Tech-driven Comparative Advantage: Evidence from Solar Expansion in China †

Hanming Fang[‡]
Ming Li[§]
Yang Yang[¶]

This version: January 12, 2026

†We would like to thank XXX for helpful discussions and comments. Li gratefully acknowledges the National Natural Science Foundation of China (Nos. 72403216 and 72192804) for financial support. Yang gratefully acknowledges the support from the Research Grants Council of Hong Kong (No. 14504022) and the National Natural Science Foundation of China (No. 72203192). All remaining errors are our own.

‡Department of Economics, University of Pennsylvania, 133. S. 36th, Philadelphia, PA, 19104, USA; and the NBER. Email: hanming.fang@econ.upenn.edu

§School of Management and Economics, The Chinese University of Hong Kong, Shenzhen, Longxiang Rd. 2001, Shenzhen, Guangdong, China. Email: liming2020@cuhk.edu.cn

¶CUHK Business School, The Chinese University of Hong Kong, 12 Chak Cheung Street, Hong Kong SAR, China. Email: zoeyang@cuhk.edu.hk

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Abstract

This paper examines how large-scale solar deployment in China reshapes the spatial distribution of productive activity by alleviating electricity constraints and generating new sources of comparative advantage. We construct a novel dataset linking satellite-based measures of utility-scale photovoltaic installations from 2010 to 2022 with administrative firm-level records. We first show that solar expansion improves local electricity conditions. Capacity additions raise effective supply, reduce both planned and unplanned outages, and lower electricity prices, creating a technology-driven foundation for subsequent industrial growth. To identify the effects on economic activity, we exploit staggered and continuous variation in solar capacity across cities using panel regressions with high-dimensional fixed effects, complemented by dynamic estimators following De Chaisemartin and d'Haultfoeuille (2024) and an instrumental-variable approach. Across all specifications, we find that solar deployment increases firm entry and enhances firm performance, with the largest effects in electricity-intensive industries and resource-abundant regions. These effects are not driven by industrial policy targeting, proximity to the photovoltaic supply chain, or long-distance transmission infrastructure. Our findings demonstrate the dual role of renewable energy as both environmental policy and industrial strategy, transforming latent natural endowments into durable sources of technology-based comparative advantage.

Keywords: Solar Energy, Comparative Advantage, Electricity Markets, Firm Entry, Industrial Development

JEL Code: O13, O25, Q42, Q48, L26

1 Introduction

Over the past two decades, technological change has begun to reshape the geography of economic activity. While standard frameworks in development and spatial economics typically treat geographic characteristics as slow-moving fundamentals, recent progress in general-purpose technologies shows that innovation can endogenously change the economic returns to natural endowments (Audretsch and Feldman, 1996; Desmet and Rossi-Hansberg, 2014; Feyrer, Mansur, and Sacerdote, 2017). When new technologies raise the productivity of location-specific inputs such as solar irradiation, wind availability, and land intensity, regions that were once peripheral or resource-abundant but economically underdeveloped can become competitive production locations. The expansion of utility-scale solar facilities in sun-rich yet historically marginal areas provides a clear example: technological improvements have made it feasible to convert an abundant natural attribute into a productive input with measurable economic value. We refer to this process as *technological emergence*, meaning the rise of new economic centers within an established spatial hierarchy driven by the interaction between innovation and local endowments. This mechanism reflects a shift in the production frontier in which certain natural features become more productive through technological progress, thereby reshaping patterns of regional comparative advantage.

Despite growing interest in how technology affects regional development, research across spatial, trade, and development economics provides limited empirical evidence on rapid, innovation-induced changes in regional competitiveness. Classical trade models treat technologies and factor endowments as fixed and exogenous across locations (Ricardo, 1817; Dornbusch, Fischer, and Samuelson, 1977), and work in new economic geography places emphasis on geographic fundamentals, historical contingencies, and agglomeration forces, suggesting that the spatial distribution of economic activity evolves gradually and is shaped by historical advantages (Krugman, 1991; Fujita, Krugman, and Venables, 2001). Meanwhile, persistent regional disparities have prompted place-based policies, yet their impacts tend to be modest and context-specific, with little attention to how innovation may reshape local development trajectories (Kline and Moretti, 2014; Neumark and Simpson, 2015; Ashenfarb, 2024). These gaps point to the need for empirical evidence on whether advances in general-purpose technologies can reorder regional economic hierarchies by converting latent endowments into productive assets.

Recent evidence on the global expansion of solar energy suggests that this sector offers a particularly useful setting for studying such technology-driven spatial change. A global asset-level census identifies 68,661 non-residential PV facilities across 131 countries as of 2018, reflecting an increase of more than 80 percent in installed capacity between 2016 and 2018 and illustrating the speed and breadth of solar expansion worldwide (Kruitwagen et al., 2021). Medium-run projections suggest that continued declines in renewable costs and efficient adoption could raise the global renewable share to about 70% by 2040, increasing average welfare by roughly 4.6% (Arkolakis and Walsh, 2023). Longer-run estimates indicate that fossil fuels will account for only about 21% of global electricity generation by mid-century, down from 62% in 2020, reflecting the growing prominence of solar technologies in the global energy mix (Nijsse et al., 2023). These patterns suggest that solar is not only a major contributor to decarbonization but also a transformative general-purpose technology with the potential to reshape global patterns of industrial activity and regional comparative advantage. Because utility-scale solar deployment depends directly on geographic endowments such as land availability and irradiation, the sector offers a particularly clean setting for identifying how technological progress changes the economic value of place and, in turn, the spatial organization of economic activity.

To examine whether technology-driven changes can contribute to regional rebalancing or instead primarily reallocate economic activity across space, we study China's large-scale rollout of utility-scale solar power, a setting where rapid technological progress has interacted with local endowments in ways that can be observed and measured. China provides a well-suited empirical setting for several reasons. First, the expansion of solar technology since 2010 has been both rapid and shaped by national and provincial policies, generating substantial variation in the timing and scale of deployment across regions. Kruitwagen et al. (2021) document that non-residential PV capacity grew by more than 81% between 2016 and 2018, with China accounting for nearly half of all new installations detected during this period. Second, the country exhibits substantial heterogeneity in solar irradiance, land availability, and industrial structure, allowing for the identification of treatment effects and heterogeneous responses across regions and industries. Third, China's administrative microdata, which link firm outcomes to local energy and solar infrastructure, allow for detailed measurement of how energy shocks influence firm behavior and production patterns. To carry out our analysis, we assemble a dataset that merges satellite-based information on solar installations with administrative firm records. This dataset enables us to study how solar deployment affects electricity supply, industrial activity, and the spatial allocation of economic activity.

Our analysis begins by documenting how solar deployment improves local electricity conditions, thereby creating the basis for changes in regional productivity. We construct a city–year panel of electricity shortages from 199 regional newspapers between 2010 and 2022 and find that increases in installed solar capacity are associated with economically and statistically significant declines in both planned and unplanned outages. To complement these results, we use firm-level value-added tax invoice data and show that solar expansion is linked to lower effective electricity prices and higher electricity consumption, indicating a relaxation of local supply constraints. We also examine the determinants of solar plant siting, showing that capacity additions are strongly predicted by global horizontal irradiance and the presence of local industrial policy support. The latter plays a more important role in regions with weaker solar potential. These results confirm that solar deployment generates localized improvements in electricity availability and provide the foundation for analyzing its broader economic effects.

We next examine whether solar-induced improvements in electricity supply translate into real economic responses at the extensive margin. Exploiting staggered and continuous growth in installed solar capacity across cities and industries, we estimate panel regressions with high-dimensional fixed effects and find that solar deployment significantly increases new firm formation. The response is concentrated in China's designated solar regions, located primarily in the northwest, which combine high solar irradiation and abundant land with historically weaker industrial bases.[1] Outside these regions, additional capacity does not generate comparable entry and, in some cases, appears to crowd out marginal firms. Entry responses are strongest in electricity-intensive and scale-sensitive sectors such as manufacturing, mining, and transportation, where improved energy availability relaxes binding production constraints. In contrast, complementary service sectors, including grid management and environmental services, expand more in non-core regions, where lower entry barriers and limited incumbent presence make these sectors more responsive to incremental improvements in energy conditions.

The dynamics of China's solar rollout provide additional opportunities to strengthen identification. Solar projects are implemented in phases, beginning with approval and early construction and continuing through to eventual grid connection, which generates continuous variation in treatment intensity and staggered timing across locations. This structure complicates the application of conventional two-way fixed effects panel estimators, as they perform poorly when treatment cohorts overlap and treatment intensity varies over time. To address these challenges, we apply the estimator of De Chaisemartin and d'Haultfoeuille (2024), which flexibly accommodates staggered adoption, continuous capacity additions, and heterogeneous treatment effects. The estimates show that firm entry in solar regions begins to rise approximately two years before installation, consistent with anticipatory investment in response to project approvals and early-stage construction. This pattern is absent in non-solar regions and is most pronounced in electricity-intensive sectors and in areas experiencing large-scale installations, suggesting that firms adjust entry decisions in anticipation of improved electricity availability.

[1] Consistent with prior assessments of China's solar resource potential and grid-parity conditions, we classify Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang as high-solar-resource regions, reflecting their superior irradiation conditions and favorable economics of solar generation (Yan et al., 2019; Yin et al., 2025).

To strengthen causal identification, we implement an instrumental variables (IV) strategy that uses global horizontal irradiance (GHI) and pre-existing electricity shortages as instruments for solar capacity additions. These instruments are time-invariant and plausibly orthogonal to contemporaneous shocks to local industrial activity, and they strongly predict the intensity and location of solar deployment. The IV estimates indicate that increases in solar capacity lead to statistically significant growth in new firm registrations, with magnitudes comparable to the baseline results. We also estimate a border discontinuity design that exploits institutional differences in electricity pricing across provincial grid boundaries. The estimated effects are consistent with the main results, providing an additional source of quasi-experimental variation that reinforces the conclusion that solar deployment expands firm entry in affected areas. The evidence indicates that solar capacity additions change the spatial distribution of industrial activity by improving electricity access in previously constrained regions, and demonstrates that technological change can create new, location-specific comparative advantages.

Having established that improvements in local electricity access are the primary channel linking solar deployment to firm entry, we next examine additional mechanisms that could contribute to the observed responses, including supply chain linkages, industrial policy targeting, electricity transmission patterns, and spatial or vertical spillovers. We begin by addressing potential supply chain explanations. Excluding 52 upstream and downstream industries directly connected to photovoltaic manufacturing and related services leaves our estimates largely unchanged, indicating that that the entry response is not limited to sectors directly connected to the solar supply chain. We then incorporate industry-level measures of policy exposure from Fang, Li, and Lu (2024) and find that targeted industrial policies amplify the response to solar deployment, particularly in sectors receiving both improved electricity access and explicit policy support. In resource-rich regions, electricity remains the primary constraint, and policy effects appear only once local energy bottlenecks are eased. As a placebo test, we exploit spatial variation in China's ultra-high-voltage transmission network. In cities where most solar-generated electricity is exported through UHV lines rather than consumed locally, the estimated entry effects are substantially weaker. This aligns with the mechanism: if firm entry responds to improvements in local electricity availability, the estimated effects should fall in UHV origin cities where additional generation is transmitted outward instead of easing local constraints. We also examine spillovers by incorporating solar capacity in neighboring cities and find strong positive effects, indicating that the benefits of solar deployment extend beyond local boundaries and contribute to broader regional gains. Finally, using electricity intensity measures derived from input–output tables, we show that solar expansion increases firm entry not only in electricity-intensive industries but also among their upstream suppliers, indicating that vertical production linkages also play an important role in shaping the entry response.

This paper contributes to three strands of literature. First, our study relates to the growing work on the energy transition and regional development. A large body of work examines how renewable energy reshapes local economic activity and can redirect the trajectory of regional economies. Recent research shows that new renewable infrastructure can generate substantial spatial reallocation effects, influencing land values, welfare, and the distribution of economic activity across regions (Quentel, 2023). Other studies emphasize that these outcomes depend critically on institutional and financial conditions: politically targeted or misallocated solar power plant deployment can crowd out private investment, exacerbate capital misallocation, and slow local growth (Chen and Chu, 2024). Building on this, research in spatial economics shows that place-based policies and regional interventions can produce persistent changes in industrial structure and productivity (Shenoy, 2018), suggesting that the effectiveness of renewable investment depends on where and how it is deployed. A complementary line of research documents substantial heterogeneity in solar grid parity, resource potential, and profitability across China, reflecting differences in solar radiation, electricity costs, and grid conditions (Yan et al., 2019; Yin et al., 2025). At the behavioral level, the adoption of durable clean technologies is shaped by consumers' high discount rates and their sensitivity to upfront costs (De Groote and Verboven, 2019). Our paper contributes to this literature by demonstrating that large-scale solar deployment enhances local electricity provision when placed in naturally advantaged areas, and that these energy improvements can shift the geography of economic activity by enabling previously underutilized regions to grow into viable industrial locations.

This study also adds to research examining electricity shortages, reliability, and their economic consequences. A substantial literature shows that unreliable electricity supply imposes sizeable costs on firms and households. Evidence from China shows that power shortages directly reduce industrial productivity and weaken the performance of energy-intensive sectors (Fisher-Vanden, Mansur, and Wang, 2015), while related work from India shows that outages disrupt production schedules, distort firm size distributions, and depress investment (Allcott, Collard-Wexler, and O'Connell, 2016). Higher electricity costs further constrain firms' operating capacity and competitiveness, as documented in the Indian manufacturing sector (Abeberese, 2017). More recent research highlights the value that firms and households place on reliability: when faced with frequent or prolonged outages, consumers invest in defensive technologies such as battery storage, providing revealed-preference evidence of the welfare gains associated with improved reliability (Brown and Muehlenbachs, 2024). Reliability risks are also amplified by climate conditions, as heatwaves place additional stress on the grid and raise the likelihood of outages, thereby tightening an already binding constraint on economic activity (Liang et al., 2025). Research in electricity markets shows that reliability issues become more salient as renewable penetration increases, because correlated supply fluctuations and market design features play a larger role in shaping system performance (Borenstein, Bushnell, and Mansur, 2023). Reliability plays a role in downstream electrification as well. Evidence from Chinese cities shows that power disruptions suppress EV adoption by increasing charging uncertainty and lowering confidence in the grid (Qiu et al., 2024). By showing that large-scale solar deployment strengthens local electricity provision and lowers effective energy costs, our study highlights an upstream channel through which renewable investment can ease persistent supply constraints and promote better firm performance.

Third, this paper contributes to research on renewable energy policy and the industrial organization of clean-technology sectors. A substantial body of work examines how policy interventions shape the development, pricing, and spread of renewable energy technologies. Work on solar trade policy shows that tariffs increase downstream costs, suppress adoption, and generate sizable welfare losses through supply-chain pass-through and strategic avoidance behavior (Houde and Wang, 2022; Bollinger et al., 2024). Complementary studies emphasize the importance of social learning and local coordination in accelerating household and community transitions to renewable technologies (Gillingham and Bollinger, 2021), while analyses of renewable investment document positive but typically modest local employment effects (Fabra et al., 2024). At a more aggregate level, research shows how cost declines and innovation dynamics drive the long-run evolution of clean-energy markets (Arkolakis and Walsh, 2023), and work on the shale gas revolution illustrates how major technological shocks can redirect innovation and reshape the pace and direction of the energy transition (Acemoglu et al., 2023). Studies focused on China further show how targeted industrial policies, supply-chain specialization, and state coordination supported the rapid rise of its solar manufacturing sector (Banares-Sanchez et al., 2024). Our paper contributes to this literature by showing that large-scale renewable deployment functions as industrial infrastructure. Rather than affecting the price or adoption of solar technologies, it alters the production environment for downstream firms by easing electricity constraints and reducing effective energy costs, leading to measurable changes in regional industrial structure.

The remainder of the paper is organized as follows. Section 2 provides background on global and domestic solar development. Section 3 describes the data sources and summary statistics. Section 4 outlines the empirical strategy and presents the main results on electricity access and firm entry. Section 5 examines competing and complementary mechanisms. Section 6 assesses their economic implications for firm entry and performance. Section 7 concludes.

2 Background on Solar Power Development in China

The global rise of solar power has been shaped in large part by developments in China, which has moved from a subsidy-dependent market to the world's most competitive solar industry. In its early phase, expansion relied heavily on central government support. Between 2009 and 2011, China launched the MOF/MOHURD Solar PV Building Application subsidy, the nationwide Golden Sun Programme, and initiated the MOHURD BIPV O&M code (JGJ/T 264-2012, issued December 2011), together forming the first policy suite specifically supporting BIPV and rooftop PV.[2] The introduction of a nationwide feed-in tariff (FIT) in 2011 strengthened these incentives, with per-kWh subsidies often exceeding RMB 0.40 in many provinces.[3] These policies triggered a surge in investment, and by 2013 China had become the world's largest market for new solar capacity. The heavy use of subsidies also generated substantial fiscal pressures. By 2018, the renewable energy subsidy fund faced a deficit exceeding RMB 100 billion, with around half of the gap arising from support to the solar PV sector (Dong, Zhou, and Li, 2021). The first stage of China's solar expansion was therefore characterized by rapid, policy-driven growth financed largely through subsidies.

Building on this policy-driven foundation, the economics of solar power in China shifted markedly within less than a decade. Industrial policies, rapid declines in module prices, and steep learning effects promoted competition and supply-chain integration, which together drove significant cost reductions. By 2019, the levelized cost of unsubsidized solar electricity had already reached parity with coal-fired generation in many provinces (Yan et al., 2019). As costs declined, policy support was gradually scaled back. During the same period, benchmark on-grid tariffs were lowered across all three regional categories. As shown in Panel A of Figure 1, the industry adjusted by shifting toward larger-scale projects. While the number of new plants fluctuated from year to year, average plant capacity increased markedly, indicating a clear move toward utility-scale installations. Together, these trends reflect a move from subsidy-led expansion toward growth increasingly supported by cost reductions and market conditions.

Regional heterogeneity has also shaped the trajectory of China's solar expansion. The

[2]The Solar PV Building Application subsidy was introduced by the Ministry of Finance and the Ministry of Housing and Urban-Rural Development in 2009, providing RMB 20/Wp for PV building applications (see International Energy Agency, "Solar Roofs Programme," available at https://www.iea.org/policies/4991-solar-roofs-programme). The Golden Sun Programme, launched in 2009, offered subsidies of up to 70% for off-grid systems and 50% for grid-connected projects, with a national target of 500 MW by 2012 (see International Energy Agency, "Golden Sun Programme," available at https://www.iea.org/policies/4992-golden-sun-programme). In December 2011, MOHURD issued the "Code for the Operation and Maintenance of BIPV Systems" (JGJ/T 264-2012), effective May 1, 2012, aligning China's BIPV policy with international standards such as the EU Energy Performance of Buildings Directive (2010/31/EU).

[3]A feed-in tariff is a policy that guarantees renewable energy producers a fixed price for electricity supplied to the grid, usually through long-term contracts.

decline in costs and the scaling-up of installations described above have unfolded unevenly across provinces, reflecting large differences in natural endowments. As shown in Figure A1, the LCOE is lowest in regions with abundant sunlight and inexpensive land, particularly Inner Mongolia, Ningxia, Gansu, Qinghai, and Xinjiang, where costs fall well below local coal benchmarks. City-level evidence reinforces these regional patterns. Yan et al. (2019) document that 76 cities had already reached plant-side grid parity by 2018, meaning that PV LCOE was at or below the local desulfurized coal benchmark. An additional 99 cities had GPIp values between 1.01 and 1.09, indicating that the cost gap to grid parity was very small. Their analysis also highlights substantial variation in solar resources: annual PV electricity generation reaches about 1,976 kWh/kWp in high-irradiance locations such as Tibet, compared with roughly 732 kWh/kWp in lower-irradiance cities such as Chongqing. They further note that benchmark coal-fired generation prices in Inner Mongolia are approximately 0.30 CNY/kWh in the eastern grid and 0.28 CNY/kWh in the western grid, providing a useful reference point for evaluating plant-side grid parity.

According to recent satellite-based estimates, Xinjiang, Inner Mongolia, Hebei, Gansu, and Qinghai together host more than 500 km^2 of PV installations, accounting for 36.9% of China's total PV area (Yang, Jiang, and Liu, 2025). Panel B of Figure 1 illustrates this concentration, with the majority of large-scale solar projects clustered in the northwest. The scale is substantial: the electricity generated annually by panels deployed on the Gobi Desert alone is sufficient to meet roughly half a year of electricity demand in a typical prefecture-level city in eastern China. Using high-resolution geospatial and meteorological data, Yin et al. (2025) estimate China's technical solar potential at about 39.6 PWh under conservative assumptions and up to 442 PWh under more favorable conditions, far exceeding current national electricity consumption. These figures exhibit the exceptional quality of solar resources in northwestern provinces. The concentration of installed capacity and sizable remaining resource potential points to the natural strengths of these regions for utility-scale solar development and helps explain their central role in China's current energy investment priorities.

[Figure 1 About Here]

Institutional features of China's electricity market further amplify these regional dynamics. Because tariffs are set at the provincial level and electricity generated from local solar plants is integrated into the provincial grid, the benefits of cost declines and improved reliability accrue unevenly across space. Provinces with abundant solar resources not only attract capacity investment but also pass lower effective electricity costs to industrial users, reinforcing their comparative advantage. For firms in electricity-intensive sectors, these margins are particularly salient. A large empirical literature documents how power shortages depress productivity and growth (Allcott, Collard-Wexler, and O'Connell, 2016; Fisher-Vanden, Mansur, and Wang, 2015). Since many manufacturing processes embed electricity in a near-Leontief fashion, even modest improvements in reliability and effective cost can shift the relative attractiveness of regions, affecting firm location decisions and patterns of industrial specialization. Together, these dynamics suggest how the interaction between resource endowments, institutional structures, and renewable energy deployment is reshaping the geography of industrial activity in China.

3 Data and Summary Statistics

3.1 Photovoltaic Plant Data

Our primary data set on PV deployment is constructed from high-resolution satellite imagery and provides consistent coverage of the rollout and expansion of solar plants across China from 2010 to 2022. Building on the approach of Kruitwagen et al. (2021) and subsequent refinements by Zhang et al. (2022) and Chen et al. (2024), we combine Landsat imagery covering the period 2010 to 2022 with Sentinel-2 data available from 2016 onward and apply deep learning methods, including U-Net and Transformer models, to detect PV installations and identify plant boundaries. As illustrated in Figure A2, our model identifies the spatial layout of panel arrays and facility footprints. Installed capacity is inferred from total panel surface area, with adjustments for local terrain slope to improve estimation accuracy. The final dataset covers 30,022 utility-scale PV plants, capturing nearly the full universe of such projects in China. For each plant, we record geographic location, commissioning year, and installed capacity. By leveraging the annual frequency of satellite imagery, we identify the timing of capacity additions and distinguish between newly constructed plants and subsequent expansions at existing sites. These data allow us to construct a plant-level panel of deployment over time. Summary statistics are provided in Table 1.

[Table 1 About Here]

To assess the accuracy and completeness of our solar plant dataset, we validate estimated plant locations and capacities against alternative data sources, including administrative records from the National Energy Administration, provincial investment plans, and other satellite-based datasets. Following Chen et al. (2024), who show that their polygons for China in 2020 spatially intersect with 99.6% of the 2,915.4 km^2 of PV area identified by Zhang et al. (2022), we compare our plant polygons with those in both Zhang et al. (2022)

and Feng et al. (2024) as well as with official provincial capacity statistics.[4] We exclude observations where estimated capacity deviates substantially from reported values to ensure the sample reflects credible project sizes. After this adjustment, about 85% of plants are consistently matched across years, suggesting that the satellite-based measures reliably capture both stock and incremental capacity. It is worth noting that the data set is restricted to utility-scale projects, which account for the majority of generation capacity and are most relevant for industrial electricity supply. Distributed rooftop systems, although increasingly common in eastern provinces, are excluded due to their smaller scale and primary use in residential settings. As shown in Figure A3, our estimates of total photovoltaic surface area closely align with benchmark figures from national and international sources, supporting the accuracy of the classification algorithm and the completeness of spatial coverage. The resulting dataset offers a validated and internally consistent measure of solar deployment suitable for empirical analysis.

The satellite-based data set offers several advantages. First, the data provide plant-level precision. Validation with official records and alignment with existing remote-sensing products alleviate two limitations common in purely remote-sensed datasets: the difficulty of distinguishing utility-scale plants from the growing stock of rooftop PV, and the challenge of linking detected installations to firms, since companies often operate multiple plants and registration data do not always map cleanly to plant locations. Second, the uniform detection methodology ensures comparability across provinces and, by drawing on observed infrastructure rather than self-reported statistics, mitigates concerns about misreporting or strategic inflation of capacity. Third, the annual frequency of imagery allows us to distinguish between extensive and intensive margins of solar growth, by identifying both new projects and expansions of existing facilities, rather than relying on delayed cumulative totals in official reports. These features make the data set particularly well suited for analyzing how local solar deployment shapes electricity market outcomes and firm-level activity.

[4]Existing work highlights both the feasibility and value of such national-scale PV maps. Using a pixel-based random forest classifier on Landsat-8 composite imagery, Zhang et al. (2022) produce a country-wide map of PV power plants in 2020 with a total mapped area of 2,917 km^2, achieving overall accuracies around 95% and kappa coefficients near 0.88. Complementing this, Feng et al. (2024) construct a 10-m national-scale map of ground-mounted PV power stations in China in 2020 based on Sentinel-2 imagery and a random forest classifier, documenting approximately 2,467.7 km^2 of ground-mounted PV area and reporting technical validation accuracies exceeding 89%. Most recently, Chen et al. (2024) develop a deep-learning and change-detection framework using Sentinel-2 and Landsat data to recover both spatial extent and installation dates of PV plants nationwide. Their dataset attains an F1-score of 96.08% for spatial extent and an overall accuracy of 89.86% for installation dates, and documents an increase in PV plant area from 5.86 km^2 in 2010 to 3,712.1 km^2 in 2022—more than a 600-fold expansion with an average annual increase of 285 km^2.

3.2 Supplementary Data Sets

We construct a panel of electricity shortages from 199 regional newspapers between 2010 and 2022. We collect two types of reports: (i) official outage notices, typically published in advance of planned blackouts to allow households and firms to prepare, and (ii) news articles describing unplanned or recurring shortages, such as reports of factories suspending operations due to insufficient electricity supply. We classify each article using large language models by cause, regional scope, and duration, and then aggregate the information to the city–year level to provide a consistent measure of shortage frequency and severity across regions. This measure allows us to test whether the expansion of local PV capacity improved power-supply reliability by reducing the incidence and duration of shortages, as reflected in fewer planned outage notices and fewer reports of unplanned shortfalls.

To complement the shortage data, we compile electricity price information from regulatory documents at both the provincial and city levels. As shown in Figure A1, average tariffs are systematically lower in northwestern provinces such as Inner Mongolia, Gansu, Ningxia, Qinghai, and Xinjiang, which reflects the influence of natural endowments on energy costs. Figure 2 further shows that increases in solar capacity are negatively associated with changes in industrial electricity prices, indicating that regions with greater solar expansion tend to experience relative cost declines. To account for broader regional conditions, we also collect city–year data on GDP, population, and local fiscal expenditure from the China City Statistical Yearbook for 2010–2022.

We then turn to firm-level administrative sources to examine how solar deployment translates into economic activity. The first is firm registration data from the State Administration for Industry and Commerce (SAIC), which cover the entire universe of registered firms in China. These records span 2010–2022 and provide information on geographic location, establishment and exit years, registered capital, and ownership characteristics.[5] We use these data to construct measures of firm entry and exit across regions and sectors, thereby capturing the extensive margin of economic activity. We supplement the registration data with firm annual reports filed over the same period, which contain standardized balance sheet and income statement information. These reports allow us to examine firm performance on the intensive margin, including revenues, profits, employment, and asset structure. To capture energy use directly, we also employ firm-level value-added tax (VAT) invoices for 2017–2018. These invoices provide direct measures of electricity consumption and the effective prices paid by industrial users, thereby capturing more granular variation that is not observable in provincial tariff schedules. Although limited to a shorter horizon, the VAT data offer detailed information on energy costs and usage that complements the broader coverage of

[5]See Fang, Li, and Lu (2024) for a detailed description of this data set.

the registration and annual report data.

Government policies have played a central role in shaping the growth of China's solar industry, particularly during its transition from subsidy-driven expansion to market-based competitiveness. To quantify the policy environment, we use the systematic coding of industrial policies developed by Fang, Li, and Lu (2024), which applies natural language processing to the full text of government documents and codes policy orientation (supportive, regulatory, or restrictive), issuing authority (central, provincial, city, or county), the instruments employed, and other attributes. Between 2010 and 2022, 8,930 solar-related policy documents were identified: 750 issued by the central government, 4,338 by provincial governments, 3,603 by city-level governments, and 239 by county governments. Since our empirical analysis exploits regional variation in solar deployment, we focus on the subset of city-level policy documents. Among these, 3,431 explicitly express supportive stances toward photovoltaic investment and development.[6] In the analysis that follows, we exploit the variation in city-level policies to assess how local industrial support interacts with solar resource endowments to influence deployment outcomes.

4 Empirical Methods and Results

4.1 First-Stage Evidence on Electricity Supply

The first step in our analysis is to establish whether the rapid expansion of solar capacity has translated into a measurable comparative advantage in electricity supply. Such an advantage, if present, should be reflected along two dimensions: lower effective electricity prices and greater reliability of supply. In China, however, electricity prices are set administratively at the provincial level and are often adjusted endogenously with broader renewable energy policies, making it difficult to attribute causal effects of solar expansion on price changes. For this reason, the reliability dimension provides a cleaner test. Electricity is a critical input in modern production functions, often entering in a near-Leontief manner, so even temporary interruptions can cause substantial productivity losses (Allcott, Collard-Wexler, and O'Connell, 2016; Fisher-Vanden, Mansur, and Wang, 2015; Borenstein, Bushnell, and Mansur, 2023; Brown and Muehlenbachs, 2024).

To capture the dimension of power supply reliability, we construct a city–year panel of electricity shortages from 199 regional newspapers between 2010 and 2022, combining both official outage notices and news reports of unplanned or recurring shortages. Our approach is closely related to recent efforts to compile high-frequency outage data, such as

[6] National-level initiatives, such as feed-in tariffs or renewable portfolio standards, are important for shaping overall market incentives. In our analysis, however, their effects are absorbed by year fixed effects, while our focus remains on the differential role of local industrial policies.

the nationwide dataset used to document how power shortages slow EV adoption in Chinese cities (Qiu et al., 2024). Table 2 presents regression estimates of the relationship between local PV capacity and electricity shortages. Columns (1)–(2) use the combined count of outage notices and shortage reports as the dependent variable, Columns (3)–(4) focus on planned notices, and Columns (5)–(6) on unplanned shortage news, respectively. Across all specifications, the coefficients on log capacity are consistently negative and statistically significant, indicating that solar expansion is associated with fewer planned and unplanned outages and thus improved reliability.

[Table 2 About Here]

To complement the city-level analysis, we also examine firm-level patterns using VAT invoice data from 2017–2018, which record monthly electricity usage and the effective prices paid by industrial firms. The results, reported in Appendix Table A1, are consistent with the city-level evidence. Firms located in areas with greater solar capacity face modest but statistically significant reductions in unit electricity prices. Unit prices are also strongly negatively correlated with electricity consumption, consistent with the declining marginal price schedules faced by industrial users. Moreover, firms in high-solar-capacity areas consume more electricity. Together with the reduction in outages documented above, these patterns suggest that solar deployment alleviates local electricity supply constraints by lowering effective prices, expanding electricity use, and reducing disruptions.

These first-stage results align closely with earlier evidence showing that electricity scarcity has meaningful consequences for firm performance. In China, power shortages reduce industrial output and affect production decisions (Fisher-Vanden, Mansur, and Wang, 2015), and related work from India finds that unreliable electricity dampens investment and shifts the firm-size distribution toward smaller plants (Allcott, Collard-Wexler, and O'Connell, 2016). Our results suggest that greater solar capacity improves local electricity conditions and gives regions a clearer comparative advantage in power provision. This first-stage relationship motivates the subsequent analysis of how electricity conditions shape firm behavior and regional economic growth.

4.2 Baseline Results

4.2.1 Plant Installation and Firm Entry

We estimate the effect of solar expansion on firm entry by exploiting staggered and continuous growth in installed solar capacity across Chinese cities. This variation generates plausibly exogenous changes in local electricity supply conditions over time. Our empirical strategy compares changes in firm entry across city–industry cells that experience larger increases in solar capacity with contemporaneous changes in areas with more limited expansion, controlling for high-dimensional fixed effects. The baseline specification estimates how installed solar capacity affects new firm registrations at the city–industry–year level using a two-way fixed effects panel model of the following form:

$$Y_{ijt} = \beta_0 + \beta_1 Capacity_{it} + \beta_2 Capacity_{it} \times SolarRegion_i + X_{it} + \delta_{ij} + \gamma_{jt} + \epsilon_{ijt}, \qquad (1)$$

where the dependent variable, Y_{ijt}, is the logarithm of one plus the number of new firm registrations in city i, industry j, and year t. $Capacity_{it}$ captures solar capacity in city i in year t, and $SolarRegion_i$ is an indicator for northwestern provinces (i.e., Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang) that combine high solar irradiance and ample land availability. The interaction term captures whether the effect of capacity expansion is stronger in these regions. X_{it} includes city-level controls such as GDP, fiscal expenditure, and population. δ_{ij} are city-by-industry fixed effects that account for time-invariant heterogeneity in the local industrial base, and γ_{jt} are industry-by-year fixed effects that absorb common shocks to industries nationwide. Standard errors are clustered at the city level to allow for potential autocorrelation and heteroskedasticity within cities over time.

[Table 3 About Here]

Panel A of Table 3 reports the baseline estimates of the effect of solar expansion on firm entry. In column (1), the coefficient on $log(Capacity_{it} + 1)$ is positive and statistically significant, indicating that, on average, cities with larger capacity additions experience greater new-firm entry. Once we introduce the interaction with the solar region in column (2), however, the main coefficient on $log(Capacity_{it} + 1)$ becomes small and turns negative, little or no entry response outside the solar region. By contrast, the interaction term is positive and statistically significant. The implied elasticity for cities in the solar region is about 0.00898 (=-0.00014+0.00912), so a 1% increase in installed capacity is associated with roughly a 0.9% increase in new firm registrations. The results show that the extensive-margin response to solar expansion is concentrated in the northwestern provinces, where high irradiance and abundant land coincide with historically weaker industrial bases, whereas capacity additions in non-solar regions generate little additional entry on average.

Appendix Table A2 shows substantial heterogeneity in how solar capacity expansion affects firm entry across industries. In electricity-intensive and scale-sensitive sectors such as agriculture, mining, manufacturing, sales, transportation, and real estate, the coefficients on log(Capacity + 1) are negative and statistically significant, implying that outside the core solar region additional capacity is not associated with higher entry and may even be correlated with weaker net creation at the margin. In the same sectors, the interaction term

$\log(\text{Capacity} + 1) \times \mathit{SolarRegion}$ is significantly positive, indicating that solar capacity expansion in designated solar regions yields economically and statistically significant increases in firm entry. For several complementary service sectors, the pattern differs from that in electricity-intensive industries. In energy-supply and environmental-service activities, the coefficient on $\log(\text{Capacity} + 1)$ is positive outside the core solar region, consistent with additional solar installation being accompanied by greater demand for grid management, maintenance, and environmental compliance. The interaction term with the solar-region indicator is negative and statistically significant in these sectors, indicating that their expansion is more limited in solar-abundant provinces where much of the supporting infrastructure is already in place. Construction shows the opposite pattern. The interaction with the solar-region indicator is positive and significant, consistent with solar deployment generating local demand for installation, site preparation, and related services where large-scale projects are concentrated.

To investigate whether the entry effects of solar expansion operate through improvements in electricity access, we then examine heterogeneity across industries with differing electricity dependence. Using VAT invoice data, we construct an industry-level measure of electricity intensity, defined as the ratio of electricity expenditure to total input costs. Appendix Figure **??** illustrates the distribution of this measure across industries, showing substantial heterogeneity in electricity dependence. This measure identifies industries that are more reliant on electricity in their production process. Panel B of Table 3 reports the results. Columns (1) and (2) show that increases in solar capacity are associated with significantly higher firm entry in electricity-intensive industries, with the effects particularly pronounced in the designated solar region. Column (3) shows that outside this region, the estimated effects are small and statistically insignificant. These findings indicate that industries with higher electricity demand respond more strongly to solar deployment, providing direct evidence for the electricity channel as the operative mechanism.

4.2.2 City-Pair Evidence

We next adopt a city-pair specification to examine how local energy conditions shape the spatial allocation of investment. The origin city o is defined as the location of the parent firm, and the destination city d is where a new subsidiary is established. This specification allows us to examine whether firms facing tighter electricity constraints in their home cities shift activity toward locations with more favorable energy conditions. The regression model is specified as:

$$Y_{odt} = \beta_0 + \beta_1 Capacity_{dt} + \beta_2 Capacity_{dt} X_{ot} + \delta_{od} + \gamma_{ot} + \epsilon_{odt}, \tag{2}$$

where Y_{odt} denotes the number of new subsidiaries established in destination city d by firms headquartered in origin city o during year t. $Capacity_{dt}$ captures solar capacity in the destination city, and X_{ot} reflects the energy conditions in the origin city, measured alternatively by solar capacity, outage frequency, or average electricity price. The city-pair fixed effects, δ_{od}, absorb all time-invariant bilateral characteristics (such as distance or historical trade linkages), and investor city-by-year fixed effects, γ_{ot},flexibly control for any time-varying shocks in the origin city, such as changes in local demand, policy, or economic structure. Standard errors are clustered at the city-pair level.

Panel A of Table 4 presents the city-pair results. Column (1) shows a positive association between destination solar capacity and subsidiary formation, indicating that firms are more likely to expand into cities with larger capacity. Column (2) shows that the pull effect of destination capacity is strongest when the origin city itself has relatively limited capacity, consistent with firms reallocating activity toward locations with better energy conditions. Column (3) indicates that higher outage frequency in the origin city increases the likelihood of establishing subsidiaries elsewhere, suggesting that firms reallocate activity to mitigate the risks of unreliable electricity supply. Column (4) indicates that higher electricity prices in the origin city also push firms to establish subsidiaries elsewhere, reflecting the pressure of higher production costs. These results demonstrate that push factors in origin cities, such as scarce capacity, unreliable supply, and high electricity costs, together with pull factors in destination cities, such as abundant solar deployment and lower costs, jointly shape the spatial reallocation of firms.

Panel B examines heterogeneity by solar-region designation and origin-city electricity conditions. Column (1) shows that destination solar capacity attracts significantly more subsidiary investment within designated solar regions, consistent with policy-supported deployment amplifying the pull of capacity expansion. The negative triple interaction indicates that within designated solar regions, the marginal pull of destination solar capacity declines as origin-city capacity increases. Column (2) examines electricity reliability in the origin city. Firms headquartered in cities with more frequent outages are more likely to expand into destinations with greater solar capacity, consistent with reliability constraints acting as a push factor for spatial reallocation. We find no statistically significant evidence that this effect varies with solar-region designation. Column (3) shows that higher origin-city electricity prices significantly increase expansion toward solar-region destinations, as indicated by the positive triple interaction between destination capacity, origin prices, and solar-region status. Although the solar-region indicator enters negatively, this likely reflects baseline differences across destinations. Conditional on destination capacity, higher electricity prices in the origin city lead firms to reallocate more strongly toward solar-intensive locations. The results indicate that solar deployment shapes investment location choices primarily by alleviating long-run energy cost and capacity constraints, rather than through policy-region designation alone or short-term reliability shocks.

4.3 Dynamic Effects: The De Chaisemartin and d'Haultfoeuille (2024) Estimates

The rollout of solar projects in China has two features that are central to our empirical design. First, capacity additions occur as a continuous and ongoing process rather than as a single discrete shock. Second, installation is phased over time, with project approval, construction, and grid connection typically unfolding over several years. This structure complicates the use of conventional two-way fixed effects panel estimators that implicitly treat exposure as a one-time binary change. To accommodate staggered timing, continuous treatment intensity, and potentially heterogeneous effects, we apply the dynamic estimator developed by De Chaisemartin and d'Haultfoeuille (2024), which is specifically designed for multi-period settings with evolving treatment exposure.

Figure 3 presents dynamic estimates of the effect of solar expansion on firm entry relative to the year of plant installation. Panel A compares cities in the designated solar region with those in other regions. In the solar region, coefficients in the early pre-period are negative and relatively stable until roughly two years before installation, begin to increase in the following year, and approach zero at the installation date. This shows that most of the change in entry behavior occurs within the two-year window around installation. The timing is consistent with the typical two- to three-year cycle from project approval to grid connection and with evidence that employment and investment around large energy projects often respond ahead of actual operation (Fabra et al., 2024). In contrast, coefficients for other regions stay near zero throughout the window, indicating anticipatory responses are concentrated in resource-rich areas. Panel B adds a triple–difference dimension by distinguishing industries by electricity intensity. In the solar region, the coefficients are statistically indistinguishable from zero throughout the early pre-period, begin to increase roughly one year before installation, and remain positive in the years that follow. This pattern indicates that increases in firm entry are concentrated in electricity-intensive industries once solar capacity becomes operational. In other regions, the corresponding coefficients fluctuate around zero and do not exhibit a significant increase, suggesting that the relative entry of electricity-intensive industries remains unchanged outside the solar region.

4.4 Instrumental Variable Approach

The previous analyses exploit staggered and continuous variation in solar capacity expansion, interpreting the rollout of solar projects as a plausibly exogenous source of variation in local electricity supply. The dynamic estimates based on De Chaisemartin and d'Haultfoeuille (2024) show no evidence of differential pre-trends, supporting the validity of the identifying assumptions underlying the panel and dynamic specifications. Nonetheless, concerns may remain that solar capacity additions are not fully orthogonal to local economic conditions. Regions with greater fiscal resources, stronger industrial demand, or more targeted policy support may have been prioritized for installation, raising the possibility that unobserved factors jointly influence both solar expansion and firm entry. While the panel and dynamic specifications absorb time-invariant city characteristics and common time-varying shocks, they may not fully address potential endogeneity arising from reverse causality or omitted variables.

To strengthen causal identification, we implement an IV approach that isolates exogenous variation in solar deployment, drawing on two well-established instruments from the literature. The first instrument is global horizontal irradiance (GHI), a stable geographic determinant of solar potential that varies with long-run climatic and locational factors rather than with contemporaneous economic conditions. GHI affects firm entry only through its influence on the feasibility and productivity of solar generation. The second instrument exploits cross-city variation in pre-existing electricity shortages, measured by the frequency of outages prior to large-scale solar deployment. Cities facing more binding supply constraints have stronger incentives to expand generation capacity, making historical outage frequency predictive of subsequent solar installation. A potential concern is that firms or industries may avoid locations with unreliable electricity supply. We address this by constructing outage measures from the pre-deployment period and by estimating specifications with city–industry and industry-year fixed effects, which absorb time-invariant location characteristics and common industry shocks.

These two instruments capture different but related channels: natural endowments that determine the technical potential for solar power, and pre-existing supply constraints that shape local responsiveness to capacity expansion. Conditional on fixed effects, their influence on firm entry operates through their impact on solar deployment, supporting both instrument relevance and the plausibility of the exclusion restriction.

We estimate a long-difference 2SLS specification at the city–industry level:

$$\Delta \text{Capacity}_i = \alpha_1 + \delta\, \text{IV}_i + \mathbf{\Gamma}_1' \mathbf{X}_i + \eta_i \quad \text{(First Stage)}, \tag{3}$$

$$\Delta Y_{ij} = \alpha_2 + \beta\, \Delta \widehat{\text{Capacity}}_i + \mathbf{\Gamma}_2' \mathbf{X}_i + \epsilon_i \quad \text{(Second Stage)} \tag{4}$$

where $\Delta\text{Capacity}_i$ denotes the change in installed solar capacity in city i between 2010 and 2023; ΔY_{ij} is the long difference in the log number of new firm registrations in city i, industry j over the same period. IV_i represents the instrumental variables, including GHI and regional electricity shortages, which predict long-run variation in solar deployment but do not directly affect firm entry. $\mathbf{X}_i$ is a vector of city-level controls measured in 2023 to capture observable cross-sectional differences; and η_i and ϵ_i are the error terms in the first and second stages, respectively. The coefficients δ and β capture the predictive strength of the instruments and the causal effect of solar capacity growth on firm entry, respectively. Focusing on long differences over more than a decade helps mitigate concerns related to time-invariant unobserved heterogeneity and short-run fluctuations.

Panel A of Table 5 reports results from the long-difference IV specification using the full sample. Columns (1) and (2) jointly use GHI and historical electricity shortages, along with their interaction, as instruments for local solar capacity. The first-stage estimates in column (1) show that solar capacity is positively associated with GHI, while outage frequency enters with a negative coefficient. The positive interaction between GHI and outages indicates that solar deployment responds more strongly to irradiance in cities facing tighter pre-existing supply constraints. The second-stage results in column (2) show that instrumented solar capacity growth has a positive and statistically significant effect on firm entry. The coefficient on $\log(\text{Capacity}+1)$ implies that a 1% increase in solar capacity raises firm entry by approximately 0.04% over the long run. The Kleibergen–Paap Wald F-statistics comfortably exceed conventional thresholds, and the Hansen J-test fails to reject the null of instrument validity, supporting both instrument strength and the exclusion restriction.

[Table 5 About Here]

To further strengthen identification, we exploit regional discontinuities in regulated electricity prices created by historical grid boundaries. In several cases, adjacent cities with nearly identical solar radiation face markedly different feed-in tariffs due to legacy grid divisions or provincial pricing regimes. For solar developers, irradiance determines the technical feasibility of generation, and electricity prices govern profitability. As a result, the responsiveness of solar investment to irradiance should be stronger on the high-price side of these borders. This setting provides a quasi-experimental source of variation: conditional on similar solar resources, differences in regulated electricity prices generate heterogeneous incentives for solar deployment across otherwise comparable locations. To implement this design, we focus on adjacent city pairs located on either side of provincial boundaries, where irradiance is similar but pricing policies differ due to institutional arrangements. We use two instruments based on the interaction between GHI and institutional features of the electricity market. The interaction between GHI and regulated electricity prices captures exogenous variation in solar deployment driven by differences in supply-side profitability, and the interaction between GHI and solar policy captures variation arising from policy targeting.

Panel B of Table 5 report the corresponding IV results. In the first stage, policy designation enters positively and strongly, indicating that designated regions are systematically more likely to receive solar capacity. At the same time, the negative interaction between policy designation and GHI implies that, within policy regions, solar deployment is less sensitive to marginal variation in irradiance. In the second stage, instrumented solar capacity growth continues to have a positive and statistically significant effect on firm entry, with a coefficient of 0.14. By contrast, conditional on capacity expansion, the policy indicator itself enters negatively, consistent with the selective targeting of regions with weaker pre-existing industrial conditions. The positive coefficient on solar capacity therefore captures the causal channel through which policy-induced solar expansion promotes firm entry. IV estimates using individual instruments for both the full sample and the border-discontinuity sample are reported in Appendix Table A3. We also extend the border-discontinuity design to the full sample; the corresponding results, reported in Appendix Table A4, are consistent.

5 Competing and Complementary Mechanisms

In this section, we investigate whether the effects of solar expansion on firm entry can be explained by mechanisms other than the electricity channel. We explore four potential explanations: the influence of industries directly linked to the solar supply chain, the role of industrial policies, regional spillovers, and vertical spillovers along the production chain. This helps us distinguish the electricity channel from other contributing factors and evaluate the broader impacts of solar deployment.

5.1 The Role of the Solar Supply Chain

A first concern is that the observed increase in firm entry may simply reflect the growth of industries directly related to the solar supply chain rather than broader economic responses to improved electricity conditions. Specifically, solar deployment could lead to entry in upstream sectors, such as sand and gravel mining, special glass production, or energy equipment manufacturing, as well as in downstream activities, including solar plant installation and maintenance services. These sectors, while connected to the solar industry, may not capture the full range of industrial dynamics that reflect the broader economic response to changes in electricity availability.

To isolate the effects of solar expansion on general industrial entry, we exclude 52 industries directly or partially linked to the solar supply chain from a total of 431 industries. This ensures that our results are not confounded by potential spillovers from solar-related industries, which could otherwise lead to an overestimation of the impact of solar deployment on firm entry. Table 6 presents the results. In column (1), the coefficient on $log(Capacity + 1)$ remains positive and significant, indicating that the main result is not driven by solar supply chain industries, although its magnitude slightly decreases compared to the baseline specification. In column (2), the positive and significant interaction between solar capacity and the solar region variable confirms that entry responses are concentrated in high-potential areas, while the negative coefficient on log(Capacity + 1) suggests weaker effects outside these regions. Once socio-economic controls are added in column (3), this negative coefficient becomes statistically insignificant, indicating that the baseline pattern is not driven by omitted local conditions. These results indicate that the observed entry effect reflects a broader reallocation of economic activity toward regions where solar deployment effectively relaxes energy constraints, rather than merely capturing growth concentrated in solar supply chain industries.

[Table 6 About Here]

5.2 Industrial Policies for the Solar Sector

Another potential concern is that the estimated entry effects may be confounded by contemporaneous industrial policies that target specific energy-intensive sectors. If firms are primarily responding to subsidies, preferential land allocation, or other policy incentives rather than improved electricity conditions, then the observed expansion could reflect policy-driven clustering rather than a causal effect of solar deployment. This concern is particularly relevant given evidence that targeted subsidies can shift the spatial distribution of activity, but largely through financial incentives rather than changes in underlying fundamentals (Shenoy, 2018; De Groote and Verboven, 2019; Banares-Sanchez et al., 2024; Ashenfarb, 2024). To address this possibility, we incorporate industry-level policy measures from Fang, Li, and Lu (2024) into our analysis and explicitly test for complementarities between industrial policies and solar capacity growth.

Table 7 reports the results. Across most specifications, the coefficient on log(Capacity+1) remains positive and statistically significant, indicating that solar expansion continues to stimulate firm entry even after accounting for targeted industrial policies. The coefficient on *Policy* is positive and significant in column (2), but becomes statistically insignificant once additional controls are introduced in column (3), suggesting that part of the correlation between policies and firm entry is absorbed by broader socioeconomic factors. This pattern is consistent with evidence that clean-energy subsidies are most effective when aligned with underlying productivity and emissions fundamentals (Ashenfarb, 2024). Importantly, the interaction term log(Capacity + 1) $\times$ *Policy* is positive and highly significant across all models, indicating that solar expansion and industrial policies act as complements: firm entry responds most strongly in industries that benefit from both improved electricity supply and direct policy support.

The results also reveal important regional heterogeneity. In solar regions, as shown in column (4), the coefficient on *Policy* is negative and significant, but the interaction with solar capacity is strongly positive, implying that policy support alone is insufficient to attract new entrants unless accompanied by substantial capacity expansions. In these areas, electricity improvements remain the decisive factor, with industrial policies amplifying their effect only once energy bottlenecks are substantially relaxed. By contrast, in non-solar regions (column 5), both the direct effect of *Policy* and its interaction with capacity are positive and statistically significant, suggesting policies are effective on their own and are further strengthened by solar deployment. This pattern mirrors our earlier evidence from the EV setting, where policy interventions and infrastructure improvements acted as complements in shaping adoption dynamics.

[Table 7 About Here]

5.3 Mitigating Effect of Energy Transmission

A further concern is that the observed entry effects might not reflect improvements in local electricity availability, but instead the operation of long-distance transmission projects. Under China's West–East Electricity Transmission initiative, many large solar plants in the western cities are directly connected to ultra–high-voltage (UHV) lines that send power to eastern load centers, bypassing local consumption.[7] If most of the generated electricity is exported, local firms should not benefit from improved power conditions, and one would not expect to observe the same entry response. This setting therefore provides a natural placebo test: if the entry effects we identify indeed operate through local electricity improvements, they should be weaker in UHV origin cities, where incremental power is transmitted outward rather than consumed locally.

Table 8 reports the results. Across all specifications, the coefficient on $\log(\text{Capacity} + 1)$ remains positive and significant, confirming that solar expansion generally promotes firm entry. However, in UHV origin cities, the interaction term $\log(\text{Capacity} + 1) \times UHV$ is negative and significant, showing that the local entry response is substantially weaker when solar deployment does not translate into improved local electricity supply. In contrast, the coefficient on $\log(\text{Capacity}+1)\times Electricity$ is strongly positive, implying that industries with

[7] The West–East Electricity Transmission initiative was launched in the early 2000s under the guidance of the National Development and Reform Commission and the State Grid. The program channels surplus electricity from resource-abundant provinces in the west, such as Xinjiang, Gansu, and Inner Mongolia, to the eastern industrial heartland through newly built UHV transmission lines, which operate on a point-to-point basis and largely bypass intermediate localities.

higher electricity intensity experience greater entry gains from solar expansion, consistent with the mechanism that improved electricity availability reduces production costs. The triple interaction log(Capacity+1)$\times UHV \times Electricity$ is negative and significant, suggesting that even electricity-intensive industries derive little advantage in UHV origin cities, where most of the incremental supply is transmitted outward rather than consumed locally. This placebo test strengthens the interpretation that our findings reflect local energy conditions rather than long-distance transmission projects.

[Table 8 About Here]

5.4 Spatial Reallocation or Regional Spillovers?

A further concern is that the entry effects we document may not reflect genuine new economic activity, but rather a spatial reallocation of firms across nearby locations. For example, if solar deployment in one county improves local electricity conditions, firms might relocate from neighboring counties to take advantage of lower expected costs. In this case, the observed increase in entry would represent displacement rather than net industrial expansion, overstating the aggregate benefits of solar deployment by capturing spatial reshuffling rather than broader industrial growth.

To distinguish between these possibilities, we extend the baseline specification to incorporate neighboring solar capacity following Siegloch, Wehrhöfer, and Etzel (2025):

$$Y_{ijt} = \beta_0 + \beta_1 Capacity_{it} + \beta_2 NeighborCapacity_{it} + X_{it} + \delta_{ij} + \gamma_{jt} + \epsilon_{ijt} \tag{5}$$

where Y_{ijt} denotes new firm entry in city i, industry j, and year t; $Capacity_{it}$ is measured as the logarithm of one plus the installed solar capacity in city i; $NeighborCapacity_{it}$ is the logarithm of one plus the total installed solar capacity in all cities that share a border with city. All other variables follow the same definitions as in the baseline specification. If entry reflects displacement from nearby areas, we would expect $\beta_2 < 0$. Conversely, if solar expansion alleviates energy constraints more broadly, β_2 should be positive, indicating spillover benefits.

As shown in Table 9, both $\log(Capacity + 1)$ and $\log(NeighborCapacity + 1)$ enter positively and significantly across specifications, indicating that solar deployment stimulates new firm entry not only within the locality but also in adjacent areas. These spillover effects are especially pronounced in solar-rich regions, where the interaction terms with the solar-region indicator are strongly positive. This pattern is consistent with the institutional structure of China's electricity system: because dispatch is managed at the provincial level, solar power generated in one city is absorbed into the wider grid, easing electricity constraints across neighboring jurisdictions. The evidence therefore points to genuine industrial expansion, with benefits that extend regionally rather than reflecting a zero-sum reallocation of firms.

[Table 9 About Here]

5.5 Vertical Linkages and Supply-Chain Spillovers

A natural question is whether the effects of solar expansion extend beyond directly affected industries to reshape economic activity along the supply chain. Improvements in electricity availability may generate spillovers through vertical production linkages, stimulating upstream suppliers that provide inputs to electricity-intensive industries and downstream users that rely on their outputs. To test for such vertical spillovers, we extend the baseline specification by interacting solar capacity with electricity intensity measures derived from the input–output table as following:

$$\begin{aligned} Y_{ijt} = &\beta_0 + \beta_1 Capacity_{it} + \beta_2 Capacity_{it} \times Electricity_j + \beta_3 Capacity_{it} \times UpElectricity_j \\ &+ \beta_4 Capacity_{it} \times DownElectricity_j + X_{it} + \delta_{ij} + \gamma_{jt} + \epsilon_{ijt} \end{aligned} \tag{6}$$

where Y_{ijt} is the number of new firm registrations in city i, industry j, and year t. $UpElectricity_j$ denotes the electricity intensity of upstream firms, weighted using the input–output table, and $DownElectricity_j$ denotes the electricity intensity of downstream firms, constructed in the same way. The coefficient β_3 measures vertical spillovers whereby electricity improvements in electricity-intensive industries stimulate entry among their downstream users, while β_4 captures spillovers to upstream suppliers. Because of the structure of the input–output table, this analysis is conducted at the two-digit industry level.

Table 10 reports the estimates of vertical spillovers from solar expansion. Column (1), which pools all cities, shows a negative and significant coefficient on log(Capacity + 1), but this effect is offset by strongly positive interactions with electricity intensity and with upstream electricity use. This indicates that the aggregate impact of solar expansion on entry is concentrated in industries where electricity constitutes a major input, either directly or through linkages to upstream suppliers.

Columns (2) and (3) split the sample into solar and non-solar regions, respectively. In solar regions, as shown in Column (2), both the electricity-intensity interaction and the upstream linkage term remain positive and significant, suggesting that local electricity improvements drive entry in energy-demanding sectors and extend to their input suppliers. However, the coefficient on log(Capacity + 1) × *DownElectricity* is negative and significant, indicating that downstream customers of electricity-intensive industries are less likely to expand. A plausible interpretation is that electricity-intensive industries internalize most of the gains from cheaper and more reliable power, limiting the extent to which these benefits are passed downstream to their buyers, such as auto makers, plastics, or machinery producers. As a result, the observed entry response is concentrated in electricity-intensive users and their upstream suppliers, with muted effects further along the supply chain. In non-solar regions (column 3), the pattern is somewhat different. The coefficients on the electricity-intensity and upstream linkage interactions remain positive and significant, while the downstream coefficient is small and insignificant. This suggests that electricity improvements in less resource-rich areas continue to foster entry among electricity-intensive industries and their upstream suppliers, but without the negative displacement observed in solar-rich regions.

Columns (4)–(6) restrict the analysis to solar-rich regions and explore heterogeneity across broad industry groups. The results show sharp differences in how sectors respond to improved electricity availability. For manufacturing, the interaction between solar capacity and industry electricity intensity is strongly positive, indicating that electricity-intensive producers are the primary beneficiaries of solar expansion. By contrast, mining, a highly upstream activity, responds less directly to its own electricity needs but shows a strong positive effect from downstream electricity use, consistent with the idea that resource extraction expands when demand from electricity-intensive downstream industries rises. However, services display a different pattern: the entry response is most pronounced through the upstream channel, reflecting their dependence on manufacturing and other production activities that expand with cheaper and more reliable power.

[Table 10 About Here]

6 Economic Consequences for Firm Entry and Performance

Our analysis so far has focused on the extensive margin, finding that solar expansion stimulates new firm entry. Yet entry alone does not guarantee sustained economic growth. A critical next step is to assess how improved access to low-cost electricity also enhances the performance of incumbent firms. If solar deployment alleviates local energy bottlenecks, the resulting improvements in electricity availability and cost should not only influence entry decisions but also translate into tangible performance gains for incumbent firms, reflected in higher profitability and productivity. At the same time, the quality of new entrants matters: an increase in registrations may reflect dynamic firms with growth potential or marginal businesses unlikely to persist. Examining both the intensive and extensive margins therefore provides a more comprehensive view of how renewable energy investment shapes industrial development.

We begin with the intensive margin by estimating:

$$Y_{fijt} = \beta_0 + \beta_1 Capacity_{it} + \beta_2 Capacity_{it} Electricity_j + X_{it} + \delta_f(+\delta_{ij}) + \gamma_{jt} + \epsilon_{fijt} \tag{7}$$

where Y_{fijt} denotes firm performance, measured either by return on equity or by the logarithm of revenue, for firm f in city i, industry j, and year t. The interaction term captures whether firms operating in more electricity-intensive industries experience larger performance gains from solar deployment. All other variables are defined as in the baseline specification.

Table 11 reports the effects of solar capacity on firm performance. Panel A shows that in the full sample, solar expansion increases return on equity (ROE), a measure of financial returns to shareholders, with larger gains in electricity-intensive industries as reflected in the strongly positive coefficients on log(Capacity + 1) × *Electricity*. Panel B shows a clearer pattern for revenues, where coefficients are larger in magnitude, suggesting that output expansion being the primary margin of adjustment. As shown in column (3), in solar-abundant areas, the effects on ROE are small and statistically indistinguishable from zero, while revenues increase strongly and significantly. This suggests that in resource-rich settings where electricity constraints are already less binding, additional capacity mainly scales up production without translating into higher financial returns. In contrast, in other regions, both ROE and revenues increase significantly, and the interaction with electricity intensity remains strongly positive, indicating that additional solar capacity in these areas generates more substantial improvements in both operating scale and financial performance.

We next turn to the extensive margin, asking whether solar deployment influences the type of firms that enter. Specifically, we estimate the following specification:

$$Y_{fijt} = \beta_0 + \beta_1 Capacity_{it} + \beta_2 Entrant_{ft} + +\beta_3 Capacity_{it} Entrant_{ft} + X_{it} + \delta_{ij} + \gamma_{jt} + \epsilon_{fijt} \tag{8}$$

where $Entrant_{ft}$ is an indicator for newly registered firms. The interaction term evaluates whether the effect of solar expansion differs between new entrants and incumbents, thereby testing whether entrants exhibit systematically higher or lower subsequent performance, as measured by profitability or revenue.

Panel B of Table 11 reports the results for the extensive margin. As is typical in firm dynamics, new entrants exhibit lower ROE and revenue relative to incumbents, as shown by the consistently negative and significant coefficients on the *entrant*. However, coefficients on the interaction term $log(Capacity + 1) \times Entrant$ are positive and statistically significant, indicating that in areas with greater solar deployment, entrants perform significantly better than the average start-up. In terms of profitability, the gains are most visible in other regions, while in solar regions the effect on ROE is weaker. By contrast, revenues respond strongly in both settings, with especially large effects in solar regions, suggesting that solar expansion lowers entry barriers and fosters a more supportive operating environment for young firms. These results suggest that solar expansion improves the post-entry environment for young firms, allowing entrants to achieve stronger performance outcomes than is typical. This reflects not only more reliable and lower-cost electricity but also a reduction in the risks that ordinarily hinder start-up viability. In this sense, the effect is not merely to increase entry, but to improve the quality and resilience of the firms that enter.

[Table 11 About Here]

7 Conclusion

This paper provides new evidence on how renewable energy deployment affects industrial development through the channel of electricity supply. Using the rapid expansion of utility-scale solar photovoltaic plants in China as a quasi-natural experiment, we show that solar deployment improves local energy conditions by reducing outages and lowering effective electricity costs, thereby creating a technology-driven comparative advantage in regions that were historically rich in land and solar resources but had relatively limited industrial development.

Improved electricity access translates into meaningful changes in the industrial landscape. Solar expansion stimulates new firm entry, with the largest responses in electricity-intensive sectors and in regions endowed with abundant solar resources, where additions to capacity most effectively ease energy bottlenecks. The results are not driven by the solar supply chain or by industrial policies alone. Instead, solar deployment and policy support act as complements: electricity improvements matter most in resource-rich regions, whereas policy incentives play a comparatively larger role in areas where natural endowments are less favorable. A placebo test exploiting the West–East Electricity Transmission network shows that entry effects weaken substantially in cities that export most solar power, consistent with the mechanism operating through local electricity availability. reinforcing the interpretation that the mechanism operates through local rather than transmitted power availability. We also document spillovers across neighboring provinces and along vertical production links, indicating that solar deployment supports broader industrial expansion rather than merely reallocating activity across space.

The analysis of firm performance shows that the effects extend beyond the extensive margin. Solar deployment improves profitability and revenues of incumbent firms, with the largest gains in electricity-intensive industries. It also improves the quality of entrants. New firms established in areas with stronger solar expansion exhibit higher early-stage performance than comparable start-ups elsewhere, suggesting that renewable energy investment not only increases the number of firms but also shifts the quality distribution of entrants and enhances the productivity of existing businesses. Solar deployment therefore strengthens the industrial base by improving both the scale and the efficiency of local economic activity.

The evidence shows advances in renewable technology can convert natural endowments into durable sources of comparative advantage. By easing energy constraints, solar deployment reshapes the geography of industrial activity, upgrades firm dynamics, and enhances regional competitiveness. The evidence highlights that renewable energy investments can serve not only environmental objectives but also act as productive infrastructure that supports industrial upgrading and regional growth. The results offer broader lessons for economies seeking to align climate policy with long-run growth and competitiveness.

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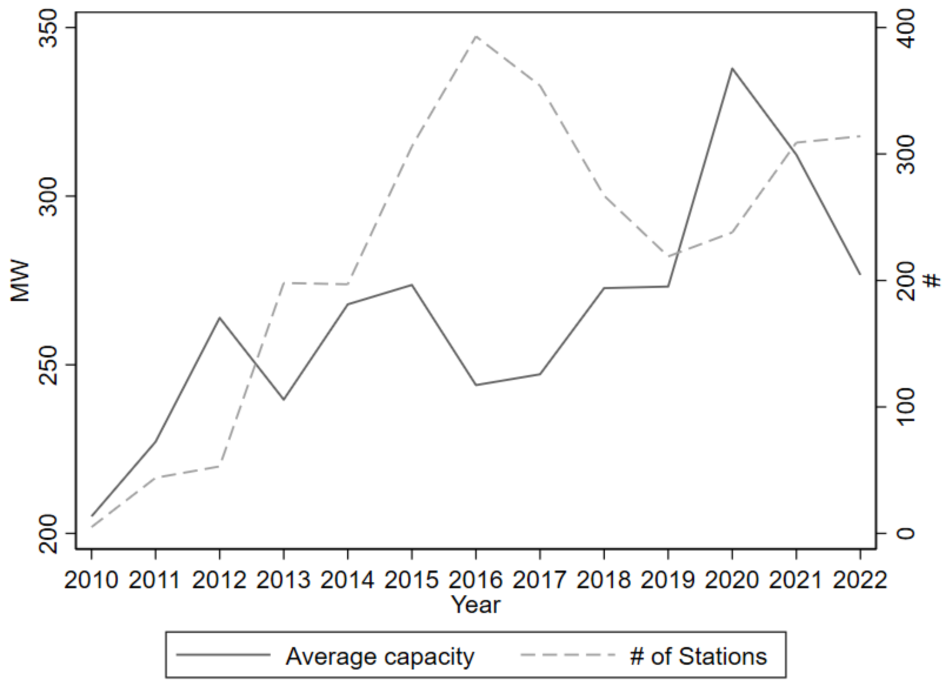
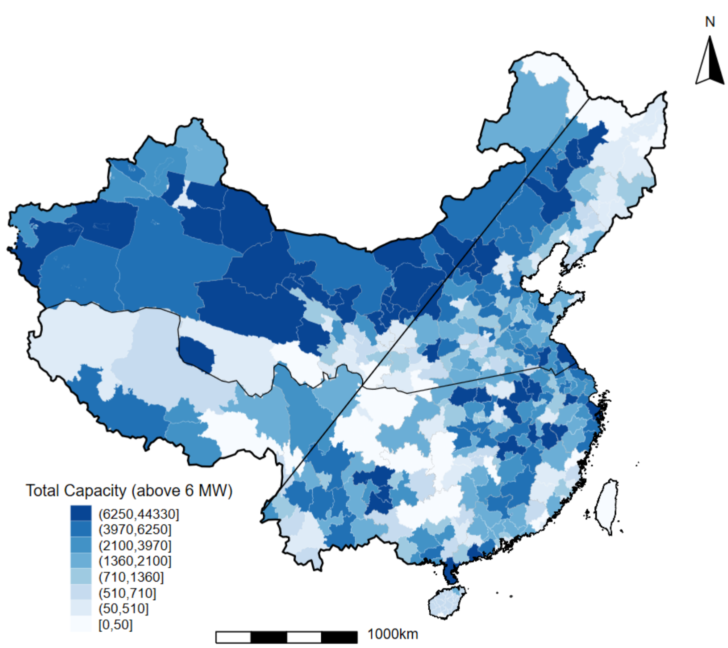
Figure 1: Trends and Regional Distribution of Solar Plants in China

Panel A: Evolution of Solar Plant Capacity

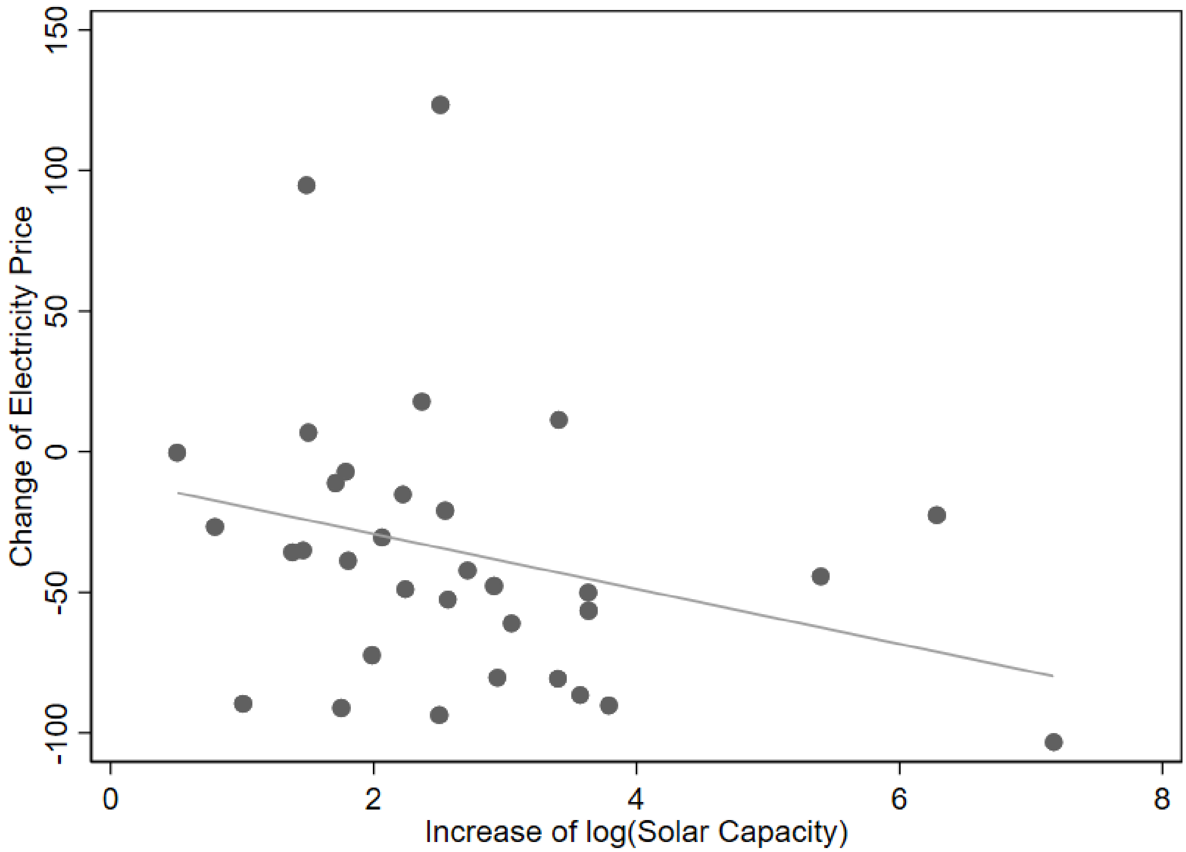


Panel B: Regional Distribution of Solar Plants in 2022



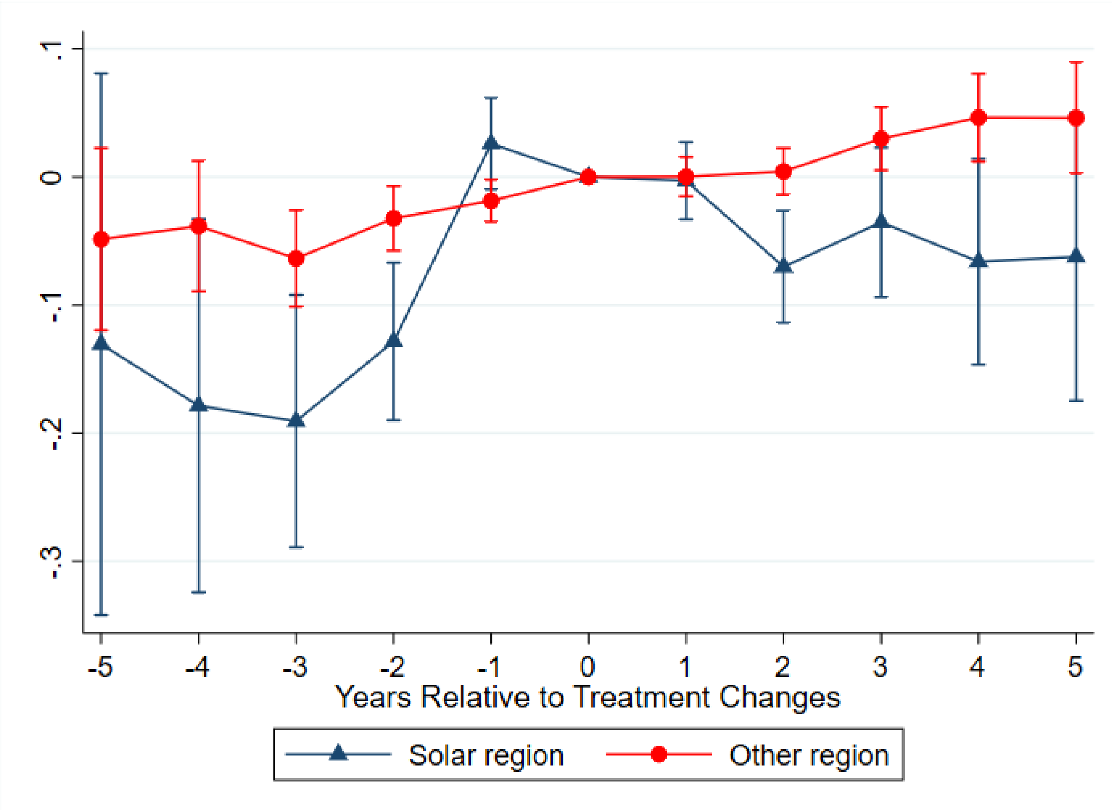
Notes: Panel A plots the evolution of average solar plant capacity (MW) and the number of plants from 2010 to 2022, based on satellite-identified installations. Panel B shows the geographic distribution of solar plants with a total installed capacity above 6 MW across Chinese prefectures in 2022. Darker shading indicates greater installed capacity. The map was produced using ArcGIS software.using ArcGIS software.

Figure 2: Solar Plant and Electricity Price



Notes: This figure plots the relationship between changes in industrial electricity prices and increases in local solar capacity. The horizontal axis shows the log increase in installed photovoltaic capacity, and the vertical axis shows the change in average industrial electricity prices across provinces. Each point represents a province.

Figure 3: Dynamic Effects of Solar Capacity Expansion on Firm Entry



Notes: This figure presents dynamic estimates of the effects of solar capacity expansion on firm entry. It reports event–study coefficients comparing cities in the designated solar region with those in other regions, where the horizontal axis measures years relative to the installation year. Confidence intervals at the 95% level are displayed.

Table 1: Summary Statistics

Panel A: Full Sample

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
City–Industry–Year Level					
Registered capital (RMB mn)	1,882,608	246.70	30,949.80	0.00	28,700,000.00
New firms (#)	1,882,608	72.00	728.19	0.00	196,222.00
City–Year Level					
Total solar capacity (GW)	4,368	1.41	3.18	0.00	44.34
Global horizontal irradiance (GHI)	4,355	1,494.08	121.33	1,082.82	1,804.82
Electricity price (RMB/kWh)	4,251	0.57	0.10	0.33	0.84
Electricity shortage news (#)	4,368	5.56	20.09	0.00	387.00
Outage notices (#)	4,368	13.35	30.43	0.00	1,917.00
Supportive solar policy (indicator)	4,368	0.13	0.34	0.00	1.00
UHV origin city (indicator)	4,368	0.03	0.16	0.00	1.00
UHV destination city (indicator)	4,368	0.03	0.16	0.00	1.00
Total fiscal income (RMB bn)	4,251	221.55	522.22	0.84	7,770.00
Population (10k)	4,251	421.32	344.54	18.50	3,213.00
GDP (RMB bn)	4,251	243.78	378.51	31.86	4,465.28

Panel B: By Solar Region Status

	Solar region			Non-solar region		
Variable	*Obs.*	*Mean*	*Std. dev.*	*Obs.*	*Mean*	*Std. dev.*
City–Industry–Year						
Registered capital (RMB mn)	352,989	54.32	2,017.83	1,529,619	291.03	34,321.89
New firms	352,989	36.71	439.93	1,529,619	80.15	779.49
City–Year						
Solar capacity (GW)	819	3.07	5.71	3,549	1.03	2.04
GHI	819	1,548.05	96.16	3,536	1,481.58	123.13
Electricity price (RMB/kWh)	567	0.43	0.06	2,388	0.59	0.08
Shortage news	819	3.55	18.71	3,549	5.89	20.88
Outage notices	819	9.59	20.65	3,549	14.06	30.96
Supportive solar policy	819	0.07	0.26	3,549	0.15	0.36
UHV origin city	819	0.06	0.23	3,549	0.01	0.14
UHV destination city	819	0.00	0.00	3,549	0.03	0.18
Fiscal income (RMB bn)	793	79.66	117.28	3,458	254.09	571.35
Population (10k)	793	207.73	168.86	3,458	470.29	355.72
GDP (RMB bn)	793	98.29	120.63	3,458	277.15	408.46

Notes: This table reports summary statistics for the main variables used in the analysis. Panel A presents statistics for the full sample. Panel B reports statistics separately for cities classified as solar regions and non-solar regions. Variables are measured at either the city–industry–year or city–year level, as indicated. Monetary values are expressed in real RMB. Indicator variables take values of zero or one.

Table 2: First-stage Evidence: Solar Energy and Comparative Advantage

Dep. Variable	log(1 + #Total Shortages)$_{it}$		log(1 + #Notices)$_{it}$		log(1 + #News Reports)$_{it}$	
Model	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity$_{it}$ + 1)	-0.0214**	-0.0224**	-0.0196*	-0.0185*	-0.0150**	-0.0153**
	(0.00922)	(0.00954)	(0.0109)	(0.0110)	(0.00651)	(0.00672)
log(GDP)		0.0813		0.177*		0.0939
		(0.0910)		(0.105)		(0.0640)
log(Population)		-0.136		-0.290		-0.191
		(0.177)		(0.204)		(0.125)
log(Fiscal expenditure)		0.209**		-0.410***		-0.0204
		(0.103)		(0.118)		(0.0722)
log(Consumption)		-0.0881*		-0.183***		-0.0492
		(0.0514)		(0.0593)		(0.0362)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,082	3,965	4,082	3,965	4,082	3,965
R-squared	0.681	0.683	0.538	0.550	0.637	0.643

Notes: This table presents estimates of the relationship between local photovoltaic capacity and electricity shortages. The dependent variable is the log of city–year counts of shortages, constructed from 199 regional newspapers between 2010 and 2022, combining official outage notices and news reports of unplanned or recurring shortages. Columns (1)–(2) use the combined count of outage notices and shortage reports, Columns (3)–(4) focus on planned notices, and Columns (5)–(6) focus on unplanned shortage news. All specifications include city and year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 3: Baseline: Plant Installation and Firm Entry

Panel A. Solar Capacity Expansion		
Dep. Variable	log(1 + # New Entry)$_{ijt}$	
Model	(1)	(2)
log(Capacity$_{it}$ + 1)	0.00124***	-0.000140
	(0.000285)	(0.000308)
log(Capacity$_{it}$ + 1)$\times$ SolarRegion		0.00912***
		(0.000368)
log(Fiscal expenditure)		0.0463***
		(0.00333)
log(Population)		-0.512***
		(0.00588)
log(GDP)		0.0759***
		(0.00255)
City-by-industry FE	Yes	Yes
Industry-by-year FE	Yes	Yes
Observations	1,882,608	1,832,181
R^2	0.921	0.923

Panel B. Electricity Intensity			
Dep. Variable	log(1 + # New Entry)$_{ijt}$		
Sample	All	Solar Region	Other Region
Model	(1)	(2)	(3)
log(Capacity$_{it}$ + 1)	0.000694*	0.00174**	-0.000744*
	(0.000359)	(0.000721)	(0.000415)
log(Capacity$_{it}$ + 1)$\times$ Electricity Intensity	0.0169**	0.0292**	0.0118
	(0.00682)	(0.0137)	(0.00787)
City-by-industry FE	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes
Observations	1,847,664	406,926	1,440,738
R^2	0.919	0.923	0.919

Notes: This table reports baseline estimates of the relationship between solar capacity expansion and firm entry. Column (1) includes solar capacity only. Column (2) adds an interaction with an indicator for designated solar regions and controls for local socio-economic characteristics. Panel B presents the relationship between electricity intensity and firm entry using an industry-level measure of electricity intensity, defined as the ratio of electricity expenditure to total input costs based on VAT invoice data. All specifications include city-by-industry and industry-by-year fixed effects. Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Subsidiary Expansion and Electricity Constraints: City-Pair Evidence

Panel A. Electricity Constraints and Subsidiary Expansion

Dep. Variable	$\log(1 + \#\ \text{Subsidiaries})_{odt}$			
Model	(1)	(2)	(3)	(4)
$\log(\text{Capacity}_j{+}1)$	0.00840***	0.0131***	0.00101	-0.192***
	(0.000969)	(0.00125)	(0.00260)	(0.0204)
$\log(\text{Capacity}_j{+}1)\times\log(\text{Capacity}_i{+}1)$		-0.000910***		
		(0.000196)		
$\log(\text{Capacity}_j{+}1)\times\log(\text{Outage}_i{+}1)$			0.00124***	
			(0.000433)	
$\log(\text{Capacity}_j{+}1)\times\log(\text{ElecPrice}_i)$				0.0314***
				(0.00320)
City Pair FE	Yes	Yes	Yes	Yes
Investor City-by-Year FE	Yes	Yes	Yes	Yes
Observations	1,161,485	1,144,281	1,061,951	928,899

Panel B. Heterogeneity by Solar Region and Origin-City Electricity Conditions

Dep. Variable	$\log(1 + \#\ \text{Subsidiaries})_{odt}$		
Model	(1)	(2)	(3)
$\log(\text{Capacity}_j{+}1)$	0.00863***	0.00261	-0.116***
	(0.00131)	(0.00265)	(0.0215)
$\log(\text{Capacity}_j{+}1)\times\log(\text{Capacity}_i{+}1)$	0.000390*		
	(0.000209)		
$\log(\text{Capacity}_j{+}1)\times\text{SolarRegion}_j$	0.0429***	-0.0132***	-0.650***
	(0.00241)	(0.00481)	(0.0521)
$\log(\text{Capacity}_i{+}1)\times\text{SolarRegion}_j$	0.0294***		
	(0.00275)		
$\log(\text{Capacity}_j{+}1)\times\log(\text{Capacity}_i{+}1)\times\text{SolarRegion}_j$	-0.0115***		
	(0.000427)		
$\log(\text{Capacity}_j{+}1)\times\log(\text{Outage}_i{+}1)$		0.00146***	
		(0.000442)	
$\log(\text{Capacity}_j{+}1)\times\log(\text{Outage}_i{+}1)\times\text{SolarRegion}_j$		-0.00135	
		(0.000987)	
$\log(\text{Capacity}_j{+}1)\times\log(\text{ElecPrice}_i)$			0.0200***
			(0.00338)
$\log(\text{ElecPrice}_i)\times\text{SolarRegion}_j$			-0.443***
			(0.0632)
$\log(\text{Capacity}_j{+}1)\times\log(\text{ElecPrice}_i)\times\text{SolarRegion}_j$			0.0982***
			(0.00826)
City Pair FE	Yes	Yes	Yes
Investor City-by-Year FE	Yes	Yes	Yes
Observations	1,144,281	1,061,951	928,899

Notes: This table presents city-pair estimates of how solar capacity in different cities interacts with electricity conditions in firms' origin cities to shape outward subsidiary expansion. The dependent variable is the log of one plus the number of new subsidiaries established in destination city j by firms headquartered in origin city i. Panel A reports baseline specifications using alternative measures of origin-city electricity constraints, including local solar capacity, outage frequency, and electricity prices. Panel B further examines heterogeneity by designated solar regions through interaction terms. All specifications include city-pair fixed effects and investor city-by-year fixed effects. Robust standard errors, clustered at the city or city-pair level as appropriate, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Instrumental Variable Estimates

Sample	Panel A: Full Sample		Panel B: Border Discontinuity Sample	
	First Stage	Second Stage	First Stage	Second Stage
Dep. Variable	$\log(\text{Capacity}+1)_i$	$\log(\#\ \text{New Entry}+1)_{ij}$	$\log(\text{Capacity}+1)_i$	$\log(\#\ \text{New Entry}+1)_{ij}$
Model	(1)	(2)	(3)	(4)
$\log(\text{Capacity}_i + 1)$		0.0403**		0.140***
		(0.0195)		(0.0425)
GHI	0.00128			
	(0.00618)			
Outage	-3.041*			
	(1.643)			
GHI×Outage	0.00205*			
	(0.00106)			
GHI×Electrity Price			-0.0192***	
			(0.00403)	
GHI×l3.Policy			-0.000831***	
			(0.000138)	
l3.Policy			1.279***	-0.0188***
			(0.210)	(0.00453)
log(Population)	0.354	-0.624*	1.415***	0.225**
	(0.882)	(0.330)	(0.300)	(0.108)
log(GDP)	-0.277	0.0651	0.787***	-0.0762**
	(0.607)	(0.0630)	(0.0567)	(0.0342)
log(Fiscal Expenditure)	-0.469	0.128	-0.352**	-0.0605
	(0.751)	(0.0946)	(0.165)	(0.0624)
Fixed effects	City, Industry×Year FE	City, Industry×Year FE	Citypair FE; Region×Year FE	Citypair FE; Region×Year FE
Observations	131,024	131,024	24,134	24,134
KP Wald F statistic	25.639		25.639	
Hansen J statistic		2.645		2.645

Notes: This table presents instrumental variable estimates from two designs. Columns (1)–(2) report estimates from the full-sample long-difference IV specification using global horizontal irradiance (GHI), outage frequency, and their interaction as instruments for local solar capacity. Columns (3)–(4) report IV estimates using the border discontinuity sample, exploiting regional discontinuities in electricity prices at historical grid and provincial borders; instruments include the interaction of GHI with electricity prices and the policy measure (l3.Policy) and its interaction with GHI. The Kleibergen–Paap Wald F-statistics and Hansen J-test statistics are reported at the bottom of the table. Robust standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Mechanism: Excluding Solar Supply Chain Industries

Dep. Variable	$\log(1+\#\text{ New Entry})_{ijt}$		
Model	(1)	(2)	(3)
$\log(\text{Capacity}_{it}+1)$	0.000806***	-0.00147***	-0.000317
	(0.000301)	(0.000318)	(0.000325)
$\log(\text{Capacity}_{it+1)} * SolarRegion$		0.00845***	0.00852***
		(0.000384)	(0.000388)
log(Fiscal expenditure)			0.0440***
			(0.00351)
log(Population)			-0.511***
			(0.00620)
log(GDP)			0.0687***
			(0.00269)
City-by-Industry FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes
Observations	1,655,472	1,655,472	1,611,129
R-squared	0.923	0.923	0.925

Notes: This table excludes 52 industries directly or partially linked to the solar supply chain from a total of 431 industries to test whether the effects of solar deployment on firm entry are driven by supply chain dynamics.All specifications include city-by-industry and industry-by-year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 7: Mechanism: Complementing Industrial Policies

Dep. Variable	$\log(1+\#\text{ New Entry})_{it}$				
Sample	All			Solar Region	Other Region
Model	(1)	(2)	(3)	(4)	(5)
$\log(\text{Capacity}_{it}+1)$	0.00381***	0.00278***	0.00357***	0.000510	0.00306***
	(0.000358)	(0.000367)	(0.000378)	(0.000743)	(0.000445)
Policy_{ijt}	0.0345***	0.00960***	0.00272	-0.0587***	0.00929***
	(0.00177)	(0.00269)	(0.00273)	(0.00693)	(0.00299)
$\log(\text{Capacity}_{it}+1) * Policy_{ijt}$		0.00597***	0.00763***	0.0167***	0.00699***
		(0.000485)	(0.000493)	(0.00113)	(0.000555)
log(Fiscal expenditure)			0.0306***	0.108***	0.0217***
			(0.00446)	(0.0105)	(0.00498)
log(Population)			-0.563***	-0.0903***	-0.683***
			(0.0106)	(0.0222)	(0.0121)
log(GDP)			0.0254***	-0.0457***	0.0417***
			(0.00354)	(0.00740)	(0.00403)
City-by-Industry FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,448,160	1,448,160	1,409,370	310,320	1,099,050
R-squared	0.900	0.900	0.900	0.902	0.899

Notes: This table reports estimates incorporating industry-level policy measures from Fang, Li, and Lu (2024). Columns (1)–(3) present results for the full sample with progressively added controls, while Columns (4)–(5) split the sample into solar and non-solar regions. All specifications include city-by-industry and industry-by-year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 8: Mechanism: Mitigating Effect of Energy Transmission

Dep. Variable	$\log(1+\#\text{ New Entry})_{ijt}$			
Model	(1)	(2)	(3)	(4)
$\log(\text{Capacity}_{it}+1)$	0.00288***	0.00183**	0.00318***	0.00206***
	(0.000586)	(0.000738)	(0.000608)	(0.000765)
$\log(\text{Capacity}_{it}+1) * UHV$	-0.00196***	-0.000745	-0.00195***	-0.000743
	(0.000748)	(0.000942)	(0.000751)	(0.000946)
$\log(\text{Capacity}_{it}+1) * Electricity$		0.0386***		0.0408***
		(0.0140)		(0.0145)
$\log(\text{Capacity}_{it}+1) * UHV * Electricity$		-0.0398**		-0.0398**
		(0.0179)		(0.0179)
log(Fiscal expenditure)			0.108***	0.110***
			(0.00735)	(0.00747)
log(Population)			-0.297***	-0.301***
			(0.0136)	(0.0138)
log(GDP)			0.00749	0.00836*
			(0.00494)	(0.00503)
City-by-Industry FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Observations	352,989	346,437	341,783	335,439
R-squared	0.923	0.921	0.924	0.922

Notes: This table reports estimates testing the role of ultra–high-voltage (UHV) transmission lines in mediating the effect of solar deployment on firm entry. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 9: Mechanism: Regional Spillover

Dep. Variable	log(1+# New Entry)$_{ijt}$			
Model	(1)	(2)	(3)	(4)
$\log(\text{Capacity}_{it}+1)$	0.000537*	0.00133***	-0.000932***	-0.000178
	(0.000297)	(0.000303)	(0.000333)	(0.000339)
$\log(\text{NeighborCapacity}_{it}+1)$	0.00295***	0.00423***	0.00280***	0.00407***
	(0.000379)	(0.000383)	(0.000403)	(0.000408)
$\log(\text{Capacity}_{it}+1) * SolarRegion$			0.00468***	0.00467***
			(0.000630)	(0.000643)
$\log(\text{NeighborCapacity}_{it}+1) * SolarRegion$			0.00387***	0.00406***
			(0.000620)	(0.000636)
log(Fiscal expenditure)		0.0387***		0.0437***
		(0.00333)		(0.00334)
log(Population)		-0.566***		-0.564***
		(0.00601)		(0.00601)
log(GDP)		0.0764***		0.0754***
		(0.00255)		(0.00255)
City-by-Industry FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Observations	1,854,593	1,815,372	1,854,593	1,815,372
R-squared	0.922	0.923	0.922	0.923

Notes: This table examines the role of regional spillovers by including both local solar capacity and neighboring solar capacity, defined as the total installed capacity in all border-sharing cities. All regressions include city-by-industry and industry-by-year fixed effects. Robust standard errors, clustered at the city level, are shown in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 10: Mechanism: Vertical Spillover

Dep. Variable	log(1+# New Entry)$_{ijt}$					
Sample	All	Solar Region	Other Region	Manufacturing	Mining	Service
Model	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Capacity}_{it}+1)$	-0.00436***	0.000475	-0.00788***	0.00825	-0.0509	-0.0149*
	(0.00120)	(0.00246)	(0.00138)	(0.00590)	(0.0501)	(0.00796)
$\log(\text{Capacity}_{it}+1) \times$ Electricity	0.0875***	0.127***	0.0772***	0.395**	-0.800*	-0.0972
	(0.0183)	(0.0375)	(0.0211)	(0.187)	(0.483)	(0.121)
$\log(\text{Capacity}_{it}+1) \times$ UpElectricity	0.0594***	0.0450*	0.0610***	0.0188	-0.290	0.778***
	(0.0127)	(0.0260)	(0.0146)	(0.0443)	(0.602)	(0.267)
$\log(\text{Capacity}_{it}+1) \times$ DownElectricity	0.00447	-0.0399**	0.0135	-0.280	3.731*	-0.0298
	(0.00989)	(0.0202)	(0.0114)	(0.208)	(2.097)	(0.0312)
City-by-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	340,704	75,036	265,668	27,898	4,810	26,936
R-squared	0.936	0.940	0.936	0.918	0.789	0.946

Notes: This table examines vertical spillovers from solar expansion using electricity intensity measures derived from the input–output table. The interaction terms combine solar capacity with industry electricity intensity, as well as with upstream and downstream electricity intensity constructed at the two-digit industry level. Columns (1)–(3) report results for all cities, solar regions, and non-solar regions, respectively. Columns (4)–(6) restrict the analysis to solar regions and examine manufacturing, mining, and services separately. All specifications include city-by-industry and industry-by-year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 11: Firm Performance: Intensive and Extensive Margins

Panel A: Intensive Margin

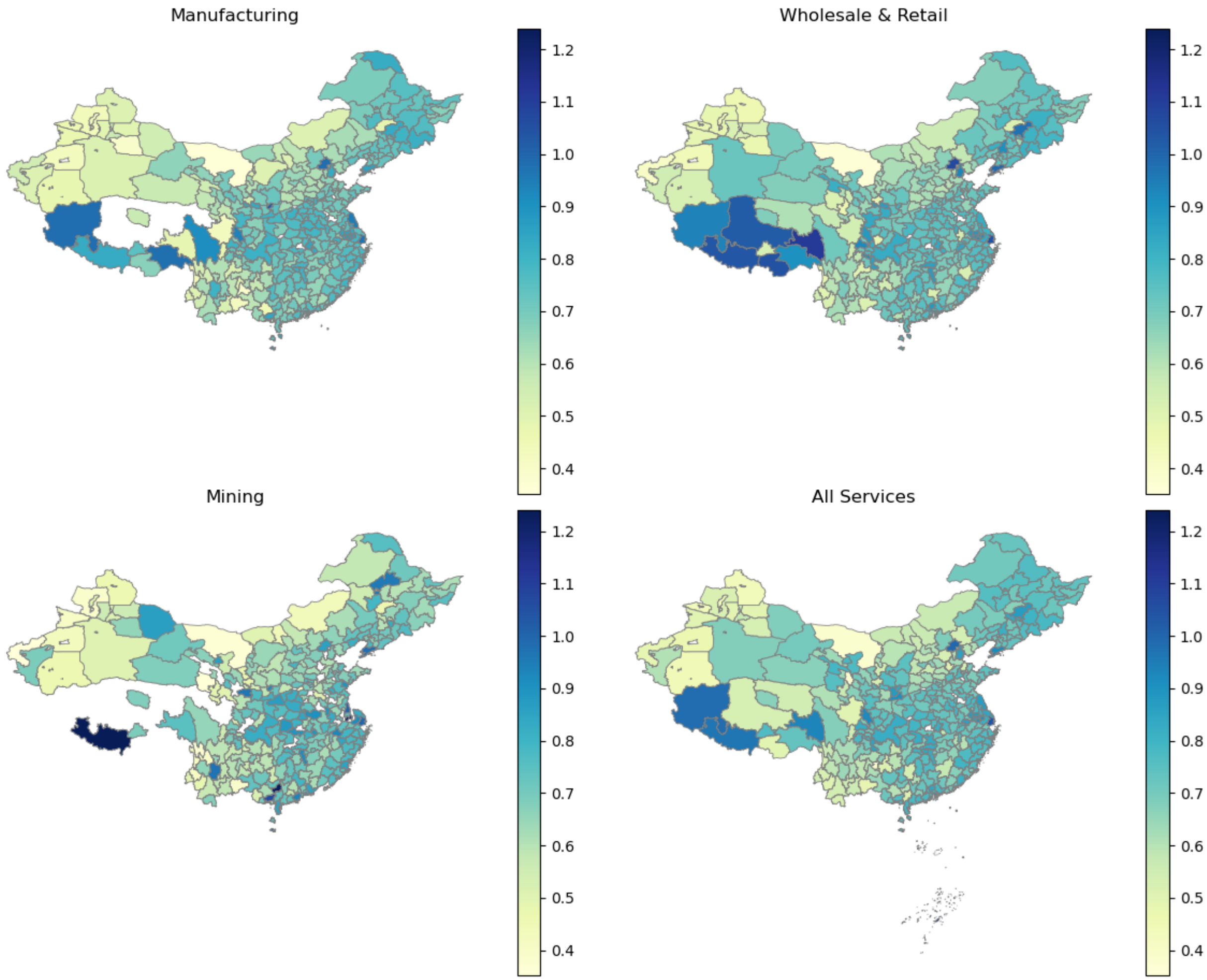
Dep. Variable	ROE_{fijt}			$\log(\text{Revenue})_{fijt}$		
Sample	All	Solar Region	Other Region	All	Solar Region	Other Region
Model	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Capacity}_{it}+1)$	0.000294***	-0.000288	0.000272***	0.0184***	0.0295***	0.0184***
	(8.26e-05)	(0.000267)	(8.71e-05)	(0.000291)	(0.00101)	(0.000305)
$\log(\text{Capacity}_{it}+1)\times$Electricity	0.0266***	0.00667	0.0287***	0.147***	0.0481***	0.155***
	(0.00127)	(0.00420)	(0.00134)	(0.00528)	(0.0185)	(0.00552)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,570,541	3,747,587	56,822,954	85,095,198	4,999,333	80,095,865
R-squared	0.368	0.370	0.368	0.711	0.693	0.712

Panel B: Extensive Margin

Dep. Variable	ROE_{fijt}				$\log(\text{Revenue})_{fijt}$		
Sample	All	Solar Region	Other Region		All	Solar Region	Other Region
Model	(1)	(2)	(3)	(4)	(5)	(6)	
$\log(\text{Capacity}_{it}+1)$	-0.00218***	-0.000581**	-0.00242***		0.00913***	-0.0219***	0.0193***
	(8.44e-05)	(0.000264)	(8.55e-05)		(0.000381)	(0.00132)	(0.000398)
Entrant	-0.0385***	-0.0363***	-0.0401***		-1.301***	-1.605***	-1.400***
	(0.000400)	(0.00131)	(0.000402)		(0.00175)	(0.00621)	(0.00180)
$\log(\text{Capacity}_{it}+1)\times$Entrant	0.0162***	0.00604***	0.0173***		0.0210***	0.0643***	0.0120***
	(7.06e-05)	(0.000225)	(7.10e-05)		(0.000279)	(0.000948)	(0.000287)
City-by-industry FE	Yes	Yes	Yes		Yes	Yes	Yes
Year FE	Yes	Yes	Yes		Yes	Yes	Yes
Observations	63,834,696	4,288,437	63,514,402		87,955,058	5,621,416	87,496,330
R-squared	0.020	0.009	0.012		0.149	0.055	0.090

Notes: This table reports the economic consequences of solar expansion for firms along both the intensive and extensive margins. Panel A examines the intensive margin, where the dependent variables are ROE and log revenue. Panel B turns to the extensive margin, distinguishing incumbents from new entrants. All regressions include firm (or city-by-industry) and year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Figure A1: Regional Distribution of Electricity Prices in China

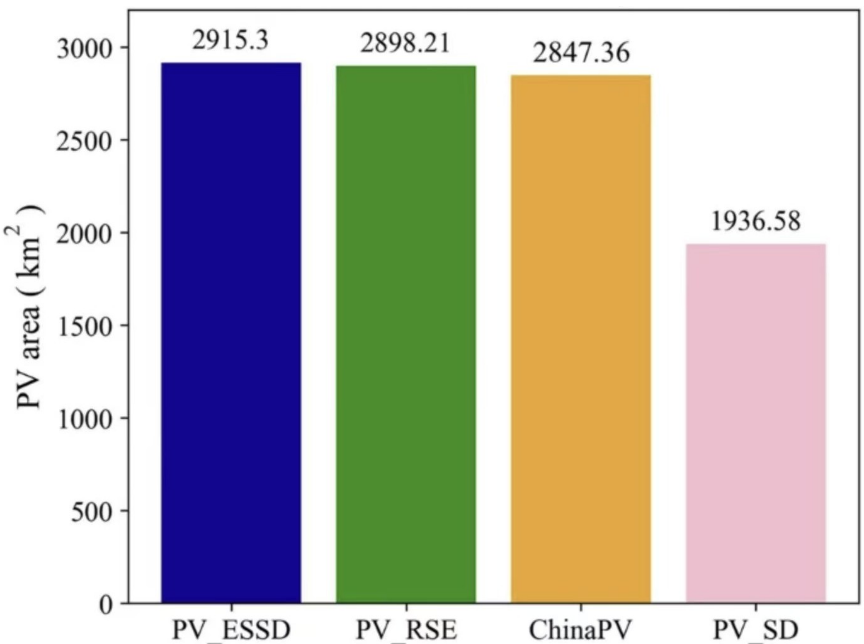


Notes: This figure shows the spatial distribution of average industrial electricity prices across Chinese prefectures, separately for the manufacturing sector, the mining sector, the wholesale and retail sector, and all service sectors. Darker colors indicate higher electricity prices. The maps were produced using ArcGIS software.

Figure A2: Example of Solar Plant from Satellite Imagery

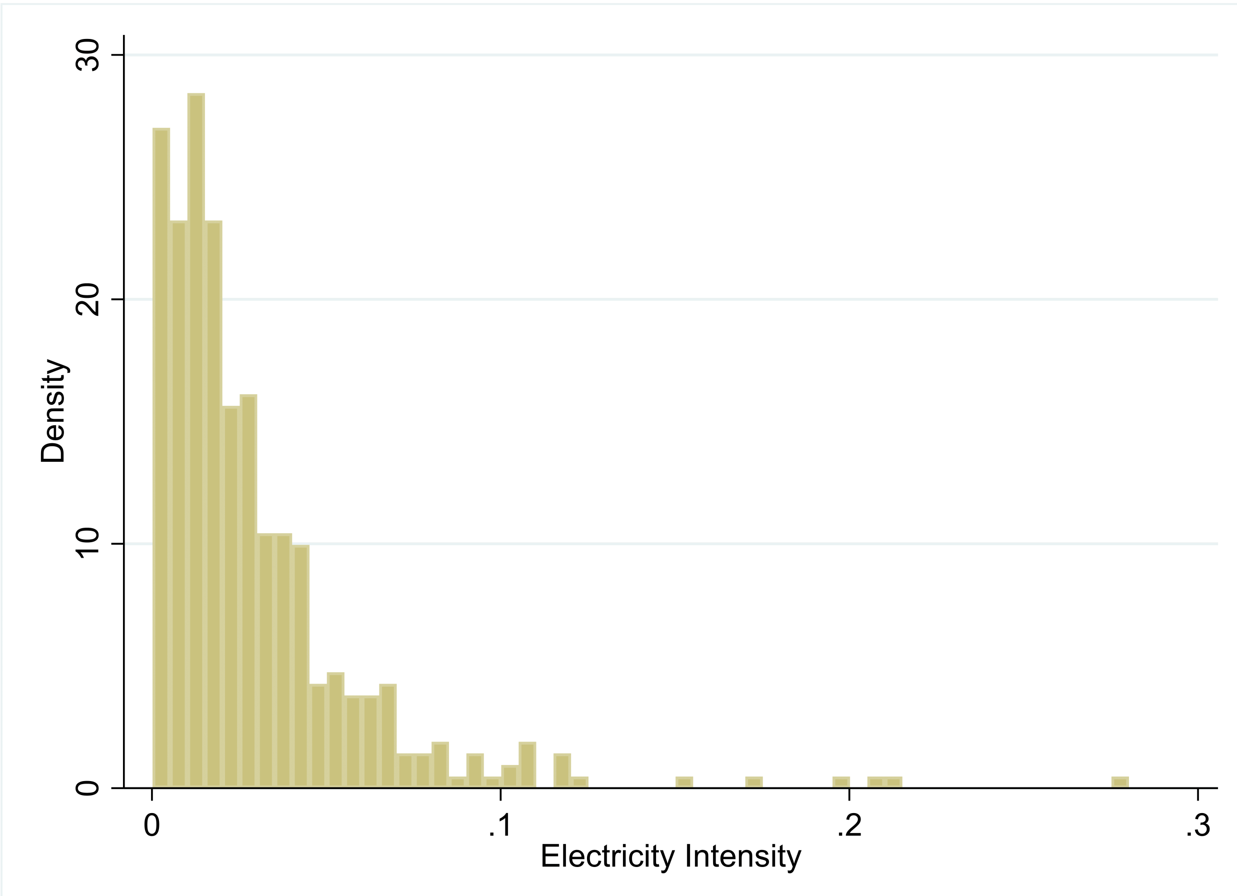
Notes: This figure provides a representative satellite image of a utility-scale solar farm in China. The image illustrates the spatial layout of photovoltaic panels and facility boundaries used in constructing the plant-level dataset. Satellite imagery was obtained through publicly available map services *Baidu*.

Figure A3: Comparison of Photovoltaic (PV) Area Estimates in China, 2020



Notes: This figure compares alternative datasets on the estimated photovoltaic (PV) installation area in China for 2020. PV_ESSD and PV_RSE are global remote-sensing–based inventories, ChinaPV is a nationally compiled dataset, and PV_SD is based on satellite-derived classification. Reported values are expressed in square kilometers. Differences reflect variation in data sources, measurement methods, and coverage.

Figure A4: Distribution of Industry-Level Electricity Intensity



Notes: This figure shows the distribution of electricity intensity across industries. Electricity intensity is defined as the ratio of electricity consumption to total output value, constructed using national input–output tables.

Table A1: First-stage Evidence: Firm Electricity Usage

Dep. Variable	Panel A. Unit Price				Panel B. log(Usage)	
Model	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity+1)	-0.00207***	-0.00330***			0.0176***	0.0355***
	(0.000114)	(0.000227)			(0.00107)	(0.00301)
log(Usage)			-0.0253***	-0.0252***		
			(3.98e-05)	(2.48e-05)		
Firm FE	Yes	No	Yes	No	Yes	No
City FE	No	Yes	No	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,162,781	8,195,054	8,155,669	8,188,732	8,155,669	8,188,732
R-squared	0.857	0.242	0.865	0.326	0.912	0.063

Notes: This table presents estimates using monthly VAT invoice data for 2017–2018. Panel A reports results for unit electricity prices (columns 1–4), and Panel B reports results for log electricity usage (columns 5–6). Columns (1)–(2) show the relationship between local solar capacity and unit prices, while columns (3)–(4) relate unit prices to electricity usage. Firm, city, and year–quarter fixed effects are included as indicated. Standard errors, clustered at the city level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Plant Installation and Firm Entry By Industry

Dep. Variable	log(# New Entry+1)				
Sample	Agriculture	Mining	Manufacturing	Energy supply	Construction
log(Capacity+1)	-0.0113***	-0.00238***	-0.00380***	0.0167***	0.00606***
	(0.00157)	(0.000812)	(0.000447)	(0.00252)	(0.00200)
log(Capacity+1)*SolarRegion	0.0171***	0.00498***	0.0124***	-0.0208***	0.0115***
	(0.00199)	(0.00103)	(0.000565)	(0.00319)	(0.00253)
Observations	100,464	82,992	764,400	30,576	61,152
Sample	Sales	Transportation	Hotelling	IT	Finance
log(Capacity+1)	-0.0152***	-0.00420***	-0.00224	0.0121***	0.00195
	(0.00189)	(0.00155)	(0.00301)	(0.00216)	(0.00119)
log(Capacity+1)*SolarRegion	0.0336***	0.00596***	0.0111***	-0.00323	0.00487***
	(0.00240)	(0.00196)	(0.00380)	(0.00273)	(0.00150)
Observations	78,624	87,360	30,576	52,416	91,728
Sample	Real estate	Commercial service	RD	Environment	Life service
log(Capacity+1)	-0.00830***	-0.00101	0.0152***	0.00507***	-0.00106
	(0.00313)	(0.00219)	(0.00173)	(0.00152)	(0.00190)
log(Capacity+1)*SolarRegion	0.0225***	0.0144***	-0.00324	-0.00358*	0.0143***
	(0.00396)	(0.00277)	(0.00219)	(0.00193)	(0.00240)
Observations	21,840	48,048	74,256	52,416	65,520
City-by-Industry FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents industry-specific regressions of firm entry on solar capacity, estimated at the city–industry–year level. The dependent variable is the log of one plus the number of new firm registrations. All specifications include city-by-industry and industry-by-year fixed effects. Robust standard errors, clustered at the city level, are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table A3: Instrumental Variable Estimates: Full Sample and Border Discontinuity Design

Sample	**Full Sample (Long-Difference IV)**		**Border Discontinuity Sample (IV)**			
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Dep. Variable	log(Capacity+1)	log(# New Entry+1)	log(Capacity+1)	log(# New Entry+1)	log(Capacity+1)	log(# New Entry+1)
Model	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity+1)		0.0412**		0.181***		0.0751**
		(0.0207)		(0.0637)		(0.0376)
GHI	0.0124***					
	(0.00196)					
GHI×Electrity Price			-0.0196***			
			(0.00405)			
GHI×l3.Policy					-0.000862***	
					(0.000140)	
l3.Policy					1.325***	-0.0170***
					(0.212)	(0.00400)
log(Population)	1.555*	-0.688**	1.391***	0.182	1.450***	0.290***
	(0.935)	(0.321)	(0.301)	(0.132)	(0.292)	(0.0915)
log(GDP)	-0.419	0.0825	0.780***	-0.107**	0.783***	-0.0261
	(0.554)	(0.0604)	(0.0571)	(0.0504)	(0.0572)	(0.0305)
log(Fiscal Expenditure)	-0.198	0.124	-0.346**	-0.0516	-0.293*	-0.0667
	(0.781)	(0.0890)	(0.165)	(0.0692)	(0.161)	(0.0543)
City, Industry×Year FE	Yes	Yes				
Citypair FE			Yes	Yes	Yes	Yes
Region×Year FE			Yes	Yes	Yes	Yes
Observations	140,937	140,937	24,134	24,134	24,416	24,416
KP Wald F statistic	37.996		23.416		37.996	

Notes: This table presents instrumental variable estimates using two complementary designs. Columns (1)–(2) report the long-difference IV results for the full sample, using global horizontal irradiance (GHI) as the instrument for solar capacity. Columns (3)–(6) report IV estimates for the border discontinuity sample exploiting regional discontinuities in electricity prices at historical grid and provincial borders: Columns (3)–(4) use the interaction of GHI and electricity prices as the instrument, while Columns (5)–(6) add the policy indicator and its interaction with GHI as additional instruments. All specifications include the fixed effects indicated in the table. Kleibergen–Paap Wald F-statistics and Hansen J-test statistics are reported at the bottom. Robust standard errors, clustered at the city level, are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Instrumental Variable Estimates: Border Discontinuity Design (Full Sample)

Dep. Variable	log(Capacity+1)	log(# New Entry+1)	log(Capacity+1)	log(# New Entry+1)	log(Capacity+1)	log(# New Entry+1)
Model	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity+1)		0.0769***		0.0405**		0.0642***
		(0.0162)		(0.0198)		(0.0132)
GHI*Electrity Price	-0.0198***				-0.0195***	
	(0.000614)				(0.000610)	
GHI*l3.Policy			-0.000863***		-0.000835***	
			(2.32e-05)		(2.29e-05)	
l3.Policy			1.292***	-0.00161	1.250***	-0.00159
			(0.0349)	(0.00186)	(0.0345)	(0.00187)
log(Population)	1.220***	-0.360***	1.230***	-0.312***	1.222***	-0.346***
	(0.0466)	(0.0367)	(0.0450)	(0.0398)	(0.0464)	(0.0353)
log(GDP)	0.689***	-0.0444***	0.691***	-0.0196	0.692***	-0.0357***
	(0.0103)	(0.0127)	(0.0104)	(0.0148)	(0.0103)	(0.0109)
log(Fiscal Expenditure	-0.578***	0.0801***	-0.506***	0.0588***	-0.580***	0.0735***
	(0.0261)	(0.0160)	(0.0253)	(0.0164)	(0.0261)	(0.0151)
Citypair FE	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	973,629	973,629	986,559	986,559	973,629	973,629
KP Wald F statistic	1041.627		1386.486		993.344	
Hansen J statistic						2.298

Notes: This table reports instrumental variable estimates exploiting regional discontinuities in electricity prices at historical grid and provincial borders for the full sample. Columns (1)–(2) use the interaction of global horizontal irradiance (GHI) and regulated electricity prices as the instrument. Columns (3)–(4) add the national solar policy indicator and its interaction with GHI as additional instruments. Columns (5)–(6) combine both sets of instruments. All specifications include city-pair and region-by-year fixed effects. Kleibergen–Paap Wald F-statistics and Hansen J-test statistics are reported at the bottom of the table. Robust standard errors, clustered at the city level, are shown in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.