE)

In contrast to India, the US and other developed countries do not face chronic supply shortages or power outages, making them useful for benchmarking the effects of solar generation in a setting with no outages. To develop a benchmark, I analyze the impacts of solar generation in ISO-NE since it offers credible data and substantial variation in solar generation. Figure 6 shows the estimated coefficients from Equation (3), representing the effects of a 1 MWh increase in current and lagged solar generation on current nonsolar electricity generation. Appendix Table A1 reports the coefficients denoted in Figure 6. Figure A2 shows that the results are similar when I use actual instead of estimated solar generation.[27]

An additional MWh of solar generation reduces contemporaneous nonsolar electricity generation by 0.99 MWh, implying near-perfect one-for-one displacement. Since most nonsolar generation in ISO-NE comes from fossil fuels, particularly the generation at the margin in the merit-order curve, this displacement reduces contemporaneous emissions. The marginal output emissions rate in New England is 923 lbs of carbon dioxide (CO_2) (≈ 0.5 tons) per

[27] The standard errors are larger with estimated solar generation, as expected given that the estimated data are noisier. When I consider actual solar generation, the coefficient for the contemporaneous effects is closer to –1.5, while for estimated generation, it is –1. The latter is biased toward zero because estimated solar generation is an upper bound, reflecting generation under ideal settings, while actual solar generation is typically lower. The coefficient on actual solar generation is greater than -1 because of omitted variable bias from rooftop solar: Utility-scale and rooftop solar are positively correlated, whereas rooftop solar and nonsolar generation are negatively correlated because rooftop solar meets part of the electricity demand otherwise met by nonsolar generation.

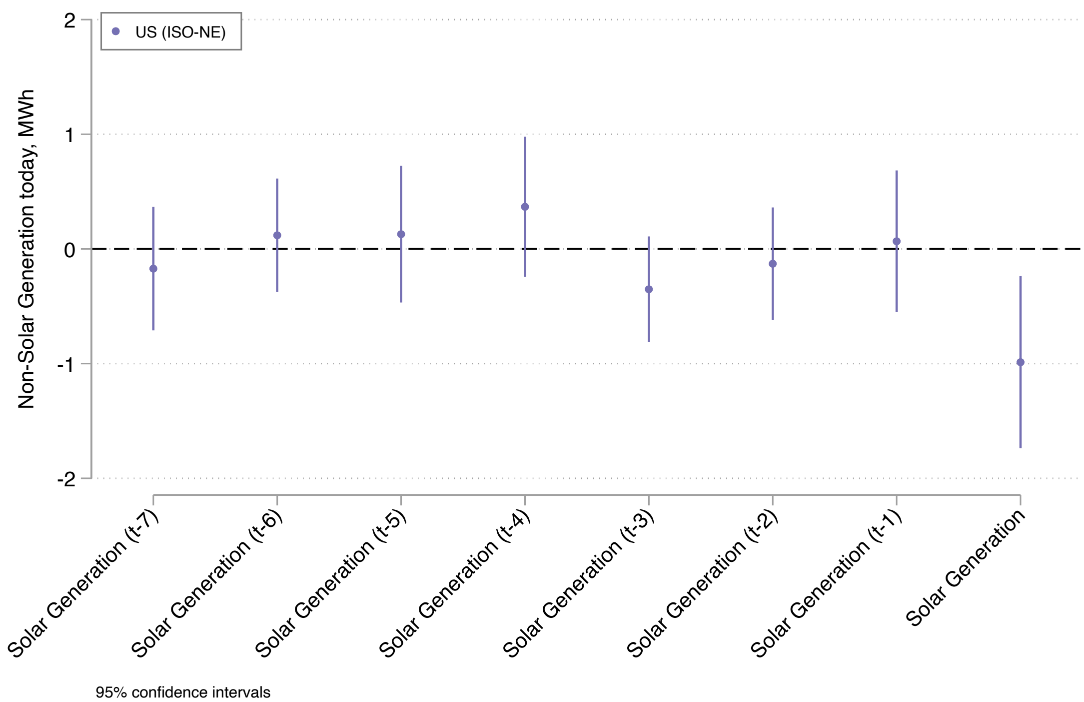


FIGURE 6. Impacts of Solar Generation on Nonsolar Generation in the US

This figure plots the coefficients of daily solar generation from $t - 7$ days to the current day t on current nonsolar generation on day t for ISO-NE. The regression includes year–month fixed effects and current and lagged controls for average irradiance, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. I cluster the standard errors by year–month because I have only one region across 6 years.

MWh (US EPA 2025). This suggests that each MWh of solar generation in the US prevents approximately 0.5 tons of CO_2 emissions. In 2024, solar power produced approximately 4,554 GWh in ISO-NE, which would imply emissions reductions of approximately 2.3 million tons of CO_2.[28] Solar generation over the last week, however, has no statistically significant impact on current nonsolar electricity generation in ISO-NE, as seen in Figure 6.

6.2. Impacts of Solar Generation in India

In India, contemporaneous solar generation does not fully displace nonsolar generation, while lagged solar generation increases current nonsolar generation. This effect is driven by intertemporal reallocation of coal generation: Solar reduces coal generation contemporaneously, but as power plants build up excess stocks, they increase their coal generation

[28]Note that this back-of-the envelope calculation is confined to emissions within ISO-NE and abstracts from emissions outside the region, which might be affected by a reduction in emissions through solar generation, for example, through policy linkages outside the ISO-NE jurisdiction such as the The Regional Greenhouse Gas Initiative cap-and-trade program.

over subsequent days. Total generation thus increases, improving reliability by increasing demand met. However, because coal generation does not decline overall, solar generation does not reduce emissions, at least in the one-week time frame of this analysis.

6.2.1. Comparing India and the US

Solar generation has distinct impacts in outage-prone India and the no-outage US setting: An increase in lagged solar generation in India increases current nonsolar generation, and contemporaneous solar generation does not completely displace nonsolar generation. I next run Equation (3) for India as I did for the US in Figure 6.[29] Figure 7 displays the estimated coefficients for India alongside the US coefficients from Figure 6. Although in the US solar power reduces emissions by displacing fossil-fuel generation, there is no evidence in my data that solar generation reduces fossil-fuel-based generation in India. Further, the lagged effects follow a clear pattern: Solar generation on the previous day has the strongest impact on current nonsolar generation, and this effect weakens over time, which suggests short-term effects of past solar generation on current nonsolar output.

Appendix Table A2 reports the coefficients from Figure 7. Figure A3 shows that the results are similar when I consider actual instead of estimated solar generation. Figure A4 shows similar results when the outcome is the quantity of wholesale electricity purchased, which is the outcome measure in Jha et al. (2023).

This suggests that solar generation in India affects nonsolar electricity supply through determinants not present in the US. While in the US, solar generation displaces nonsolar generation contemporaneously, India shows no contemporaneous effect but significant lagged effects. What might drive this divergence? Since I control for demand-side variation using weather and fixed effects, the explanation likely lies on the supply side. As I discussed in Section 2, a key supply-side distinction is that India faces outage-inducing coal supply shortages, a constraint that solar supply alleviates

6.2.2. Plant-Level Results

The analysis so far has focused on the effects of solar on nonsolar generation. To better understand what drives the distinct lagged effects, I turn to a more granular, power plant–level analysis, as specified in Equation (4). The outcome is electricity generation at plant p in state s on date t. I run this regression separately for nonsolar fuels, including coal, gas,

[29] Note that since the US analysis is restricted to ISO-NE, it includes only year fixed effects. However, since the Indian analysis covers the whole country, with its multiple states, the specification for India includes state–year fixed effects. Further, since the US analysis is focused on only one region over 6 years, I cluster those results at the year–month level to allow enough clusters. However, I cluster the results for India at the level of a state–year since that is the unit of treatment.

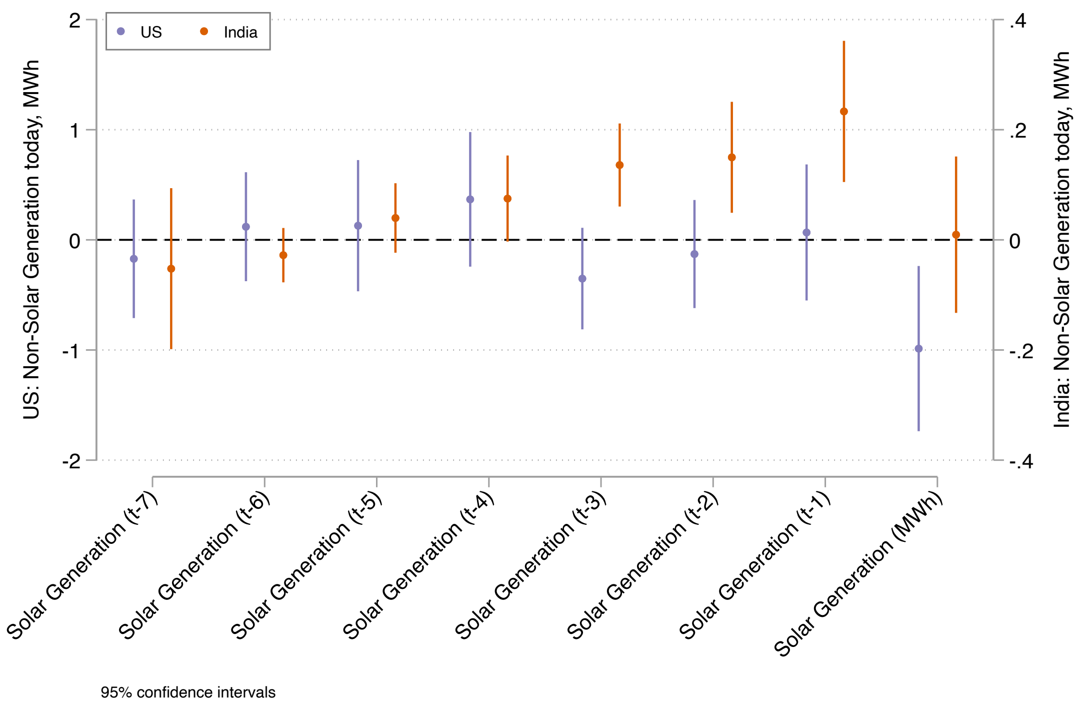


FIGURE 7. Impacts of Solar Generation on Nonsolar Generation in India and the US

This figure plots the coefficients of the effects of daily solar generation from $t-7$ days to the current day t on current nonsolar generation on day t for ISO-NE in the US and in India. The regressions include year–month fixed effects and current and lagged controls for average irradiance, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. The regression for India also includes state–year fixed effects, whereas the regression for ISO-NE includes year fixed effects since covers only one region. The regression for India is clustered at the state–year level, whereas the regression for the US is clustered at the year–month.

and hydropower.

Analyzing generation at the plant level allows me to control for time-invariant operational priorities and decision-making specific to each power plant. I include power plant fixed effects (α_p) to control for unobserved operational decisions and local constraints at the plant level, along with all other controls stated in Equation (3). This approach also enables heterogeneity analysis to isolate the mechanisms behind the aggregate results.

I begin by replicating the analysis from Section 6.2.1 at the plant level, disaggregating by fuel type. I then extend the analysis to examine coal stocks, deliveries, and heterogeneity using the more granular power plant–level data. The level of treatment remains defined at the state–day level since the effects of solar generation propagate through state-level aggregates. Accordingly, standard errors continue to be clustered at the state–year level.

$$Y_{pst} = \alpha_0 + \beta_0 \text{ solar generation}_{st} + \sum_{j=1}^{7} \beta_j \text{ solar generation}_{st-j}$$
$$+ \kappa' \mathbf{X}_{st} + \alpha_p + \rho_{sy} + \delta_{ym} + \varepsilon_{pst} \tag{4}$$

Figure 8 shows the plant-level results for coal, natural gas, and hydro, respectively, with coefficient estimates also reported in Appendix Table A3. Coal accounts for approximately 73% of electricity supply in India, while 8% comes from hydropower, and 2% from oil and gas.[30] Coal is the primary fuel of interest. As is clear from Figure 8, the effects of solar generation on total generation in Figure 7 for India are driven by its effects on coal generation.

Solar generation reallocates coal generation intertemporally: It decreases contemporaneous coal generation but increases future coal generation. One additional MWh of solar generation in a state reduces contemporaneous electricity generation at the average coal power plant by 0.01 MWh or 10 KWh. This magnitude is smaller than what we see in Figure 7 because this analysis now focuses on individual plant-level generation instead of aggregate generation.[31] Less electricity generation implies less coal use, which increases residual coal stocks.

The positive coefficients for the effect of of lagged solar generation on current coal generation imply that excess coal stocks from the previous week are used over subsequent days, increasing coal generation by the power plants. The sum of the coefficients on current and lagged solar electricity generation ($\beta_1 + \sum_{j=t-7}^{t-1} \beta_j$) is not statistically different from zero for coal-fired power plants. This rules out a net change in coal generation and suggests that solar generation does not displace coal generation overall but rather shifts it across time. In turn, total electricity generation rises, increasing electricity demand met and improving reliability. However, emissions from existing coal generation do not fall.

Other fuels play a smaller role in India's electricity mix and show limited effects in response to solar generation. Natural gas generation accounts for a low share of India's electricity supply and is not subject to fuel shortages, in contrast to coal generation, so we see no significant effects of solar on gas generation. Hydropower, by contrast, shares some characteristics with coal, such as storage and fuel availability constraints, but its response to solar generation is more complex. On one hand, solar generation provides a

[30] Solar generation accounts for an additional 8%, nuclear for 3%, wind for 5%, and biofuels for the remaining 1%. Data from the NITI Aayog Climate and Energy Dashboard.

[31] For comparison, coal power plants generate 5406 MWhs of electricity on average. More details are reported in Table A3.

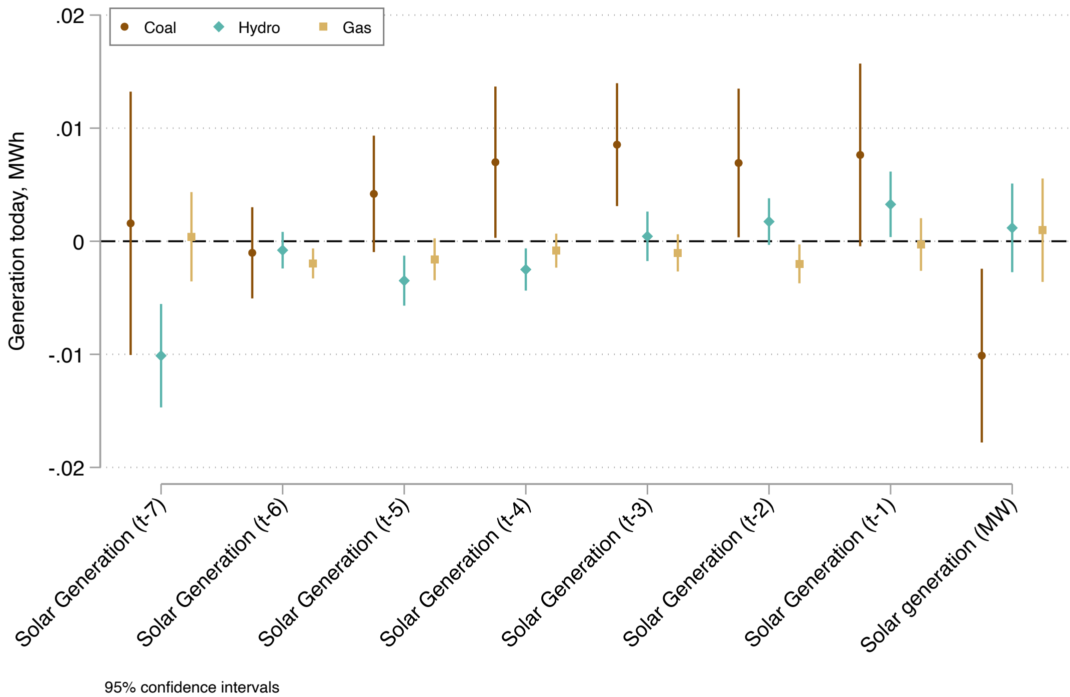


FIGURE 8. Impacts of Solar Generation on Power Plant–level Generation: By Fuel

This figure plots the coefficients of daily solar generation from $t-7$ days to the current day t on current electricity generation on day t at power plants by fuel type. The regression includes year–month, state–year, and power plant fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state–year level.

buffer for hydro reservoirs to fill up, similarly to how it affects coal generation. On the other hand, hydropower has low start-up and shut-down times and can be used to manage fluctuations from solar generation (Das et al. 2020). As a result, hydropower generation may either decline or increase in response to solar generation, depending on seasonal and operational conditions. These mixed effects are seen in Figure 8 and Table A3. Further, since hydropower generation may increase in response to solar generation to manage fluctuations, the contemporaneous response of total nonsolar generation to solar generation remains statistically nonsignificant in Figure 7 even though coal generation decreases.

6.3. Mechanisms

Coal power plants accumulate reserves in response to solar generation through two channels: First, they burn less coal when solar supply meets electricity demand, which increases residual stocks. Second, they have to fulfill less demand in the future if solar continues to meet part of the demand, which reduces the buffers plants need to hold to meet future demand. At the same time, power plants have little incentive to retain excess stocks because they are locked into fuel supply agreements and are cash constrained, which limits how much coal they can purchase upfront. Thus, power plants run down their excess stocks and increase their generation, in turn increasing total generation. Several results support this mechanism. First, an analysis of coal stocks shows that coal consumption declines contemporaneously in response to solar generation, increasing net stocks on subsequent days, whereas coal deliveries remain unchanged. Second, heterogeneity analysis shows that more coal-constrained plants exhibit more pronounced intertemporal coal reallocation.

6.3.1. Change in Coal Stocks

With data on daily coal stocks at plants, I can analyze whether the accumulation of coal stocks drives the distinct lagged effects of solar generation in India.

$$\text{opening stock}_t = \text{opening\_stock}_{t-1} - \text{consumption}_{t-1} + \text{receipt}_{t-1} \tag{5}$$

The available stock of coal at power plants equals the previous day's stock minus coal consumption plus receipts, as shown in Equation (5). To maintain a consistent definition, I focus on opening stocks of coal, which is the coal available on a given day before consumption occurs. Table 2 reports the coefficients from Equation (4) with coal consumption and receipts as the outcome variables alongside coal generation.[32] Coal consumption at power plants responds mechanically to changes in generation. A contemporaneous decrease in generation reduces coal use, while an increase in coal generation following lagged solar generation raises coal consumption. Column 3 shows that the change in coal deliveries in response to solar generation is not statistically significant.

To further examine this mechanism, I analyze weekly changes in coal stocks at coal power plants in response to solar generation in Figure 9.[33] Table A3 reports the coefficients plotted in Figure 9. I do not estimate a contemporaneous coefficient for the impact of solar generation on net coal stocks because in keeping with the definition outlined above, coal stocks reflect the opening stock of fuel in the morning, *before* that day's solar generation occurs. Increase in contemporaneous solar generation decreases coal generation, reducing coal used and in turn increasing the net stocks of coal available the next day.

These results combined with those from Table A3 and the accounting in Equation (5)

[32] Table 2 shows results for coal plants for only days with complete data on all three variables: coal consumption, coal receipts, and coal generation. Since for some days consumption and receipt data are missing, the sample size for Table 2 is smaller than in A3.

[33] $\Delta coal\ stock = coal\ stock_t - coal\ stock_{t-7}$

TABLE 2. Impacts of Solar Generation on Coal Receipts and Consumption at Power Plants

VARIABLES	(1) Coal generation MWh	(2) Coal consumption tonnes	(3) Coal receipt tonnes
Solar generation (MW)	-0.02***	-0.29***	-0.08
	(0.00)	(0.08)	(0.20)
Solar Generation (t-1)	0.01	0.07	0.10
	(0.01)	(0.08)	(0.20)
Solar Generation (t-2)	0.01**	0.12**	-0.15
	(0.00)	(0.06)	(0.10)
Solar Generation (t-3)	0.01***	0.20***	-0.05
	(0.00)	(0.06)	(0.11)
Solar Generation (t-4)	0.01**	0.14*	0.13
	(0.00)	(0.08)	(0.13)
Solar Generation (t-5)	0.01*	0.07	0.16
	(0.00)	(0.05)	(0.17)
Solar Generation (t-6)	-0.00	-0.05	0.01
	(0.00)	(0.04)	(0.14)
Solar Generation (t-7)	0.00	0.02	0.19
	(0.01)	(0.11)	(0.17)
Observations	194,923	194,923	194,923
R-squared	0.89	0.89	0.72
Dep. var. mean	789	12824	13046
Test lag + current = 0	.22	.26	.15

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression includes year–month fixed effects, state–year fixed effects, and power plant fixed effects. Controls include a dummy for whether it is a weekend, current and lagged daily temperature, and average flux for the past week. Temperature controls include cooling degree days, heating degree days, and a dummy for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state–year level. Column 1 plots the impacts of solar generation on coal generation at power plants, column 2 on consumption of coal, and column 3 on deliveries of coal.

imply that an increase in solar generation indeed reduces contemporaneous coal generation and coal use. As deliveries of coal remain unchanged, excess coal stocks accumulate, increasing the net stock of coal available. These residual stocks are drawn down over the next few days to increase coal consumption and coal electricity generation.

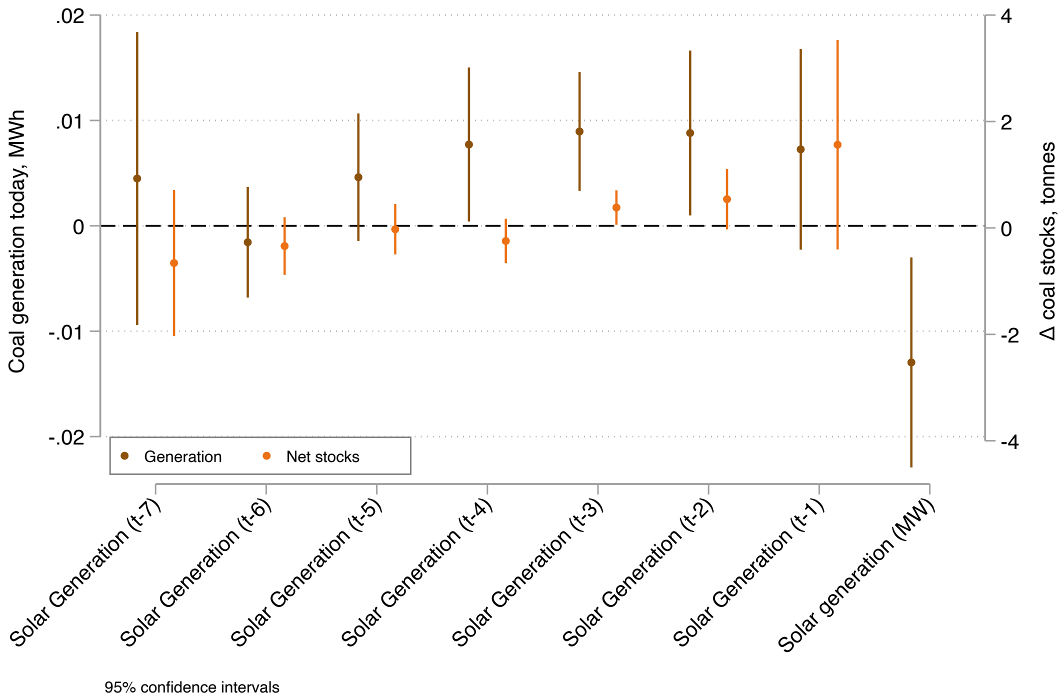


FIGURE 9. Impacts of Solar Power on Coal Stocks at Power Plants

his figure plots the coefficients of daily solar generation from $t-7$ days to the current day t on coal generation and weekly changes in coal stocks at power plants in India. The regression includes year–month fixed effects, state–year fixed effects, power plant fixed effects and current and lagged controls for average irradiance, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state–year level.

6.3.2. Heterogeneity by Severity of Coal Constraints at Power Plants

I compare how solar generation affects generation between more and less coal-constrained plants. If easing the pressure on coal is the mechanism driving the lagged results, then we would expect plants whose constraint is more binding to respond more strongly than the less constrained. I classify power plants by their likelihood of facing coal shortages – more coal constrained power plants are more likely to face coal shortages. I find that the effects of solar generation are stronger for the more coal-constrained shortage-prone plants.

Power plants can declare coal shortages in several ways. They may declare outages and take themselves out of operation if they have insufficient coal. Alternatively, plants with critical stock levels are flagged in the CEA's *Daily Coal Reports*. In 2019, the first year in my data, I identify every instance of plants declaring coal shortages, either through outages or critical stock flags. I classify plants above and below the median shortage frequency as more or less coal constrained, respectively. I restrict the classification to shortages in 2019

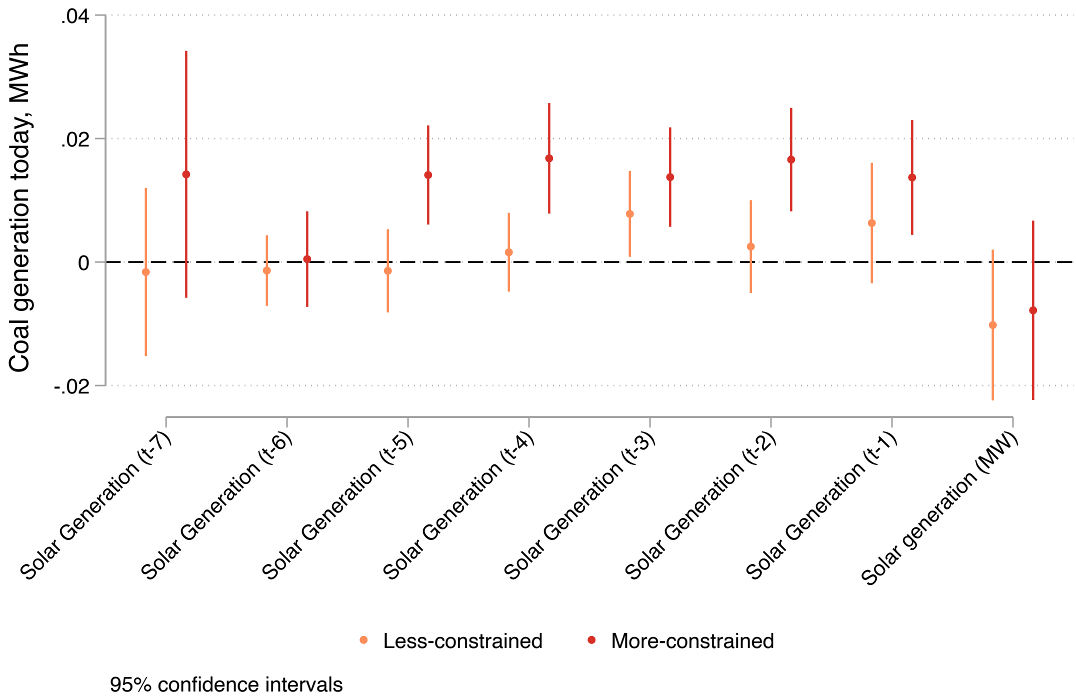


FIGURE 10. Impacts of Solar Generation on Coal-Constrained Power Plants

This figure plots the coefficients of daily solar electricity generation each day from $t-7$ days to the current day t on generation at more and less coal-constrained power plants in India. More constrained plants had a greater propensity to declare coal shortages in 2019. The regression includes year–month fixed effects, state–year fixed effects, power plant fixed effects and current and lagged controls for average irradiance, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day.

to avoid endogeneity with solar generation. Figure A5 shows the distribution of coal stocks (in days' supply) across these categories for the full period. More days of stock implies more buffer stock and less severe constraints. On average, shortage-prone plants hold 15 days of coal, compared with 21 days for less shortage-prone plants.

Shortage-prone plants are more coal constrained. I estimate Equation (3) separately for more and less constrained plants and compare the coefficients on solar generation in Figure 10. Both groups reallocate coal in response to solar generation, but the effects are stronger for the more constrained power plants. Each group shows similar contemporaneous declines in coal generation, yet the more constrained plants exhibit stronger lagged effects from the buffer provided by solar generation. This offers further evidence that the distinct lagged effects of solar generation in India arise from the easing of supply constraints at coal-fired plants.

6.4. Reliability Measure: Night Lights

Thus far, I have interpreted an increase in total electricity generation as an improvement in electricity reliability. Next, I look at a more direct measure of electricity reliability: NTL data. This confirms the causal chain that goes from increased solar generation to increased nonsolar generation to reduced outages. The closest publicly available, frequent, and measurable proxy for electricity reliability is NTL data. I train a random forest algorithm to classify outages from NTL data, using known, correctly classified observations from electricity supply monitors matched to the corresponding NTL pixels. I apply this algorithm to NTL data for the full sample to classify pixels under outage daily in each state.

For this analysis, I use high-frequency NTL data to capture short-term changes in daily outages. These data capture reliability in several ways. First, if an outage occurs during satellite overpass, the affected area will appear dark in the imagery. This is especially relevant because outages often occur around midnight since disruption to economic activity is minimal during that time. Second, NTL capture reliability indirectly if daytime outages affect lighting behavior. Outages earlier in the day may prevent consumers from turning the lights on, resulting in lights staying off at night. Mann et al. (2016) note that the correlation between the frequency of outages during daytime hours and VIIRS overpass times in 0.85.

While the NTL data offer a publicly available and direct measure of reliability, they cannot capture all reliability improvements. Illumination reflects only one aspect of electricity consumption affected by reliability improvements. Other forms of consumption—such as industrial production and appliance usage—are visible in the generation data but not in the NTL data. Approximately 50% of India's electricity consumption is commercial and industrial, and another 16% is agricultural, whereas only 1% corresponds to public lighting (Central Electricity Authority 2024). While commercial, industrial, and domestic use would include lighting uses, they also include nonlighting uses of electricity. Thus, the effects on outages estimated by means of the NTL data capture only one dimension of reliability improvements.

I use ML trained on electricity monitor readings to classify pixels as under outage and construct a measure of electricity reliability by estimating the share of pixels under outage (SOPUO) for each state. Electricity supply monitors record minute-wise voltage readings, where a reading of 0 indicates a power outage (Prayas Energy Group 2021). I aggregate these readings to get the total duration of outages each day. On average, rural locations face 4.8 hours and urban locations 24 minutes of outages each day. I approximate the location of each monitor using the neighborhood characteristics and location information

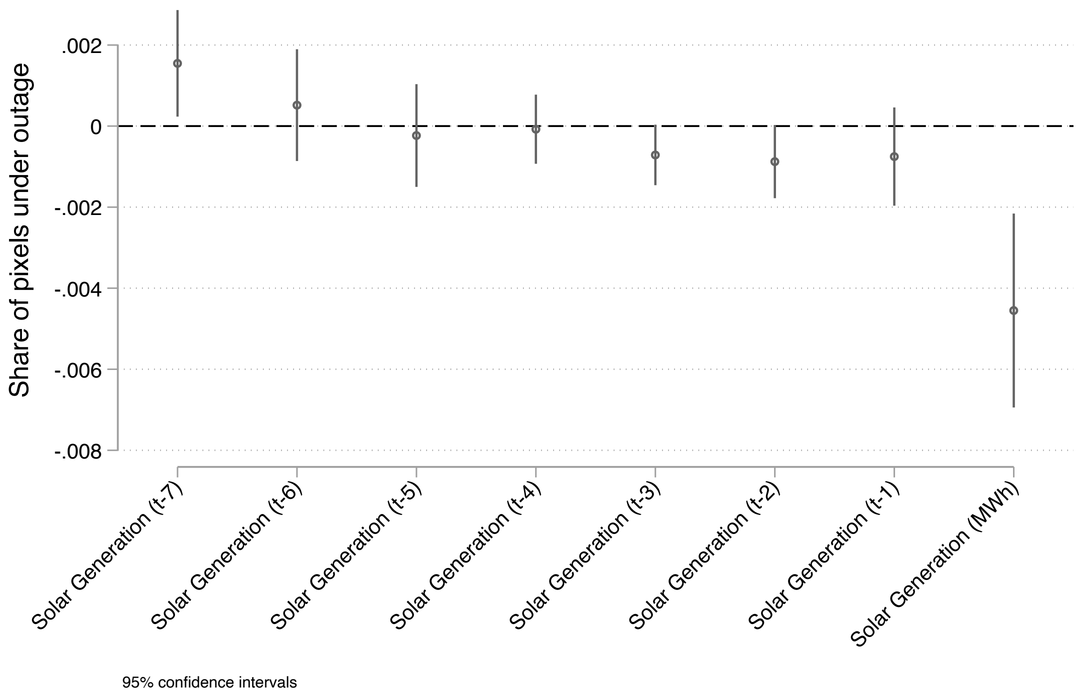


FIGURE 11. Impacts of Solar Generation on Share of Pixels Under Outage

This figure plots the coefficients of daily solar electricity generation each day from $t-7$ days to the current day t on the share of pixels under outage at state level in India. Each pixel is classified as under outage or not based on a random forest algorithm trained on ground-truth data. The regression includes year–month fixed effects, state–year fixed effects, power plant fixed effects and current and lagged controls for average irradiance, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state–year level.

provided by the Prayas Energy Group (PEG).[34] Since power outages often take place at the neighborhood level, an approximation at this level is reasonable to detect power outages. Next, I get the daily NTL readings for the approximate monitor locations and train a random forest algorithms to detect daily outages from NTL.

The model uses 30 covariates, including locational and temporal characteristics and residualized night-time radiance and z-scores across time periods for each pixel and its four nearest neighbors.[35] Appendix C describes the construction and validation of this measure in more detail. The algorithm correctly classifies pixels 72% of the time. Figure

[34]PEG was unable to share the exact location of the monitors due to non-disclosure agreements. The public dataset provides the following information about each monitor: its neighborhood, district, state, location category (village, municipality, district, or urban), and the type of location in which the monitor is installed (domestic, commercial or agricultural).

[35]The model uses 30 covariates, including the state, year, month, quarter, day of week, average radiance, and standard deviation at quarterly, annual, and overall levels, as well as residualized radiance, standard deviations, and z-scores by week and quarter for each pixel and its four nearest neighbors.

A7 in Appendix C reports the full classification results. I use this model to predict daily outages for each pixel at a 500m resolution in India. Finally, I aggregate this up to the state level to estimate the SOPUO in each state on each day – my constructed measure of electricity reliability.

Figure 11 shows the effect of current and lagged solar generation on the SOPUO for each state. Table A4 reports the coefficients. This pattern mirrors the observed contemporaneous increases in generation (Figure 7). This confirms that the set of results in this paper reflect that solar generation improves reliability. A 1 MWh increase in solar generation reduces the SOPUO by about 0.005 percentage points. Multiplying by mean solar generation, this implies a 4 percentage points decrease in the SOPUO relative to a 43% mean. This is equivalent to a 9% reduction in the SOPUO, which is similar in magnitude to the average share of solar generation in electricity generation in India (10%). This is the most direct evidence that solar generation reduces outages and improves reliability. Further, as noted above, the NTL data capture only a small share of overall electricity reliability improvements.

The lagged effects also follow a similar pattern to the results so far. Solar generation from previous days reduces the share of pixels under outage, with the effect tapering off by the end of the week. However, these effects are weaker, likely because of the limited ability of NTL data to capture all reliability improvements. These results reflect the limits of the NTL data: Because NTL capture only a small share of overall reliability improvements (and because the largest effects are contemporaneous), lagged impacts may be too small to detect. This may also indicate that most of the reliability gains occur through non-lighting electricity consumption, such as industrial production, agriculture, or air conditioning. However, I do not have data to decompose these channels.

6.5. Robustness Checks

Throughout this paper, I use estimated solar generation because it allows me to credibly isolate the exogenous variation in solar irradiance and compare results between the US and India. This approach may raise some concerns about attenuation bias. In Appendix D, I instrument for actual solar generation with estimated solar generation and show that the results and magnitudes remain similar once corrected for attenuation bias. This is reasonable because the correlation between estimated and actual solar generation is close to 1, as seen in Figure A1.[36]

In Appendix E, I present robustness checks using placebo tests and alternative model specifications. First, I construct a placebo measure of solar generation at solar power

[36]The correlation is 0.9 for the US and 0.93 for India.

plants before they start operating. The results do not replicate and are not significant with placebo generation, highlighting that the results in this paper are driven by solar generation.

Second, I demonstrate that the results are robust to alternative specifications. The main specification in this paper includes state–year fixed effects to hold installed capacity constant and control for different states' growth at different rates and year–month fixed effects to control for seasonal variation. Appendix Table A8 shows that the results are robust to the most extreme version of this specification, with state–year–month fixed effects, which compares the impacts of solar generation within a state within each month of the sample period. Similarly, the results are robust to a specification that includes each fixed effect (state, year, and month) separately and other combinations of these fixed effects that allow for greater variation.

Finally, the main specification includes 7 lags to allow the effects to propagate through a week — the typical horizon for electricity decision-making in India. Appendix Table A9 shows that the results are robust to different time lags and show a similar pattern across the different time lag specifications.

7. Discussion

I show that solar power provides an energy expansion and reduces power outages in India by easing coal shortages. The finding that solar power leads to an energy expansion is applicable to most developing countries that are growing at rates faster than supply can keep up with and facing supply shortages. Accordingly, these countries might see improvements in electricity reliability but not cuts in emissions from existing fuel sources with incremental solar power. Additionally, the distinct lagged effects of solar are driven by fuel constraints at Indian power plants. The finding that increases in past solar generation could increase current nonsolar generation in the short-term is relevant to any setting with fuel stock shortages, such as coal or hydro, for which solar could serve as a buffer.

The economics of solar power thus differs in developed and developing countries. The physical constraints tied to the intermittency of solar power apply in both developed and developing countries and may undermine electricity reliability in both these settings. However, an additional reliability concern from incremental solar power in developed countries is that as solar fulfills an increasing share of electricity demand, it might lead to retirements of less competitive fossil-fuel generators. This in turn might lead to power shortages on days with insufficient solar resource. Fossil fuel-generators are not yet being retired with incremental solar power in developing country settings where there are supply shortages, and hence the reliability concerns from insufficient power generation on low solar resource days do not exist in the economics of solar power in developing countries. On the other hand, when solar leads to an energy expansion — not an energy transition — in developing countries, then it ameliorates the issue of power shortages by solving a more immediate problem: insufficient power supply to meet electricity demand.

8. Conclusion

Solar power is widely believed to reduce greenhouse gas emissions from the power sector. However, with its rapid growth, concerns have emerged that this variable resource may reduce reliability. I show that these dynamics diverge between developed and developing countries. In India, solar power delivers a low-carbon energy expansion that improves reliability but does not necessarily reduce emissions from existing fossil-fuel sources. These results suggest a reliability-emissions tradeoff. Nonetheless, the gains in reliability are driven by renewable energy, supporting a more sustainable path to development. Overall, solar power can improve welfare in developing countries by increasing reliability. This contrasts with the United States, where the primary welfare gains from solar are environmental. Policymakers and researchers should account for these differences when evaluating solar power in different contexts.

Future work analyzing the economics of renewable energy in developing countries would be beneficial. That solar does not displace coal in India has implications for the political economy of renewable energy in its electricity sector. Reducing shortages and increasing low-cost solar supply also potentially reduces wholesale costs and prices in short-term electricity markets, which might lower utilities' incentives to ration electricity supply. Understanding these broader implications from the energy expansion provided by low-carbon and low-cost solar in developing countries is left for future research.

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Appendix A. Appendix Tables

TABLE A1. Impacts of Solar Generation on Nonsolar Generation in ISO-New England

VARIABLES	(1) Non-Solar Gen (EIA) Solar Gen estimated	(2) Non-Solar Gen (ISO-NE) Solar Gen estimated	(3) Non-solar (ISO-NE) Solar Gen (ISO-NE)
Solar Generation	-0.99**	-0.90**	-1.44***
	(0.38)	(0.37)	(0.22)
Solar Generation (t-1)	0.07	0.13	-0.19
	(0.31)	(0.29)	(0.17)
Solar Generation (t-2)	-0.13	-0.15	-0.30**
	(0.25)	(0.25)	(0.13)
Solar Generation (t-3)	-0.35	-0.27	-0.18
	(0.23)	(0.22)	(0.15)
Solar Generation (t-4)	0.37	0.33	0.07
	(0.31)	(0.28)	(0.16)
Solar Generation (t-5)	0.13	0.16	0.12
	(0.30)	(0.30)	(0.16)
Solar Generation (t-6)	0.12	0.08	0.13
	(0.25)	(0.24)	(0.15)
Solar Generation (t-7)	-0.17	-0.14	0.05
	(0.27)	(0.27)	(0.16)
Observations	2,185	2,185	2,185
R-squared	0.84	0.84	0.85
Solar gen mean	7769	7769	8410
Dep. var. mean	266028	269130	269130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regression includes year × month fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the year × month level. Electricity generation data come from EIA 930 Reports, ISO-NE Operational Reports, and estimated solar generation from Global Energy Monitor and ERA5 Reanalysis Dataset. Columns 1 and 2 report results from estimated solar generation on nonsolar generation reported in the EIA reports and ISO-NE reports respectively. Column 3 reports the effects of actual solar generation on nonsolar generation from ISO-NE reports.

TABLE A2. Impacts of Solar Electricity Generation on Nonsolar Electricity Generation in India: State-level analysis

	(1)	(2)
	Nonsolar Generation	Nonsolar Generation
VARIABLES	Estimated Solar	Actual Solar
Solar Generation (MWh)	0.01	-0.16***
	(0.07)	(0.04)
Solar Generation (t-1)	0.23***	0.13***
	(0.06)	(0.05)
Solar Generation (t-2)	0.15***	0.06*
	(0.05)	(0.04)
Solar Generation (t-3)	0.14***	0.06**
	(0.04)	(0.03)
Solar Generation (t-4)	0.07*	0.05**
	(0.04)	(0.02)
Solar Generation (t-5)	0.04	0.02
	(0.03)	(0.02)
Solar Generation (t-6)	-0.03	0.01
	(0.03)	(0.02)
Solar Generation (t-7)	-0.05	-0.05
	(0.07)	(0.04)
Observations	59,580	52,230
R-squared	0.97	0.97
Solar gen mean	456	354
Dep. var. mean	6363	5506
Test lag + current = 0	0.08	0.52

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The regression includes year × month fixed effects, state × year fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level. Column 1 plots the coefficients on current *estimated* solar generation and generation each day over the past week as in regression (3). Column 2 plots the coefficients on current *actual* solar generation and generation each day over the past week as in regression (3).

TABLE A3. Impacts of Solar Generation on Powerplant-level generation, by Fuel Type

	(1)	(2)	(3)	(4)
VARIABLES	Coal Gen	Gas Gen	Hydro Gen	Coal Stocks
Solar generation (MW)	-0.0101**	0.0010	0.0012	1.0764
	(0.0039)	(0.0023)	(0.0020)	(0.9456)
Solar Generation (t-1)	0.0076*	-0.0003	0.0033**	0.6959*
	(0.0041)	(0.0012)	(0.0015)	(0.3663)
Solar Generation (t-2)	0.0069**	-0.0020**	0.0017*	0.5998**
	(0.0033)	(0.0009)	(0.0010)	(0.2823)
Solar Generation (t-3)	0.0085***	-0.0010	0.0004	0.3705**
	(0.0027)	(0.0008)	(0.0011)	(0.1655)
Solar Generation (t-4)	0.0070**	-0.0008	-0.0025***	-0.3113
	(0.0034)	(0.0008)	(0.0009)	(0.2399)
Solar Generation (t-5)	0.0042	-0.0016*	-0.0035***	-0.0366
	(0.0026)	(0.0009)	(0.0011)	(0.2521)
Solar Generation (t-6)	-0.0010	-0.0020***	-0.0008	-0.3398
	(0.0020)	(0.0007)	(0.0008)	(0.2910)
Solar Generation (t-7)	0.0016	0.0004	-0.0101***	-0.7464
	(0.0059)	(0.0020)	(0.0023)	(0.7443)
Observations	509,688	165,060	463,672	312,394
R-squared	0.8630	0.6941	0.6161	0.0512
Solar gen mean	624	754	545	650
Dep. var. mean	628	65	71	715
Test lag + current = 0	0.23	0.32	0.17	0.15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The regression includes year × month fixed effects, state × year fixed effects, power plant fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level. Columns 1-3 plot the coefficients on current solar generation and generation each day over the past week for the respective fuels as in regression (3). Column 4 plots the coefficients on solar current solar generation and generation each day over the past week on net coal stocks

TABLE A4. Impacts of Solar Generation on Share of Pixels Under Outage

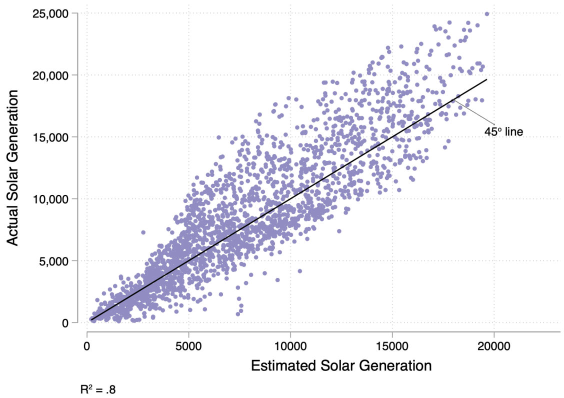
	(1)
VARIABLES	Share of Pixels Under Outage
Solar Generation (MWh)	-0.0046***
	(0.0012)
Solar Generation (t-1)	-0.0008
	(0.0006)
Solar Generation (t-2)	-0.0009*
	(0.0005)
Solar Generation (t-3)	-0.0007*
	(0.0004)
Solar Generation (t-4)	-0.0001
	(0.0004)
Solar Generation (t-5)	-0.0002
	(0.0006)
Solar Generation (t-6)	0.0005
	(0.0007)
Solar Generation (t-7)	0.0015**
	(0.0007)
Observations	22,709
R-squared	0.9223
Solar gen mean	799
Dep. var. mean	43
Test lag + current = 0	0.00

Robust standard errors in parentheses

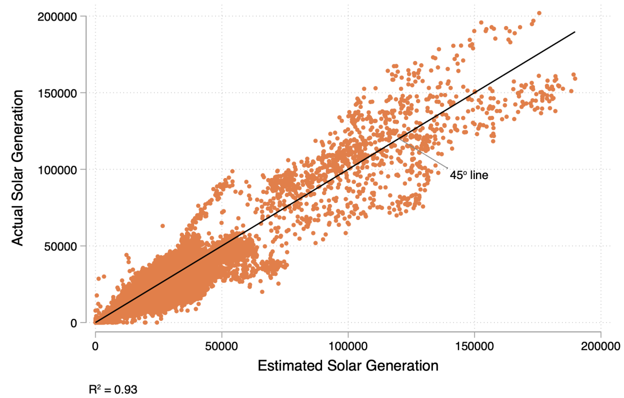
*** p<0.01, ** p<0.05, * p<0.1

The regression includes year × month fixed effects, state × year fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level. Share of pixels under outage represents the share in each state estimated using ML trained on electricity monitor readings to classify pixels as under outage.

Appendix B. Appendix Figures



(a) US



(b) India

FIGURE A1. Estimated vs. Actual Solar Generation

Solar generation estimated as a function of the plant's installed capacity and solar irradiance. Installed capacity data are from the Global Energy Monitor, and irradiance data are compiled from the ERA5 reanalysis dataset. Actual solar generation data for the US are from ISO New England's operation reports and for India from the CEA's *Daily Renewable Reports*. The black line indicates the 45-degree line.

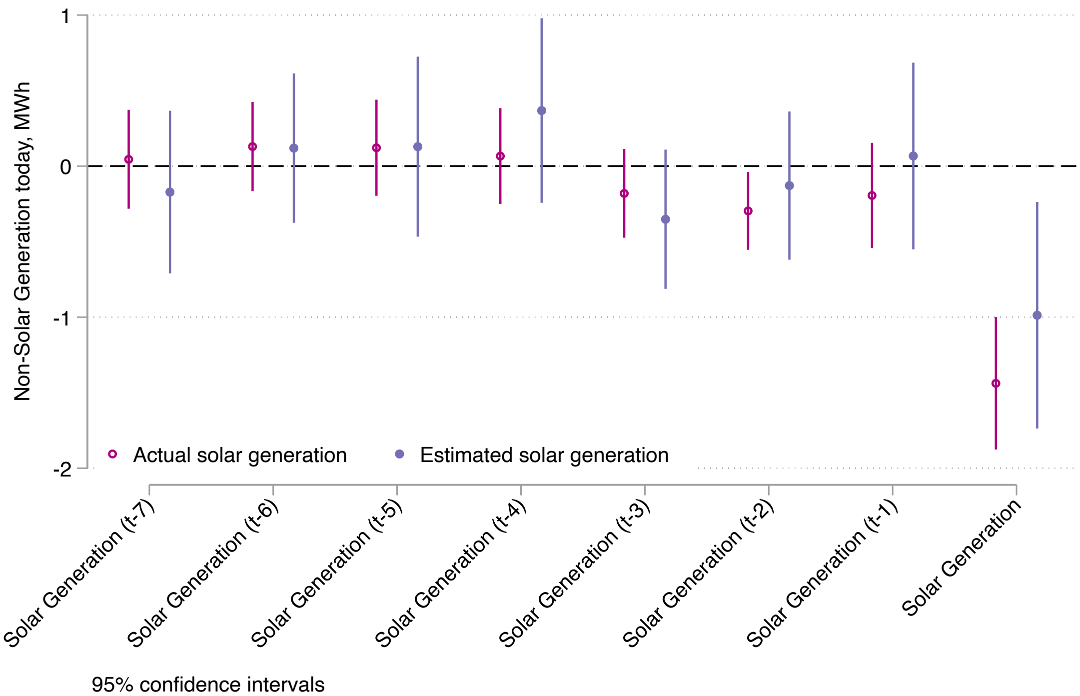


FIGURE A2. US: Impacts of Actual and Estimated Solar Generation on Non-Solar Generation

This figure plots the effects of actual and estimated solar generation on non-solar generation in ISO-New England in the US. The regression includes year × month fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the year × month level.

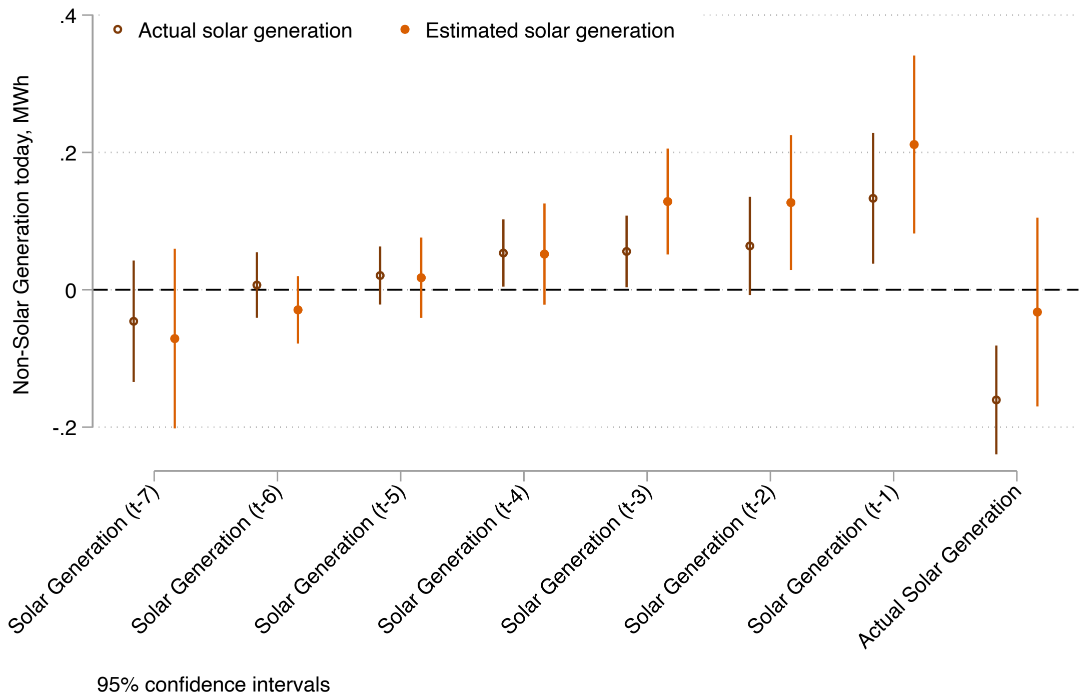


FIGURE A3. India: Impacts of Actual and Estimated Solar Generation on Non-Solar Generation

This figure plots the coefficients of actual and estimated daily solar generation from $t-7$ days to the current day t on nonsolar generation at the state level in India. The regression includes year–month fixed effects, state–year fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state $\times$ year level

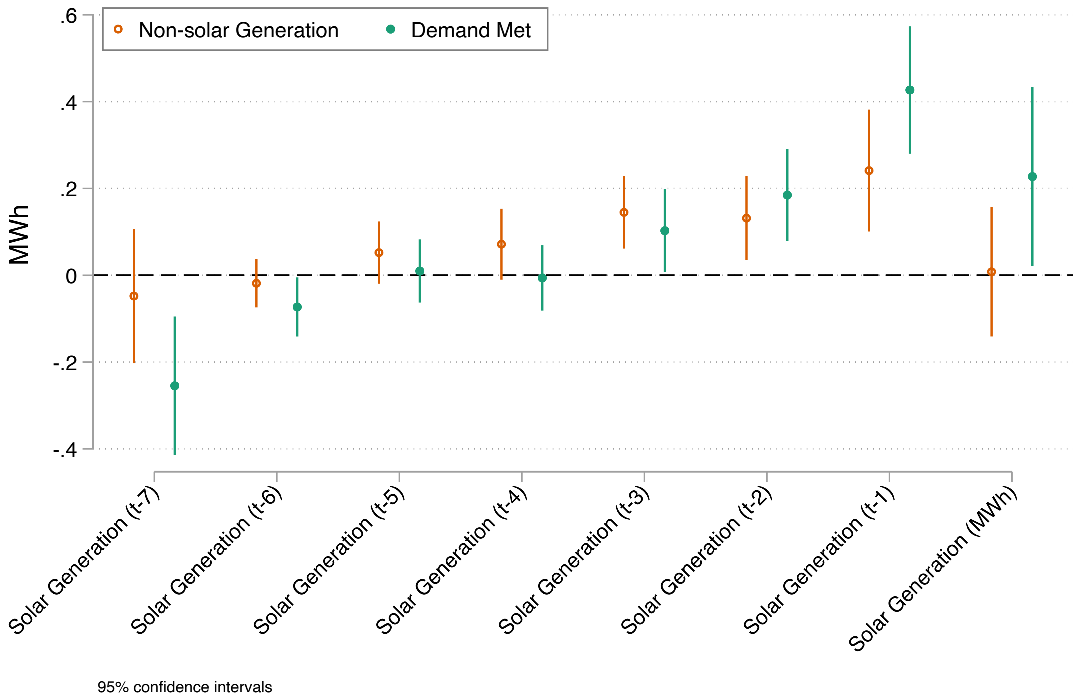


FIGURE A4. Impacts of Solar Power on Electricity Demand Met

This figure plots the coefficients of daily solar generation from $t-7$ days to the current day t on electricity demand met at the state level in India. The regression includes year–month fixed effects, state–year fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state–year level.

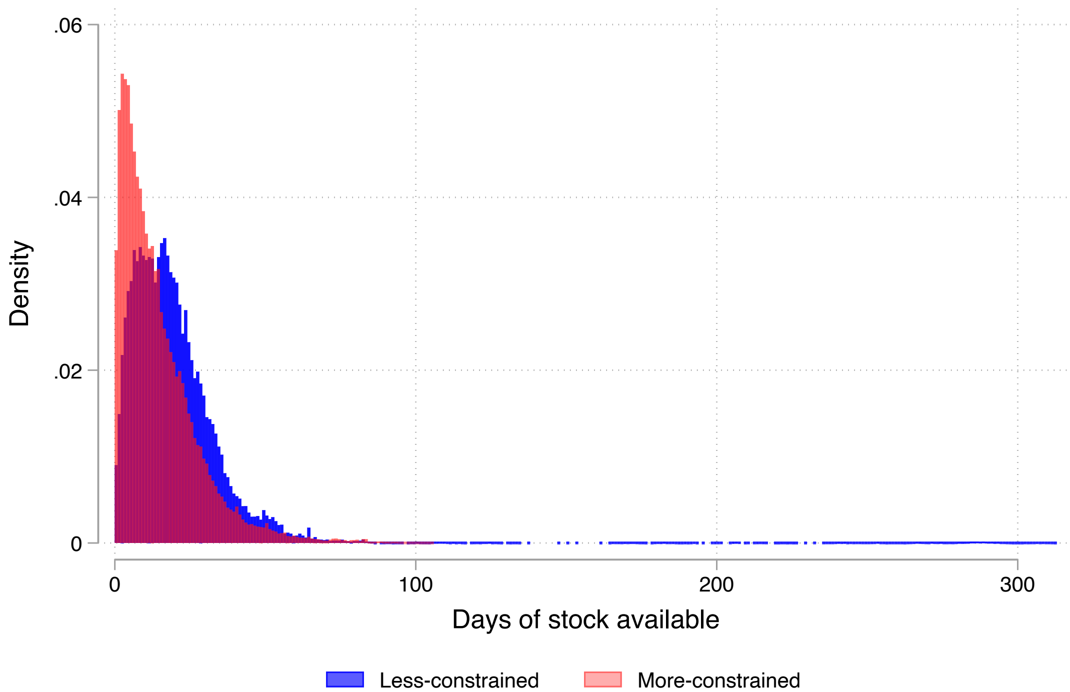


FIGURE A5. Distribution of days of stock by coal-constrained powerplants

Days of available stock at powerplants are estimated based on the average coal consumption at powerplants and their daily levels of stock availability.

Appendix C. Constructing the Measure of Outages using Night Lights Data

I compare outages recorded by electricity supply monitors in specific locations with corresponding pixel-level nighttime lights (NTL) data to construct a measure of outages from NTL. I obtain monitor readings from the Electricity Supply Monitoring Initiative (ESMI) of the Prayas Energy Group (PEG) .[37] PEG installed 528 monitors in households, farms, and commercial establishments across 22 states and union territories in India. These devices collected minute-wise voltage readings between 2014 and 2019.[38]

Ideally, the outages recorded by ESMI would be compared directly with NTL radiance at the exact monitor location. However, PEG does not disclose precise coordinates for the installed monitors. Instead, they provide information on the type of location (domestic, commercial, or agricultural), its neighborhood, and the district and state. Using these details, I approximate each monitor's location. Because outages often occur at the neighborhood level, knowing the approximate neighborhood is sufficient: if one location in a neighborhood experiences an outage, others nearby likely do as well. Figure A6 shows the approximate monitor locations.

C.1. Summary Statistics

Table A5 reports summary statistics on outages recorded by ESMI monitors and on NTL radiance for the corresponding pixels. PEG classifies locations from most rural to most urban: villages, municipalities, districts, and urban areas. This ordering aligns with average radiance values for the corresponding pixels—more urban locations are brighter. Outages also follow this pattern: both frequency and duration of outages decline as locations become more urban.

C.2. Nighttime lights and monitor readings

I compare outages recorded by ESMI monitors with NTL readings for the corresponding pixels to test whether NTL can capture outages. I train a random forest algorithm on 30 covariates, including state, year, month, quarter, day of week, average radiance, and its standard deviation at quarterly, annual, and overall levels. The model also uses residualized radiance, standard deviations and z-scores by week, quarter, and overall for each pixel and its four nearest neighbors. The algorithm is trained on about half of the sample of about 92,000 observations and evaluated on the other half. I classify a monitor as under

[37]More details about the ESMI initiative can be found here.

[38]Not all monitors collected data throughout 2014–2019; most were active for only part of the period.

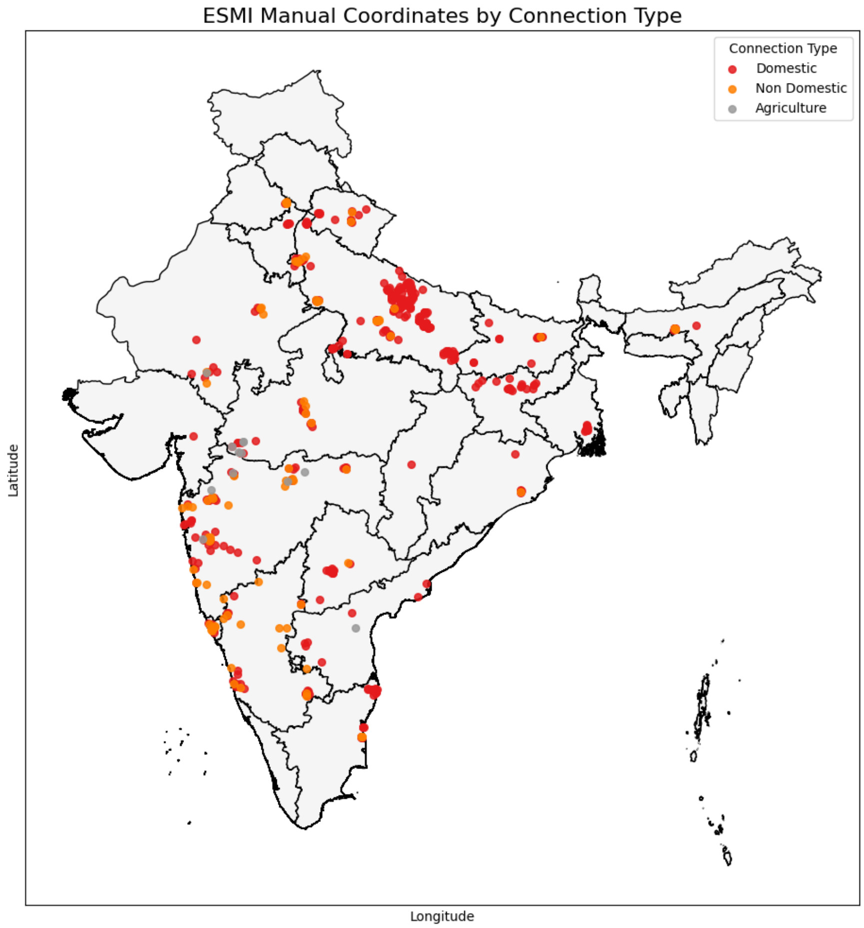


FIGURE A6. Monitor locations across India

This figure plots the approximate location of the Electricity Supply Monitoring Initiative (ESMI) monitors tracking power outages in India.

daily outage if its total outage duration during the day is greater than the average outage duration per day. I examine the total outage duration instead of only nightly outages because my outcome of interest is total outages, not only nightly outages. However, both measures of outages are highly correlated: Mann et al. (2016) show that the correlation between daily and nightly outages in 0.85.

Table A6 breaks down the classification of the algorithm based on the testing data and Figure A7 displays the results. Each dot in Figure A7 represents a pixel-monitor-day prediction. Green dots indicate correct outage predictions; grey dots indicate correct no-outage predictions. Blue dots are false negatives (an outage occurred but was not predicted), and red dots are false positives (an outage was predicted but did not occur). Overall, the algorithm predicted 72% of cases correctly. Thus, while using NTL to predict outages is not

TABLE A5. Summary statistics for ground-truth data

	N	Locations	Outage Frequency Mean	Outage Frequency SD	Outage Duration Mean	Outage Duration SD	Radiance Mean	Radiance SD	Radiance P25	Radiance P75
Village	29,601	198	0.16	0.36	4.8	5.5	4.6	8.7	0.8	4.4
Municipality	12,963	65	0.07	0.25	2.0	3.4	17.9	20.5	5.2	22.3
District	33,036	159	0.04	0.20	1.0	2.7	28.1	19.6	13.8	38.0
Urban	22,207	105	0.04	0.20	0.4	1.9	43.6	26.5	25.7	56.9

Outage data come from monitor readings collected by the Electricity Supply Monitoring Initiative by the Prayas Energy Group. Nighttime lights data are daily VIIRS radiance.

TABLE A6. Evaluation Matrix for Outage Prediction

	Precision	Sensitivity	Observations
Outage	0.56	0.59	18339
No Outage	0.80	0.78	38817
Weighted average	0.72	0.72	57156
Accuracy	0.72	0.72	57156

Precision refers to the share of correct predictions ($\frac{TP}{TP+FP}$). Sensitivity is the share of positives that were correctly identified ($\frac{TP}{TP+FN}$). Accuracy is the share of all correctly identified instances ($\frac{TP+TN}{TP+TN+FP+FN}$). TP refers to true positives, TN true negatives, FP false positives, and FN false negatives.

a perfect measure, it provides a useful proxy for identifying daily outages at the regional level.

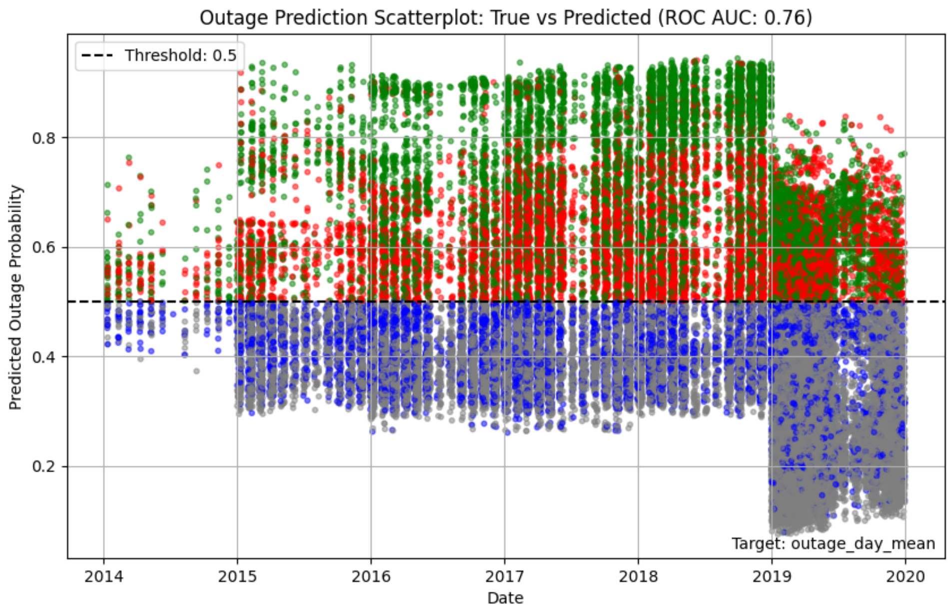


FIGURE A7. Validating outage predictions using electricity supply monitor readings

This figure plots evaluates the random forest algorithm used to predict whether a pixel is under outage. Each dot is a pixel-day-monitor reading. Green dots represent outages that are correctly classified, red dots are false positives, blue dots are false negatives, and grey dots are true negatives.

Appendix D. Instrumenting Actual Solar Generation with Estimated Solar Generation

In my paper, I rely on estimated solar generation for analysis because it allows me to credibly isolate exogenous variation in solar irradiance and produce comparable analysis for the US and India. However, estimated solar generation is vulnerable to attenuation bias. While attenuation bias is likely minimal in this analysis because the correlation between estimated and actual solar generation is close to 1, I use an instrumental variables (IV) approach to confirm that the results are similar while correcting for attenuation bias. Equations (A1) and (A2) outline the IV approach, wherein I instrument for actual solar generation using estimated solar generation. Table A7 presents the first stage, which is very strong, as expected since estimated solar generation is simply a proxy for actual solar generation. Figures A8-A12 denote the results in the paper using the IV specification.

Full model:

(A1)

$$Y_{st} = \alpha_0 + \beta_0 \ actual\_solar\_generation_{st} + \sum_{j=t-7}^{t-1} \beta_j \ actual\_solar\_generation_{sj} + \kappa' \mathbf{X}_{st} + \rho_{sy} + \delta_{ym} + \varepsilon_{st}$$

First stage:

$$\begin{aligned} actual\_solar\_generation_{st} = {} & \gamma_0 + \pi_0 \ estimated\_solar\_generation_{st} \\ & + \sum_{j=t-7}^{t-1} \pi_j \ estimated\_solar\_generation_{sj} + \psi' \mathbf{X}_{st} + \lambda_{sy} + \tau_{ym} + \epsilon_{st} \end{aligned} \tag{A2}$$

TABLE A7. First-Stage Results

	(1)	(2)	(3)	(4)
	US	US	India	India
VARIABLES	Actual Solar	Actual Solar	Actual Solar	Actual Solar
Estimated Solar Generation	1.08***	1.18***	0.91***	0.56***
	(0.01)	(0.04)	(0.00)	(0.04)
Weekend		32.13		-10.71
		(68.71)		(16.04)
Irradiance		-84.80		192.42***
		(71.55)		(68.74)
CDD		-22.91		-70.03***
		(33.35)		(25.31)
HDD		-11.39		65.13***
		(12.99)		(23.78)
Degree day		-226.04		181.44
		(185.03)		(118.57)
Observations	2,192	2,192	48,447	48,447
R-squared	0.94	0.93	0.94	0.98
Y × M FE	N	Y	N	Y
S × Y FE			N	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Daily solar electricity generation estimated using the product of installed capacity data from the *Global Energy Monitor* and flux at the point located closest to each powerplant compiled from ERA5 Reanalaysis Dataset.

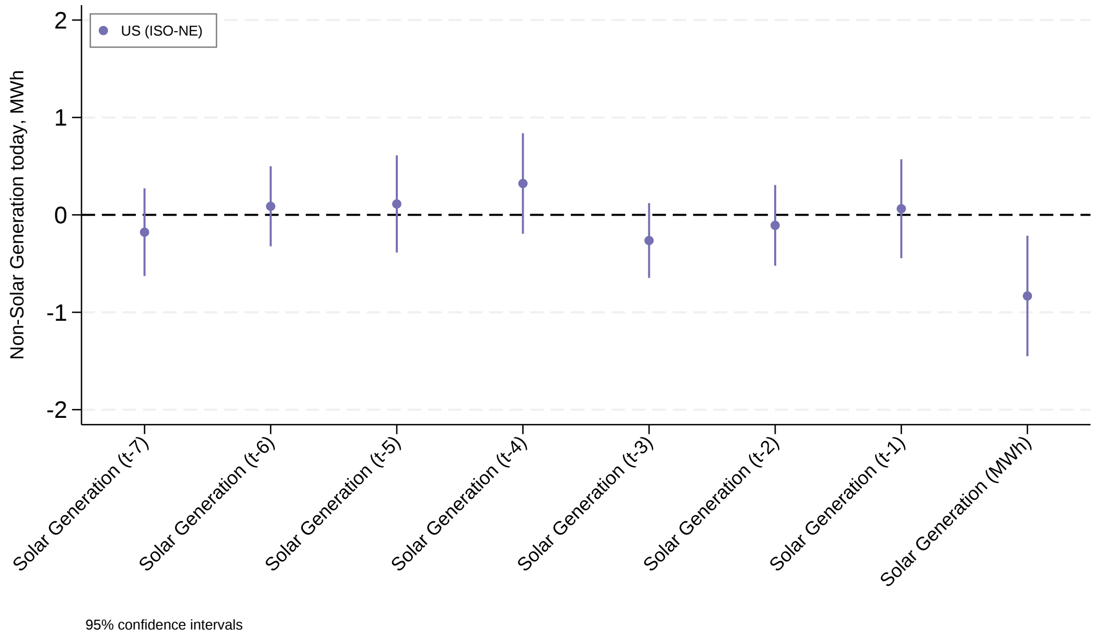


FIGURE A8. Impacts of Solar Generation on Non-Solar Generation in ISO-New England (US)
Instrumenting for Actual Solar Generation with Estimated Solar Generation

This figure plots results from a two-stage least squares regression, where I instrument for actual solar generation using estimated solar generation. The regression that includes year × month fixed effects. Controls include a dummy for whether it is a weekend and current and lagged daily temperature and average flux for the past week. Temperature controls include cooling degree days, heating degree days, and a dummy for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the year × month level.

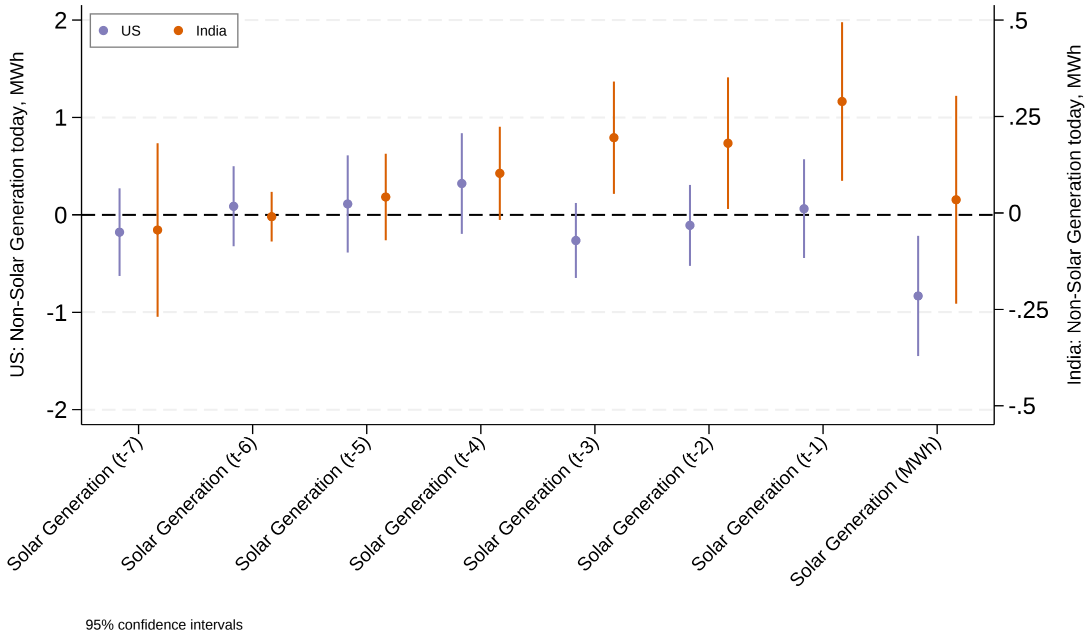


FIGURE A9. Impacts of Solar Generation on Non-Solar Generation in India and the US
Instrumenting for Actual Solar Generation with Estimated Solar Generation

This figure plots results from a two-stage least squares regression, where I instrument for actual solar generation using estimated solar generation. The regressions include year × month fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. The regression for India also includes state × year fixed effects, whereas the regression for IS-NE includes year fixed effects since it is only one region. The regression for India is clustered at the state × year level, whereas the regression for the US is clustered at the year × month level to increase the number of clusters.

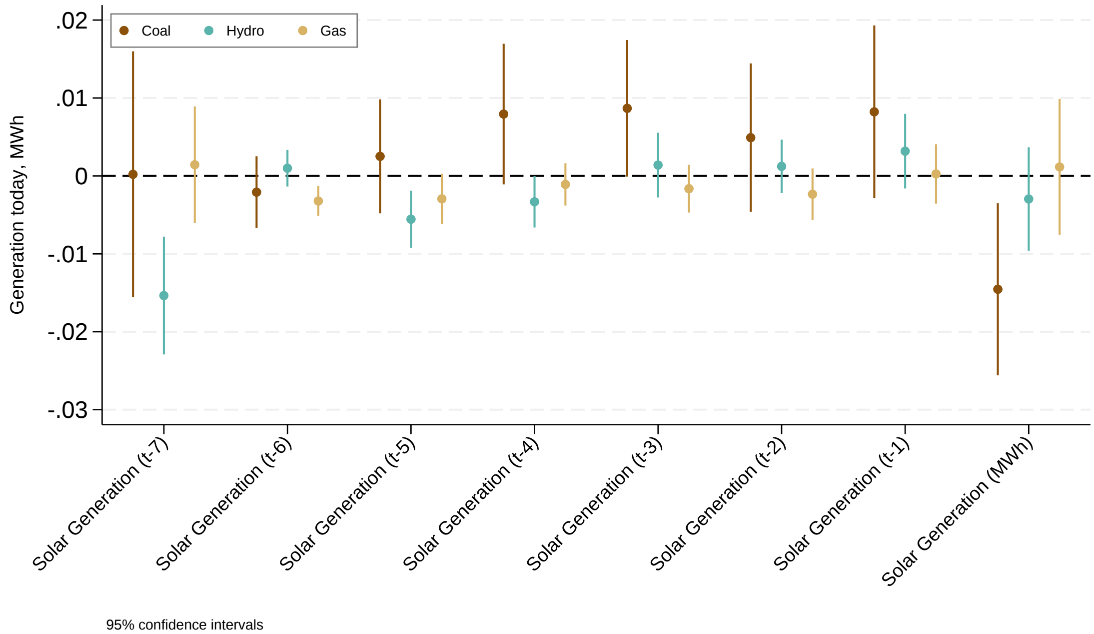


FIGURE A10. Impacts of Solar Generation on Powerplant-level Generation: by Fuel
Instrumenting for Actual Solar Generation with Estimated Solar Generation

This figure plots results from a two-stage least squares regression, where I instrument for actual solar generation using estimated solar generation. The regression includes year × month, state × year, and powerplant fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level.

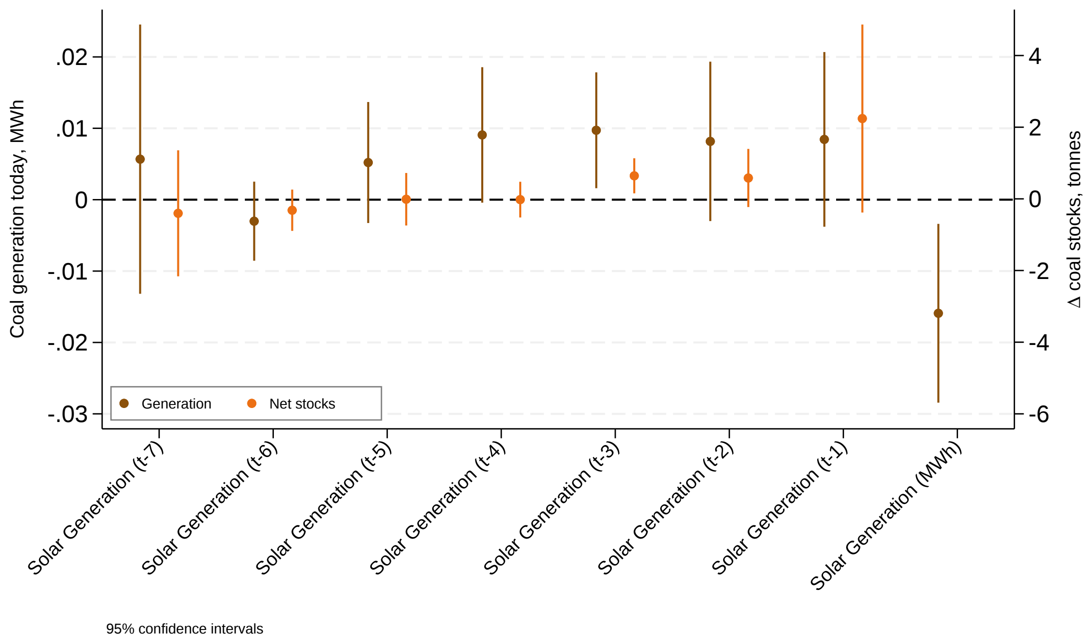


FIGURE A11. Impacts of Solar Generation on Coal Stocks at Powerplants
Instrumenting for Actual Solar Generation with Estimated Solar Generation

This figure plots results from a two-stage least squares regression, where I instrument for actual solar generation using estimated solar generation. The regression includes year × month, state × year, and powerplant fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level.

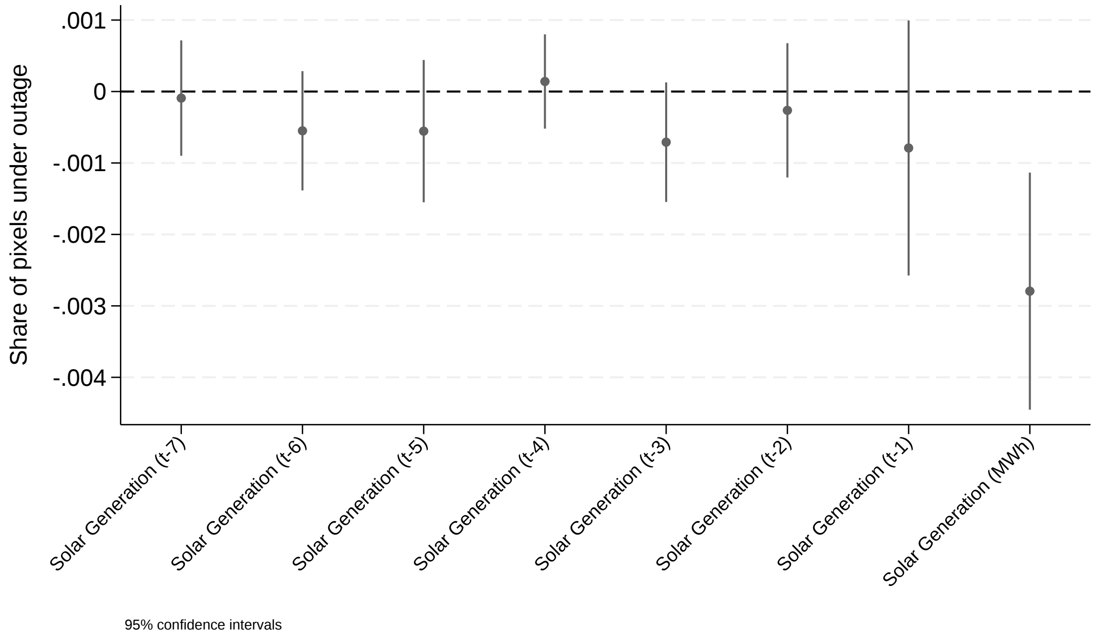


FIGURE A12. Impacts of Solar Generation on Share of Pixels under Outage
Instrumenting for Actual Solar Generation with Estimated Solar Generation

This figure plots results from a two-stage least squares regression, where I instrument for actual solar generation using estimated solar generation. The regression includes year × month and state × year,fixed effects and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level.

Appendix E. Robustness Checks

E.1. Placebo tests

I construct a placebo measure of estimated solar electricity generation at solar powerplants before they start operating. I use the same method for constructing estimated solar generation using daily irradiance and capacity as in (1), but it serves as a placebo since this is estimated generation before powerplants start operating and feeding electricity into the grid. If the results are driven by solar electricity generation, then we would not see any significant effects on placebo generation since the powerplants are not actually operating in the placebo. This placebo test ensures that the results are not driven by some endogenous variables tied to the location of powerplants and the irradiance received by this location.

$$
\begin{aligned}
Y_{st} &= \alpha_0 + \beta_0 \; solar\_generation_{st} + \sum_{j=t-7}^{t-1} \beta_j \; solar\_generation_{sj} \\
&\quad + \gamma_0 \; placebo\_solar\_generation + \sum_{j=t-7}^{t-1} \gamma_j \; placebo\_solar\_generation_{sj} \\
&\quad + \kappa' \mathbf{X}_{st} + \alpha_{sy} + \alpha_{ym} + \varepsilon_{st} \qquad \text{(A3)}
\end{aligned}
$$

I run the same analysis as equation (3), but now also add placebo solar generation to the analysis (equation (A3)). *solar_generation* denotes the actual solar generation at powerplants that are currently operating on date t, whereas *placebo_solar_generation* includes estimated solar generation at powerplants that are not operating on date t, but will start operating at some future date $\tau > t$. In include both actual and placebo solar generation since they might be correlated and excluding actual solar generation may lead to omitted variable bias in the γ coefficients on placebo generation. All other controls are the same as the previous analysis in (3).

If the results are driven by solar generation and not some other factor endogenous to the location of solar powerplants and the irradiance received at these locations, then $\gamma = 0$ for $\gamma \in (0, 7)$. Further, $\gamma_s \neq \beta_s$ for any $s \in (0, 7)$. Figure A13 plots the coefficients on current and lagged placebo solar generation and actual solar generation. Unlike actual solar generation, lagged placebo solar generation has no significant impacts on non-solar generation, providing further support to the conclusion that the effects are driven by solar electricity generation.

The negative coefficients on current placebo solar generation and a week ago $(t - 7)$ are

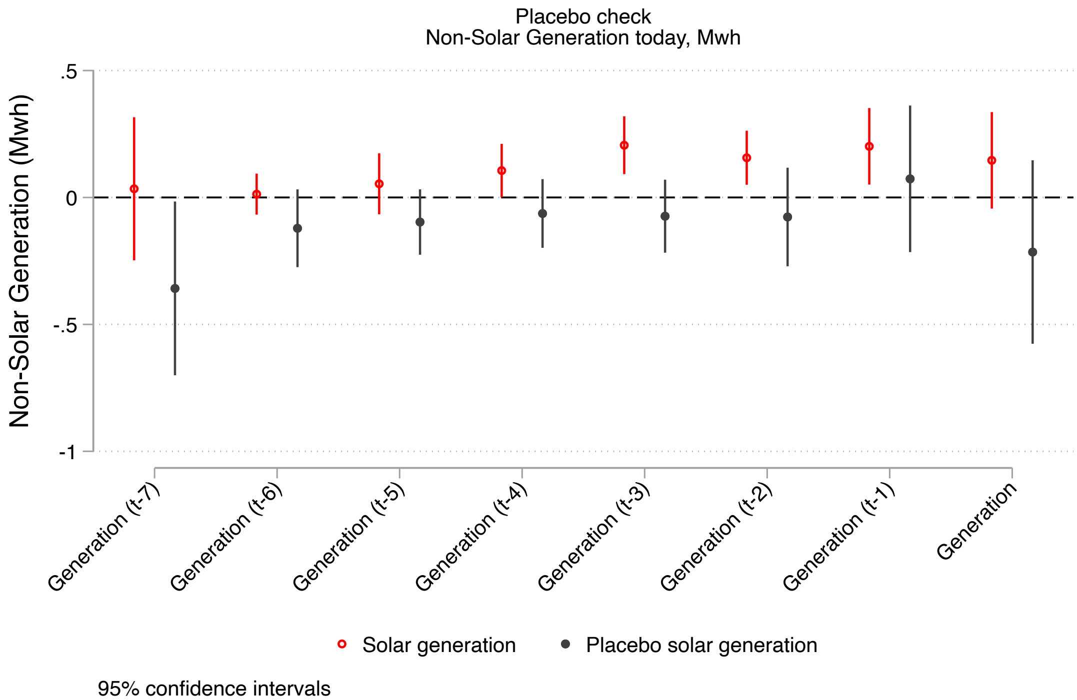


FIGURE A13. Placebo test for solar generation (2020-2023)

The sample in this figure excludes the first and the last full years of data because by construction, these years would have no placebo generation or actual solar generation. This figure plots the coefficients of daily actual solar electricity generation and placebo solar generation each day from $t-7$ days to the current day t on non-solar generation in India. Placebo generation represents the generation at powerplants *before* they start operating. The regression includes year × month fixed effects, state × year fixed effects, and current and lagged controls for average flux, cooling degree days, heating degree days, and dummies for whether it is a cooling degree day or a heating degree day. Standard errors are clustered at the state × year level.

surprising. One potential explanation is that the placebo measure is imperfect. The data on solar powerplants are discrete at the annual level. This implies that the operating start date is an imprecise measure and depending on the idiosyncratic reporting decision, a plant that starts operating in the middle of a year may appar as operating for some period when its still not operating, or may appear as inoperable for some period when it is in fact operating. If the former is true, it would bias the main result towards zero, implying that the current results are a lower bound on the actual impact of solar generation. If the latter is true, then the placebo generation measure might include some actual generation as well. Further, there might be some impacts of solar generation in the run up to full-fledged operation as the powerplant sets up its operations. These factors may explain the negative coefficients. Nonetheless, the negative coefficients on placebo generation reinforce the finding that the positive impacts of lagged solar generation are indeed driven by actual solar electricity generation.

E.2. Alternate fixed effects specifications

The main specification in this paper includes state × year and year × month fixed effects. This is my preferred specification because it controls for all the important endogenous factors: state × year fixed effects control for different states growing at different rates and allow us to hold installed solar farm capacity constant and isolate changes in solar electricity generation driven by changes in solar irradiance because solar farm capacity changes at the state-year level in the data. Year month fixed effects help control for seasonal variation in demand effects and the impacts of seasonality on electricity supply.

Nonetheless, Table A8 shows that the results are not sensitive to the chosen specification and the findings hold across different fixed effects specifications. Column 2 shows results with state × year × month fixed effects, which is the most extreme version of the fixed effects. Using this specification, we compare impacts of changes in solar electricity generation driven by solar irradiance within a month, within a state, within a year. Column 3 controls only for month fixed effects instead of year-by-month fixed effects, allowing for averages in weather conditions across years. Column 4 controls for state fixed effects instead of state-by-year fixed effects. Finally, column 5 has the least restrictive controls with separate state, year, and month fixed effects respectively. The coefficients are roughly of similar magnitude across these specifications and hence the results are robust to the choice of specification.

TABLE A8. Robustness to alternate specifications

	Non-solar Generation				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Main spec.	S $\times Y \times M$	S $\times Y + M$	S + Y $\times M$	S + Y + M
Solar Generation (MWh)	0.01	0.09	0.01	-0.05	-0.05
	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)
Solar Generation (t-1)	0.23***	0.28***	0.23***	0.21***	0.21***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Solar Generation (t-2)	0.15***	0.18***	0.15***	0.13***	0.13***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)
Solar Generation (t-3)	0.14***	0.18***	0.14***	0.12***	0.11***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)
Solar Generation (t-4)	0.07*	0.14***	0.08**	0.05**	0.05**
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Solar Generation (t-5)	0.04	0.10***	0.05	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Solar Generation (t-6)	-0.03	0.03	-0.03	-0.05**	-0.05**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Solar Generation (t-7)	-0.05	0.14**	-0.03	-0.12**	-0.10*
	(0.07)	(0.05)	(0.08)	(0.05)	(0.05)
Observations	59,580	59,580	59,580	59,580	59,580
R-squared	0.97	0.99	0.96	0.94	0.94
FE	S $\times Y + Y \times M$	S $\times Y \times M$	S $\times Y + M$	S + Y $\times M$	S + Y + M

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Lagged temperature and flux

standard errors clustered at the state × year level

Daily solar electricity generation estimated using the product of installed capacity data from the *Global Energy Monitor* and flux at the point located closest to each powerplant compiled from ERA5 Reanalaysis Dataset.The regression includes year × month fixed effects and current and lagged controls for average flux, cooling degree days, and dummies for whether it is a cooling degree day or a heating degree day.

E.3. Alternate time lags

TABLE A9. Robustness to alternate lags: Non solar generation

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Solar Generation (MWh)	0.05	0.03	0.01	-0.00	-0.00	0.00
	(0.11)	(0.10)	(0.09)	(0.08)	(0.08)	(0.07)
Solar Generation (t-1)	0.47***	0.23***	0.23***	0.23***	0.23***	0.23***
	(0.17)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
Solar Generation (t-2)		0.29**	0.14***	0.14**	0.14***	0.15***
		(0.14)	(0.05)	(0.06)	(0.06)	(0.05)
Solar Generation (t-3)			0.19	0.13***	0.13***	0.13***
			(0.11)	(0.04)	(0.04)	(0.04)
Solar Generation (t-4)				0.07	0.08*	0.07*
				(0.09)	(0.04)	(0.04)
Solar Generation (t-5)					-0.01	0.04
					(0.09)	(0.03)
Solar Generation (t-6)						-0.07
						(0.08)
Observations	59,580	59,580	59,580	59,580	59,580	59,580
R-squared	0.97	0.97	0.97	0.97	0.97	0.97
Solar gen mean	456	456	456	456	456	456
Dep. var. mean	6363	6363	6363	6363	6363	6363
Test lag + current = 0	.0625	.0628	.0648	.069	.0741	.0799

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Daily solar electricity generation estimated using the product of installed capacity data from the *Global Energy Monitor* and flux at the point located closest to each powerplant compiled from ERA5 Reanalaysis Dataset.The regression includes year × month fixed effects and current and lagged controls for average flux, cooling degree days, and dummies for whether it is a cooling degree day or a heating degree day.