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Abstract

Employing a spatial equilibrium model and exploiting staggered solar farm installations across Chinese counties, this study reveals that solar energy development reduces local GDP per capita by an average of 2.7%. This negative effect, primarily from competition for high-value land, is more pronounced in counties with high land opportunity costs. We observe a 2% increase in the local population despite lower wages and higher housing prices, implying improvements in local amenities. This paper reframes the resource curse debate by examining the impacts of renewable energy, specifically solar power.

Keywords: solar energy, land competition, economic growth, welfare.

JEL Codes: I31, O13, Q43, Q56, R14.

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1 Introduction

The relationship between natural resource abundance and economic growth has been a long-standing debate in the literature (van der Ploeg, 2011). The "resource curse" hypothesis suggests that resource-rich countries and regions, typically those abundant in fossil fuels and minerals, tend to experience slower economic growth compared to their resource-poor counterparts (Sachs and Warner, 1995). This perspective has been challenged by proponents of the "resource blessing" argument, who posit that natural resources can stimulate economic development when managed effectively (Alexeev and Conrad, 2009). The mechanisms underlying the divergent outcomes have been extensively studied in the context of conventional resources.[1] However, the applicability of these paradigms to renewable resources remain understudied, representing a significant gap in our understanding of resource-driven economic dynamics.

This paper investigates the economic and welfare implications of the rapid expansion of solar energy. Over the past decade, solar power has become a key renewable resource in the global energy landscape, with China emerging as a global leader. As of 2023, China's installed solar capacity reached 609 gigawatts (GW), representing 37% of the global total.

Solar energy differs notably from conventional fossil fuels that warrants a distinct analysis. First, as a renewable resource, solar energy provides an alternative to finite fossil fuels and offers environmental benefits such as reduced greenhouse gas emissions and lower pollution. Second, from an economic perspective, solar energy demands considerable upfront investment in infrastructure, such as photovoltaic panels and transmission lines, but it benefits from low operational costs (Borenstein, 2012). Third, solar farms require substantial land areas, with photovoltaic panel installations and related infrastructure typically occupying an average of 2.5 hectares per megawatt of capacity (Capellán-Pérez et al., 2017). Fourth, the intermittency of solar power generation can introduce grid instability, necessitat-

1. Regarding resource curse, empirical studies have proposed crowding out of manufacturing (Harding and Venables, 2016), weakened learning-by-doing spillovers (Gylfason et al., 1999), and institutional deterioration (Mehlum et al., 2006; Ross, 2006) as main explanations. In terms of resource blessing, Lederman and Maloney (2007) show that resource-rich countries can achieve accelerated growth, especially with strong institutions in place. Collier and Goderis (2008) argue that resource booms facilitate industrialization and infrastructure development, leading to increased investment in human capital and technology. Gylfason (2001) emphasizes that effective utilization of natural resources can enhance income levels and living standards, highlighting the importance of sound economic policies. See van der Ploeg (2011) for an overview of the literature.

ing additional investments in energy storage or backup systems (Yin et al., 2020). Collectively, these unique features–both advantageous and challenging–suggest that the implications of solar energy development may differ significantly from those of traditional natural resources.

To organize our empirical analysis, we develop a Rosen-Roback-style locational equilibrium model. The model considers a county endowed with finite land and population. It assumes land as the primary input for solar energy production and that the local government allocates land among residential housing, solar farms, and other production facilities. Residents make location choices based on the equilibrium wage rates, housing prices, and amenities, choosing between the county and an outside alternative. The model yields predictions regarding the economic impact of solar energy development. On one hand, it suggests potential negative effects through competition for high-value lands, which reduces government land sales revenue and subsequent productivity-enhancing investments. On the other hand, it indicates positive impacts through increased energy supply and potential changes in labor supply. The direction and magnitude of labor supply changes depend critically on how solar energy development affects residential welfare via its impacts on wage rates, costs of living, and amenities. Given these complex and potentially offsetting effects, both the net economic impact and the overall welfare implications of solar energy development remain ambiguous.

We empirically estimate the impacts of solar energy development by combining geocoded solar farm data with county-level socioeconomic indicators. The identification strategy exploits the staggered construction of 4,496 solar farms across Chinese counties between 2005 and 2019. We find that solar energy development has a negative impact on local economy. Counties with solar farm installations experienced an average decline of 2.7% in GDP per capita. The parallel pre-trend observed in the event-study specification supports the identification assumption that counties with early, late, or no solar farm installations exhibit similar economic trajectories prior to the installation. To account for the variation in the installed capacity across solar farms, we also employ a difference-in-differences specification complemented by a Bartik-style instrument variable. The instrument interacts the time-varying national solar energy capacity and cross-sectional local solar radiation endowments to address the endogeneity concerns arising from the non-random distribution of solar capacity over space. Notably, this approach yields comparable estimates to the event-study specification, reinforcing the robustness of our finding.

We next explore whether land competition, as suggested by our conceptual model, is a primary mechanism underlying the negative economic impacts of solar energy development. We document that 21.3% of solar farms are sited on previously impervious surfaces–a land type that is typically more economically valuable than croplands, grasslands, forests, and other land uses. We find that the negative economic impacts of solar energy are particularly pronounced when solar farms occupy these high-value lands. Using detailed land transaction records, we show this land competition leads to a declined land transaction, which reduces local government revenue from land sales by as much as 20%. Given that land sales indirectly contribute about 14% to local GDP in China, this 20% reduction in land revenue translates to an estimated 2.8% decline in GDP, which closely aligns with our empirical findings. Moreover, the adverse economic impacts of solar energy development are mitigated in counties with lower land opportunity costs, marked by steeper slopes, lower economic levels, smaller industrial shares, or lower urbanization rates. The economic impact can even be positive in counties where solar farms are installed on low-economic-value lands such as forests and water body. These findings corroborate our hypothesis that competition for high-value land is the main mechanism driving the negative economic impacts of solar energy development.

The economic implications of land competition extend beyond the reduction in government revenue. Our theoretical model posits that land sales revenue exclusively finances local production infrastructure. Consequently, declining land sales revenue reduce local economic attractiveness through diminished infrastructure investment. We document a decline in the county-level total factor productivity following solar power installation, and find that solar energy development dampens the entry of new firms roughly by 10%, particularly in the service and agricultural sectors. This indirect crowding-out effect could possibly exacerbate the observed GDP decline.

We present evidence of enhanced non-economic quality of life or amenities resulting from solar energy development. One key strength of our model lies in its ability to infer changes in overall amenities through observed population dynamics while accounting for shifts in wage rates and housing prices, even when the full spectrum of amenities is not readily observable. Our analysis reveals an approximately 2% increase in local population, despite concurrently a decline of about 5% in wage rates and an increase of 5% in housing prices. This pattern infers an improvement in overall amenities that outweighs the economic drawbacks. Corresponding to this inference, we find some, albeit noisy, evidence of improved air quality and the phasing out of fossil-based power plants following solar farm installation.

Our study contributes to the extensive literature examining how resource abundance affects economic performance (Sachs and Warner, 1997; Gylfason et al., 1999; Gylfason, 2001; Mehlum et al., 2006; Ross, 2006; Lederman and Maloney, 2007; Collier and Goderis, 2008; van der Ploeg, 2011; Harding and Venables, 2016). Specifically, we contribute to the recent strand of literature that exploits within-country variations in energy resources to investigate localized impacts on income, employment, housing prices, and environmental amenities (Black et al., 2005; Papyrakis and Gerlagh, 2007; Michaels, 2011; Caselli and Michaels, 2013; Muehlenbachs et al., 2015; Jacobsen and Parker, 2016; Feyrer et al., 2017; Allcott and Keniston, 2018; Bartik et al., 2019).

Our study focuses distinctively on renewable energy, departing from previous studies that largely examine fossil fuels or minerals. The fundamental differences between renewable and conventional energy resources underscore the need to revisit the resource curse versus resource blessing debate in the context of renewable energy. However, research on the economic impacts of renewable energy remains relatively limited. Only a few recent studies have explored the fiscal and employment effects of solar and wind energy development, which generally reveal positive outcomes (Fabra et al., 2024; Gilbert et al., 2024; Scheifele and Popp, 2024). Our paper extends this nascent literature by providing the first comprehensive assessment of the socioeconomic impacts of renewable energy, incorporating a wide range of economic and welfare indicators including but not limited to GDP, population, wage rates, housing prices, and firm dynamics.

We advance the literature by proposing a novel mechanism to explain the resource curse argument: land competition. While previous literature has emphasized the significant land demands of solar development (Miskin et al., 2019; Hernandez et al., 2015; Trainor et al., 2016; Baker et al., 2013), our work is, to the best of our knowledge, the first to examine how solar-related land competition can precipitate economic downturns in an urban context. Prior research linking renewable energy development with land use has primarily focused on the capitalization of wind energy development into agricultural land values (Haan and Simmler, 2018; Kaffine, 2019) and the visual disamenities associated with wind turbines (Gibbons, 2015; Guo et al., 2024). Our work extends this literature by examining a different dimension: the impact of solar energy development on land sales revenue, a critical pathway through which it influences the local economy. This perspective is particularly salient for developing countries that undergo rapid urbanization and renewable energy expansion simultaneously.

Our work also contributes to the literature by employing an equilibrium framework, which enables us to examine the complex interplay among various economic variables and their consequent welfare implications. Pioneered by Moretti (2011) and Kline and Moretti (2014) in the study of place-based policies, this framework has recently been applied to investigate the impact of resource abundance (Allcott and Keniston, 2018; Bartik et al., 2019) . Within this framework, population change serves as a proxy for the net welfare effects of solar energy development, as individuals demonstrate their preferences by moving to more favorable locations (commonly referred to as "vote with their feet"). This theoretically grounded approach to measuring net welfare directly speaks to the fundamental question of whether renewable energy development enhances local well-being. In this regard, our work bridges the gap between two previously distinct strands of literature: studies focusing on labor and housing markets and those examining the environmental benefits of renewable energy development (Rivera et al., 2024; Millstein et al., 2017; Buonocore et al., 2016; Novan, 2015; Cullen, 2013; Fell and Kaffine, 2018; Fell et al., 2021).

Finally, our findings yield significant policy implications for solar farm siting decisions. We argue that these decisions should factor in land opportunity costs alongside commonly considered factors such as local energy demand and solar radiation endowments. *Ceteris paribus*, solar farms should be situated away from high-value land or areas with future potential for productive activities. More broadly, our results underscore the necessity of integrating local urbanization trajectories into energy transition planning. This perspective connects our work to the broad literature on how land allocation and land use regulation shape urban development patterns (Henderson et al., 2022; Shertzer et al., 2018; Hsieh and Moretti, 2019).

The remainder of this paper is organized as follows. Section 2 provides a brief background of China's solar energy. Section 3 develops a conceptual model to analyze the impacts of solar energy. Section 4 describes the data and empirical method. Section 5 presents the empirical results on the economic impacts and Section 6 presents the results on the welfare implications. Section 7 concludes.

2 Background

2.1 Overview of solar energy development in China

China has emerged as a global leader in solar power deployment, as evidenced by Figure 1, which demonstrates the country's remarkable growth in solar capacity. It shows that China's installed solar capacity has surged from less than 10 GW in 2009 to an impressive 600 GW by 2023. The proportion of solar capacity in China's overall installed energy capacity has expanded significantly, now exceeding 20%. Additionally, China's contribution to global solar capacity has risen sharply, exceeding 40%. Despite fluctuations in some years, the overall trajectory clearly reflects China's growing reliance on solar energy to meet its domestic energy needs and its increasing contribution to global renewable energy transition.

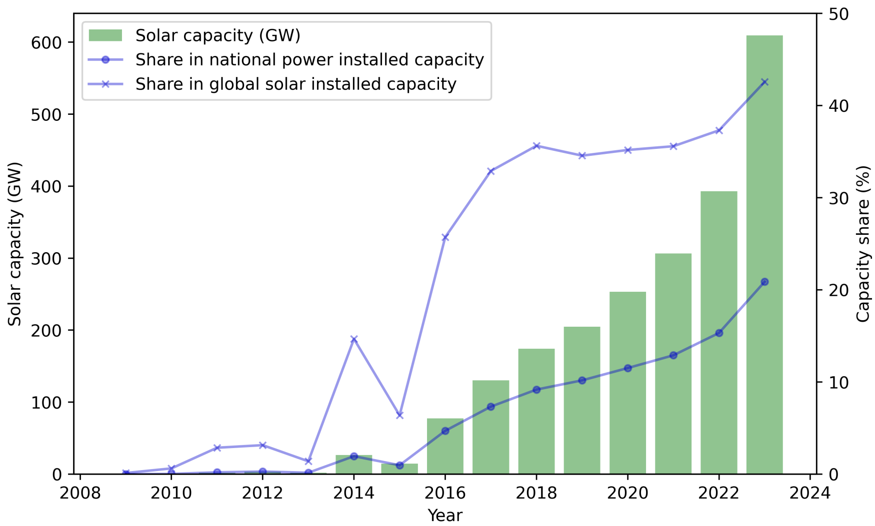

FIGURE 1 Installed Solar Power Capacity in China from 2009 to 2023

Notes: The bars represent the cumulative installed solar power capacity in China. The line marked with solid circle markers illustrates China's percentage of solar power capacity relative to its total power capacity, which includes all energy sources like fossil fuels and other renewable sources. The line marked with multiplication sign markers ($\times$) indicates China's percentage of the global solar power capacity that is installed within China. Data sources: China's National Energy Administration and International Energy Agency.

China is also a global leading provider of solar photovoltaic (PV) modules. As of 2023, China accounted for approximately 86% of global solar PV module production (International Energy Agency, 2023). This dominance extends beyond module production, encompassing the entire solar PV supply chain, including polysilicon, ingots, wafers, and cells. Looking ahead, China has outlined ambitious goals for the expansion of its solar energy infrastructure. The country has aimed to install 3,000 GW of solar capacity by 2035, a five-fold increase from the current level, with plans to further expand this capacity to 5,000 GW by 2050. On the power generation front, China has set equally impressive benchmarks, targeting solar energy generation of 3,500 Terawatt hours by 2035 and 6,000 Terawatt hours by 2050 (Energy Research Institute and Commission, 2019).

2.2 Policies

A key factor in China's solar growth has been the unwavering government support, including subsidies, tax incentives, and programs like the Golden Sun Program and Top Runner Program.[2] Among these supporting policies, the subsidies have played a crucial role. China introduced feed-in tariff (FIT) schemes in the late 2000s. The FIT policy guaranteed a fixed price for solar electricity fed into the grid, with the government collecting a surcharge from consumers to cover the difference between the FIT price and the benchmark tariff (i.e., the cost of sulfur-scrubbed coal power). As the industry matured and costs declined, China began phasing out subsidies starting in 2015. China officially achieved grid parity for solar power in early 2019. Despite the move towards grid parity, China continues to provide subsidies to solar power generators that were built before 2021.

It is important to note that these subsidies are financed through a national surcharge on electricity bills, with the central government managing the funds. Local governments are exempt from these costs, placing the financial burden squarely on the central government. Therefore, these subsidies do not factor into the economic impacts of solar energy development on county-level GDP examined in this study.[3]

2. The Golden Sun program provides subsidies to grid connected and off-grid solar PV power generation projects. The Top Runner Program is designed to increase the use of high-efficiency PV products, thus maximizing energy yield, initiating PV industry transformation.

3. Chinese policies have emphasized the development of distributed solar energy systems since 2020, which generate electricity in close proximity to the point of consumption and minimize the costs of long-distance power transmission (National Energy Administration, 2023). However, distributed solar energy accounts for only a very small share during our studying period from 2005 to 2019.

3 Conceptual Framework

Our analysis builds on a spatial equilibrium model, drawing from the canonical Rosen-Roback framework which was later refined by Moretti (2011). Our goal is to illustrate how solar energy development impacts economic and welfare outcomes at the local level. The model considers a county with a fixed population of $\bar{N}$ and a finite land area of $\bar{L}$. Residents face a choice between settling in the county, where they provide one unit of labor to produce a globally traded good, or pursuing an outside option. The county's land is allocated among three key uses: residential housing, solar farm, and other production facilities. This assumption captures the competing demands for land resource in an urban environment transitioning towards renewable energy.

3.1 Preferences

The indirect utility of individual i in county c is:[4]

$$V_{ic} = V(w_c, r_c, A_c; \epsilon_{ic}) \tag{1}$$

where w_c is the nominal wage rate, r_c the housing price, and A_c a measure of local amenities (e.g., air quality) of county c. The random term ϵ_{ic} captures individual i's idiosyncratic preference for county c. Without loss of generality, we assume that the individual's utility increases with the nominal wage rate and local amenities ($\frac{\partial V_{ic}}{\partial w_c} > 0$, $\frac{\partial V_{ic}}{\partial A_c} > 0$) and decreases with the cost of housing ($\frac{\partial V_{ic}}{\partial r_c} < 0$).

In this model, the utility of residing in county c is determined by three factors: the real wage (defined as the nominal wage rate adjusted for the cost of housing), the county's amenities, and the individual's idiosyncratic preference for county c. The decision to live in county c is made by comparing this location-specific utility to the reservation utility $\bar{V}$ associated with the outside option. Assuming that the random term ϵ_{ij} follows the normalized Extreme Value Type I Distribution, we are able to show that the proportion of population settling in county c is given by (Bayer and Timmins, 2007):

4. In deriving the indirect utility function, we assume a utility function where an individual's well-being is determined by the consumption of a numerarie good, a unit of housing, and a vector or amenities. The price of the numerarie good is normalized to one. Consequently, the indirect utility function is formulated by substituting the optimal consumption levels into the direct utility function, with the expenditure on the numeraire good implicitly represented by the difference between wage rate and housing price.

$$\lambda_c = \frac{V_c}{V_c + \bar{V}} \tag{2}$$

where $V_c = V_c(w_c, r_c, A_c)$ is the deterministic part of the county's utility.

3.2 Production

In county c, a competitive sector is composed of numerous firms, all operating under an identical Constant Returns to Scale Cobb-Douglas production function.[5] The aggregate output of county c is represented by the equation:

$$Y_c = \phi_c Q(N_c, L_c^Y, E_c) \tag{3}$$

where ϕ_c represents the county's productivity, N_c is the aggregate labor input, L_c^Y denotes the land input, and E_c represents the aggregate energy input.

The non-contingent inverse labor demand function for county c is expressed as:

$$w_c = \phi_c \tilde{w}_c(N_c, L_c^Y, E_c) \tag{4}$$

We assume the function exhibits specific properties: $\frac{\partial \tilde{w}_c}{\partial N_c} < 0$, indicating that the wage rate decreases as labor supply increases; $\frac{\partial \tilde{w}_c}{\partial L_c^Y} > 0$ and $\frac{\partial \tilde{w}_c}{\partial E_c} > 0$, implying that the nominal wage rate increases with a rise in production land or energy input.[6]

Following Diamond (2016) and Moretti (2011), we posit that the residential housing supply is influenced by two key factors: the availability of developable land and the aggregate demand for housing. For the sake of simplicity, we express the residential housing supply function as:

$$r_c = r(P_c^R, N_c) \tag{5}$$

where r_c represents the housing price in county c, P_c^R denotes the cost of residential land, which reflects the availability of land for residential development, and N_c signifies the total number of residents in county c, serving as a proxy for housing demand. Both $\frac{\partial r_c}{\partial P_c^R} > 0$ and $\frac{\partial r_c}{\partial N^c} > 0$, indicating that the housing price increases

5. To maintain model tractability, we abstract from explicitly modeling the solar energy generation process. Instead, we adopt a simplified approach wherein land is treated as the sole physical input for solar energy generation in our subsequent analyses.

6. More precisely, Equation (4) represents the marginal product of labor, as labor demand should be expressed as a function of wages, land costs, and energy prices. However, we maintain this alternative expression for analytical tractability.

with both rising land costs and growth in the county's population.

3.3 Government

The local government of county c seeks to optimize a combination of economic performance and residential welfare, assigning varying weights to each objective (Henderson et al., 2022). We model the government's decision-making process as the maximization of a weighted sum of these two objectives. This function guides the allocation of land among three primary uses: residential housing, solar farms, and other production facilities. The resulting optimization problem can be formalized as:

$$\max_{L_c^R, L_c^Y, L_c^S} \Omega(Y_c, V_c) \tag{6}$$

where $\Omega(\cdot)$ represents the government objective function. The economic performance is measured by Y_c, the aggregate output, and the residential welfare is represented by V_c, the indirect utility of a representative resident. L_c^R, L_c^Y, and L_c^S are the land allocations for residential housing, production, and solar farms, respectively.

3.4 Impacts of solar energy development

Before laying out model predictions, we make two key assumptions. First, we treat land as the primary physical input for solar energy generation, directly determining production scale. We abstract from other inputs such as labor and solar radiation in this analysis. This simplification, focusing on land as the binding resource constraint, allows us to better analyze the opportunity costs of land allocation between solar farms and alternative uses. Second, we assume solar energy development affects local productivity through its impact on land sales revenue, an assumption grounded in Chinese land finance practices. Since 2008, China's central bank has mandated that land sales revenue be exclusively allocated to infrastructure construction (Henderson et al., 2022). Consequently, when solar farms occupy land that could otherwise generate sales revenue, they indirectly affect local productivity.[7]

Based on the model setup and these assumptions, we characterize the economic and welfare effects of solar energy development as follows:

7. This approach to modeling resource booms aligns with conventional literature, such as Bartik et al. (2019) and Allcott and Keniston (2018), who incorporate resource booms directly into the total factor productivity of aggregate production functions.

Effect on Economic Output: Solar energy development can have ambiguous effects on local aggregate output, stemming from the interplay of two primary mechanisms.

a) Factor supply: Solar energy development reduces available land for alternative uses, potentially constraining land for production and lowering aggregate output. Meanwhile, solar energy development can augment energy supply and enhance electricity utilization in local production processes, which may positively impact aggregate output. Additionally, solar energy development may influence local population, a mechanism we will elaborate on shortly, potentially exerting an ambiguous effect on aggregate output by altering local labor supply;

b) Productivity: Land allocation to solar farms reduces the county's land sales revenue and thereby limiting local government capacity for productivity-enhancing infrastructure investment, which reduces aggregate output.

Effect on Residential Welfare: The effect of solar energy development on local residential welfare is ambiguous, which is primarily manifested through population changes that reflect the county's altered attractiveness to potential residents. The net effect is contingent upon the relative magnitude and direction of solar energy development's influence on three key factors: a) Nominal wage rates: The impact is ambiguous, hinging on changes in government investment, local energy supply, and population itself; b) Housing prices: The net effect remains ambiguous. Solar farm expansion constrains residential land availability, potentially raising housing prices. This price pressure may be amplified or dampened by changes in local population, which are indeterminate; c) Local amenities: The impact could be positive, for instance, if solar farms contribute to improved environmental quality.

It is important to note that, theoretically, we should not observe negative impacts of solar energy development on both aggregate output and residential welfare, as this would violate the optimization principle. For a detailed derivation of these results, see Appendix A.

4 Data and Method

4.1 Data

Solar farms. We use China's farm-level solar data from 2005 to 2019. Almost all solar plants in China are built after 2005 (see Figure 1), and we exclude data after 2019 to avoid potential confounding effects of COVID-19. The data include each solar farm's longitude, latitude, installed capacity, construction date, and grid connection date. All the solar farms used in the regressions are centralized solar systems. We exclude distributed solar energy systems for two reasons. First, one primary purpose of distributed solar systems in China is to alleviate poverty and improve economic conditions. Including these systems in the regression may obscure the true relationship between solar energy growth and local economic impacts, as these solar projects themselves are a response to existing economic challenges.[8] Second, distributed solar energy accounts for only a small share during our studying period. Figure 2 shows the geographical distribution of solar farms, which are dispersed across northern, eastern, southwestern, and northeastern China. In total, there are 4,496 solar farms.

Economic variables. We compile county-level GDP, GDP by sector, population, government revenue from land sales from the National Bureau of Statistics of China. We also collect county-level firm entry and exit data from the Business Registry Database of the State Administration of Industry and Commerce, and the land transaction data from the Real Estate Registration Center of the Ministry of Natural Resources.[9]

Environmental variables. We obtain daily air quality data from the Ministry of Ecology and Environment, covering over 2,500 air quality monitoring sta-

8. China has implemented a targeted approach to poverty alleviation through the deployment of distributed solar photovoltaic systems, particularly in rural areas. This initiative, known as the Solar Energy for Poverty Alleviation Program, was launched in 2014 with the goal of providing stable energy access and generating income for impoverished households. By 2020, the program aimed to add over 10 Gigawatt of solar capacity, benefiting more than 2 million households across approximately 35,000 villages.

9. The data on land transaction are derived from around 1.8 million individual land transaction records covering the years 2000 to 2020 from the LandChina website managed by the Real Estate Registration Center of the Ministry of Natural Resources (https://www.landchina.com/). Each land parcel transaction is geocoded using the specific address of the land parcel, and the size of the land area involved in the transaction is also recorded. Only land parcels designated for residential and industrial/commercial purposes are available for bidding in the land transaction market and have associated prices. Therefore, the calculation of land transaction volume is specifically based on these two types of land parcels.

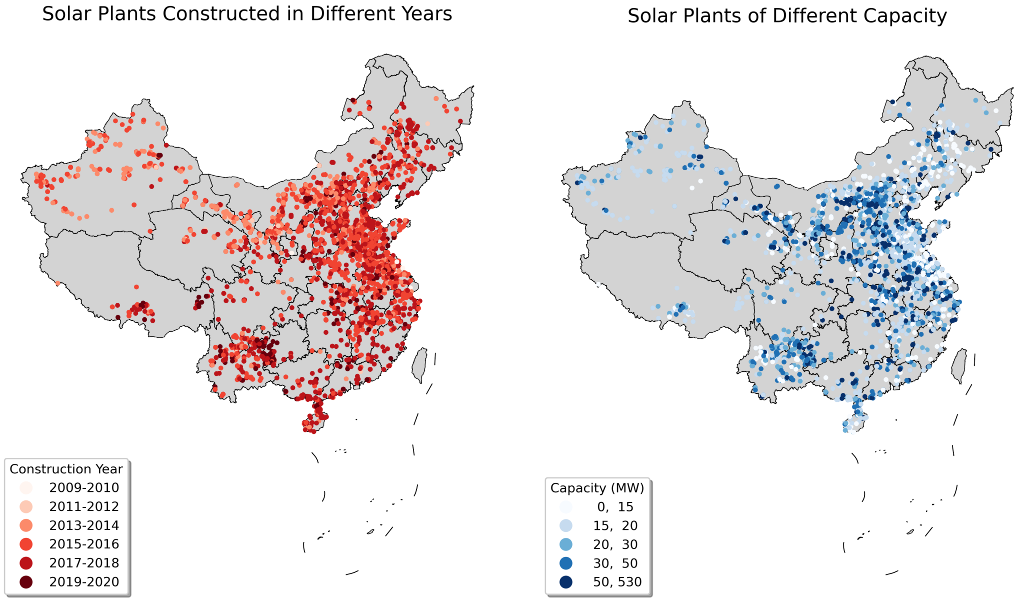

FIGURE 2 Solar farms by grid connection year and installed capacity

tions across China since 2014. The data include the Air Quality Index (AQI) and concentrations of $PM_{2.5}$, PM_{10}, CO, SO_2, and O_3. We use air quality stations' coordinates to construct county-level air quality and pollution variables: the data is first interpolated to a $0.1° \times 0.1°$ resolution using the Inverse Distance Weighted method, and then averaged to county level.

Geographical variables. We gather land use data from the China Land Cover Dataset, which has a spatial resolution of 30 meters and identifies nine major land types: Cropland, Forest, Shrub, Grassland, Water, Snow and Ice, Barren, Impervious, and Wetland (Yang and Huang, 2021). We match the land use data in the year prior to the solar farm installation with solar farm geographic data to determine the area of different types of land occupied by solar plants. As we do not have the geographic boundary information of each solar farm, we infer the land area occupied by each solar farm based on the capacity of the solar farm and a conversion factor that transforms installation capacity to surface area in square meters.[10] Then, we assume each solar farm occupies a circular area centered on its midpoint. Finally, we overlay the circular area onto the land use map and calculate the area of different land types within the circle.

The urbanization rate data are derived from Li et al. (2020), who provide dynamic urban boundary delineations based on the global artificial impervious area

10. Statistics show that for each 1 megawatt of solar farm capacity, the average land area occupied is 2.5 hectare, which includes the land for photovoltaic panel installation and that for amenities.

mapping. We compute the county-level urbanization rate by calculating the proportion of these urban polygons that fall within each county's administrative boundaries across different years. In heterogeneity analysis, we also use the mean elevation and slope of each county derived from the Shuttle Radar Topography Mission.

4.2 Method

Our baseline estimation uses a difference-in-differences (DID) specification that compares the change in outcome variables before and after solar farm installation. Formally, the DID specification is as follows:

$$Outcome_{i,t} = \beta Treated_i * Post_{i,t} + \theta_i + \theta_t + \epsilon_{i,t} \tag{7}$$

where i indexes counties and t indexes years. $Outcome_{i,t}$ denotes the outcome variable in county i in year t, such as the natural log of real GDP per capita. $Treated_i$ is a binary variable indicating whether the county has at least one solar farm during the sample period, and $Post_{i,t}$ is a binary variable that equals one for post-treatment years in treated counties, and zero otherwise. Our baseline analysis defines the treatment year as the year when the full capacity of the first solar farm is connected to the grid in the county. Later on, we show that the main results are robust to defining the treatment year as the year when the first solar farm begins connecting to the grid in the county. The county fixed effects θ_i and year fixed effects θ_t are included to account for county-specific confounding factors and annual common shocks, respectively. The $\epsilon_{i,t}$ denotes the residual term. We estimate this equation using ordinary least squares (OLS) with standard errors clustered at the city level to allow for unspecified correlation in the error terms across counties within each city.

Given the great variation in installed capacity across solar farms (as displayed in Figure 2), we also use a DID design with a continuous treatment:

$$Outcome_{i,t} = \beta Capacity_{i,t} + \theta_i + \theta_t + \epsilon_{i,t} \tag{8}$$

where $Capacity_{i,t}$ denotes the cumulative installed capacity of all solar farms in county i up to year t. Since the dependent variable is in logarithmic form, β represents the estimated average percentage change in $Outcome_{i,t}$ for each megawatt increase in installed capacity. This equation is also estimated using OLS with standard errors clustered at the city level.

Considering the potential endogeneity of the treatment arising from non-random distribution of solar farms, we employ two alternative estimation methods. First, we adopt an event study to verify the identification assumption underlying the DID estimation (7) that in the absence of solar farms, counties with solar farms (i.e., the treated group) and those without (i.e., the control group) would have identical trends in $Outcome_{i,t}$. While we cannot directly test this counterfactual, we can examine whether the trends before the treatment were the same by estimating the following event study model:

$$Outcome_{i,t} = \sum_{k=-5,k\neq-1}^{5} \beta_k Solar_{i,t+k} + \theta_i + \theta_t + \epsilon_{i,t} \tag{9}$$

where $Solar_{i,t+k}$ is an indicator variable for the k^{th} year relative to the event time (the year of the first grid connection in the county). The coefficients β_k for $k \geq 0$ capture the dynamic effects of the treatment after the event has occurred. The coefficients β_k for $k < 0$ serve as a placebo or falsification test. This equation is also estimated using OLS with standard errors clustered at the city level.

Second, we construct a Bartik IV for installed capacity in model (8) as:

$$IV_{i,t} = Endowment_i * \sum_i Capacity_{i,t-1} \tag{10}$$

where $Endowment_i$ denotes the solar radiation endowment of county i, acting as the "share" component of a Bartik IV. The term $\sum_i Capacity_{i,t-1}$ represents the national cumulative installed solar capacity up to the previous year, serving as the "shift" component of a Bartik IV. The solar radiation endowment is exogenous and influences the incentive to build a solar farm. Similarly, the national capacity up to the previous year is exogenous to a county's GDP but captures other factors, such as photovoltaic technology level, that affect the incentive for solar farm development.

5 Effects on Economic Outputs

We present the baseline results in subsection 5.1, followed by robustness checks in subsection 5.2. Next, we explore the underlying mechanisms in subsection 5.3 and examine heterogeneous effects in subsection 5.4.

5.1 Baseline results

The baseline results for GDP are presented in Table 1. In all columns, the dependent variable is the natural log of real GDP per capita. Column (1) shows the DID estimates from Equation (7). We find that $\beta < 0$, suggesting that solar farm has a negative impact on GDP. The point estimate implies an average 2.7% decrease in GDP per capita. Column (2) reports the estimates of the DID model with the continuous installed capacity as the key explanatory variable, as specified in Equation (8). Column (3) presents the two-stage least squares (2SLS) estimates of Equation (8) using the Bartik IV constructed in Equation (10). The 2SLS estimate suggests that a 1-MW increase in installed capacity corresponds to a 0.3% decrease in GDP per capita. Considering the average capacity of 13.1 MW per solar power plant, this translates to an average 3.9% decrease in GDP per capita, which aligns closely with the DID estimates in column (1). The OLS estimate reported in column (2) also suggests a significantly negative effect of installed capacity, but the estimated effect size is larger. Given our data involves staggered treatment adoption, we also employ the Callaway and Sant'Anna DID methodology. The results, which confirm the robustness of our finding, are shown in Appendix B.

TABLE 1 Effects of solar farms on GDP per capita

	(1)	(2)	(3)
	DID	OLS	IV
$Treated_i * Post_{i,t}$	-0.027*		
	(0.014)		
$Capacity_{i,t}$		-0.008**	-0.003***
		(0.004)	(0.001)
Mean of $Capacity_{i,t}$		13.1	13.1
Kleibergen-Paap F statistic			26.4
Observations	33,701	33,701	30,848
R-squared	0.950	0.950	-1.402

Notes: The dependent variable is the natural log of the real GDP per capita. Column 1 presents the DID estimates based on Equation (7). Column 2 presents the intensity DID estimates based on Equation (8). Column 3 presents the IV estimates using the Bartik IV constructed in Equation (10). Standard errors reported in parentheses are clustered at the city level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

In Figure 3, we visualize the dynamic effects of solar farm on GDP using the event study specification of Equation (9). Panel A shows the coefficient estimates for the natural log of real GDP per capita. All estimates of β_k are statistically insignificant and close to zero for $k < 0$. This finding supports the identification assumption that counties with early, late, or no solar farm installations have no differential trends prior to installation. Significant negative impacts emerge two years after solar farm installation, dropping by approximately 10% below its initial level before gradually recovering. Panels B to D report the estimates for the log of industrial GDP per capita, service GDP per capita, and agricultural GDP per capita, respectively. The industrial and service sectors account for the majority of the effects, exhibiting trends similar to the overall GDP. In contrast, agricultural GDP remains unaffected. Figure 3 also suggests a potential rebound pattern of the coefficients, indicating that our estimated negative effects likely depict the short-to-medium-term consequences of solar installation.

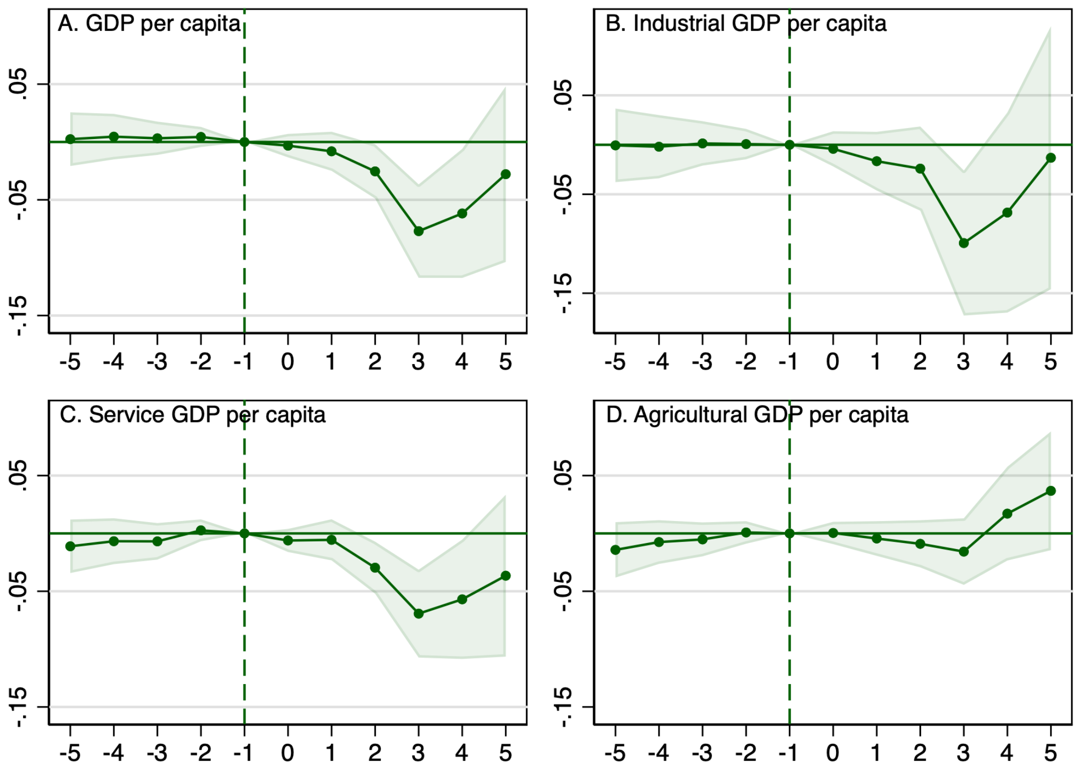

FIGURE 3 Dynamic effects of solar farms on GDP across sectors

Notes: This figure presents the dynamic effects of solar farms on GDP per capita, estimated based on the event study model (9). The dependent variable in Panel A is the natural log of real GDP per capita, while those in Panels B–D are the natural log of the real GDP per capita from the industrial, service, and agricultural sectors, respectively. The shaded areas denote the 95% confidence intervals calculated based on standard errors clustered at the city level.

5.2 Robustness checks

We examine the robustness of the estimated effect on GDP per capita by considering alternative model specifications, weighting methods, event timing, potential confounding from local governments' environmental protection efforts, and spillover effects. The robustness checks are based mainly on the event-study model that estimates the dynamic effects and tests the parallel-trends assumption. All model settings remain consistent with those in model (9), except as noted in each robustness check.

Robust to model specifications. Figure 4 examines the robustness to a set of model specifications. Panels A and B adjust the clustering level of the residual term from city level to the county level and city-year level, respectively. Panel C includes county-specific time trends to capture unobservable county-specific time-varying factors. Panel D consolidates periods beyond the specified leads and lags into the aggregate coefficients, with lead periods ≤ -5 accumulated into the -5th period and lag periods ≥ 5 accumulated into the 5th period (Schmidheiny and Siegloch, 2023). All resulting estimates are comparable to the baseline estimates presented in Panel A of Figure 3, confirming the robustness of our results to alternative specifications.

Robust to weighting methods. As alternatives to the unweighted baseline regression in Panel A, we apply weighted regressions using territorial area size, GDP per capita, and population in 2010 as weights in Panels B to D of Figure 5, respectively. Weighting by area size is justified when the impact of solar farms is expected to vary with the geographical size of the local area, as larger areas may have more land available for solar farm development. When weighting by GDP per capita, regions with higher economic output exert more influence on the estimated effects, highlighting the overall economic impact. Finally, weighting by population assumes that the effect of solar farms on the local economy is proportional to the population size, which is reasonable given that larger populations typically correspond to greater economic activity and energy demand. Figure 5 demonstrates the robustness of the negative effects on the local economy across various weighting specifications.

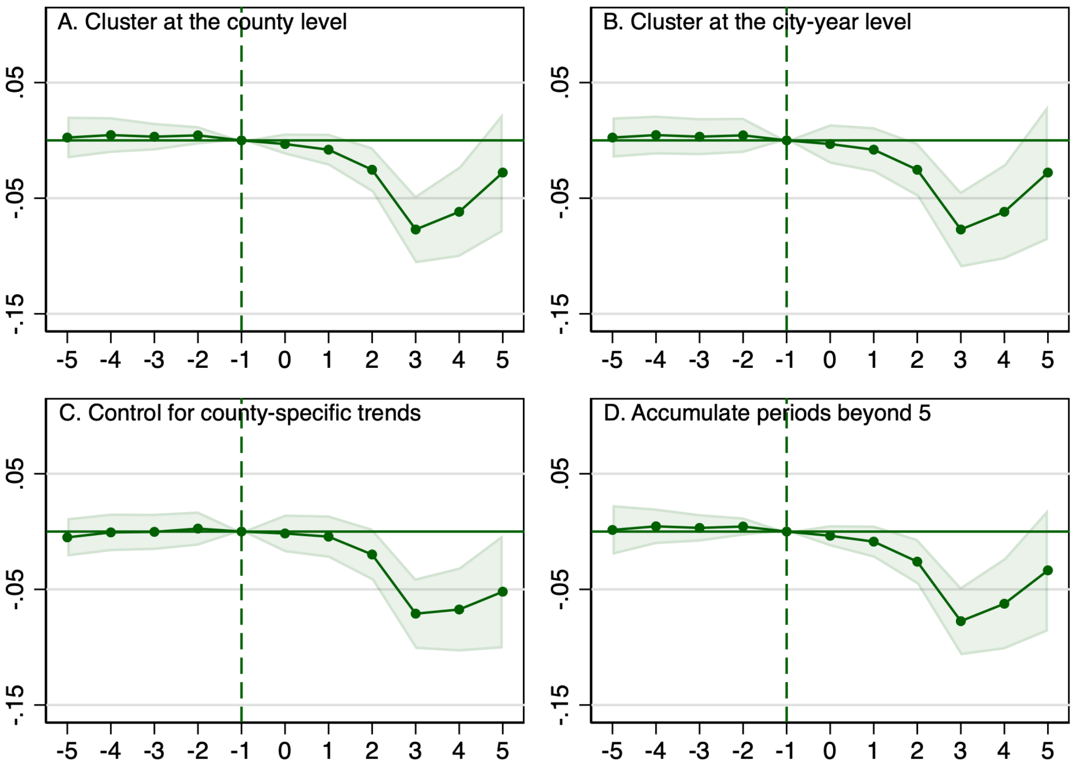

FIGURE 4 Robustness checks: Alternative model specifications

Notes: This figure examines the robustness of the baseline event-study estimates for the natural log of the real GDP per capita. Panels A and B cluster the error term at the county and city-year level, respectively. Panel C controls for county-specific year trends. Panel D accumulates periods beyond pre and post 5th periods into the -5 and 5 periods respectively. Standard errors are clustered at the city level in Panels C and D. The shaded areas denote the 95% confidence intervals.

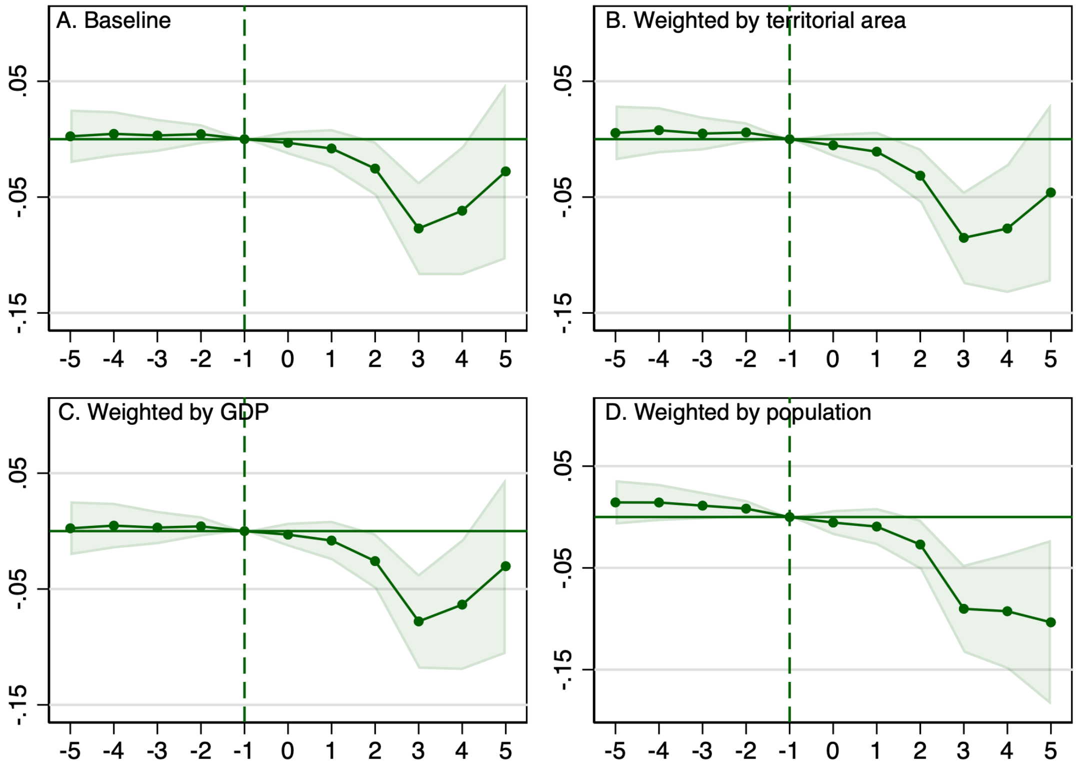

FIGURE 5 Robustness checks: Weighted regressions

Notes: This figure examines the robustness of the baseline estimates using weighted regressions. The dependent variable in all panels is the natural log of the real GDP per capita. Panel A presents the baseline results for comparison. Panel B uses the log of each county's territorial area as weights. Panel C weights observations by the log of real GDP per capita, and Panel D by the log of population. Standard errors are clustered at the city level. The shaded areas denote the 95% confidence intervals.

Robust to event timing. While the baseline regression uses the year when the full capacity of the first solar farm is connected to the grid as the event time in each county, this robustness test uses the year when the first solar farm begins connecting to the grid, which occurs several months to years earlier. The results, shown in Figure 6, reveal that the negative effects on total GDP, industrial GDP, and service GDP are consistent with the baseline findings.

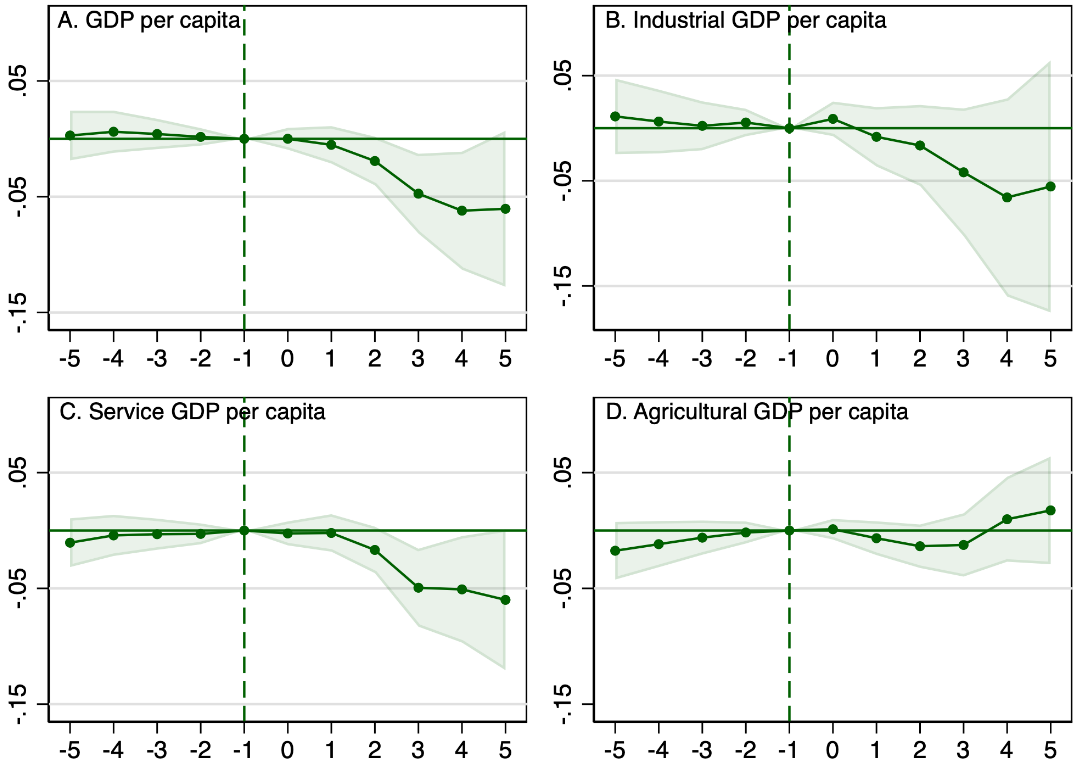

FIGURE 6 Robustness checks: Alternative event timing

Notes: This figure examines the robustness of the baseline estimates using alternative event timing, specifically when the first solar farm begins connecting to the grid. The four panels display results for the log of real GDP per capita, real industrial GDP per capita, real service GDP per capita, and real agricultural GDP per capita, respectively. Standard errors are clustered at the city level. The shaded areas denote the 95% confidence intervals.

Potential confounding effect of environmental attitude. A potential threat to our identification is that the local governments' willingness to protect the environment might be positively correlated with solar farm installation and negatively correlated with economic performance due to the costs of environmental regulation. Our baseline analysis relieves this concern by including various fixed effects and supporting the parallel-trends assumption. To explicitly address this concern, we examine whether the timing of solar farm installation is correlated with local governments' attitudes toward environmental protection. We adopt two measures of these attitudes – the frequency of air pollution-related terms in government annual reports and the length of environmental policy documents (Zhang and Chen, 2021). We estimate the effect of solar farm installation on government attitudes using modified versions of the event-study model (9) with these attitude measures as dependent variables. Figure 7 shows that these measures are not significantly correlated with solar farm installation, either before or after the installation. These results relieve the concern that the timing of solar farm installation could be affected by the environmental attitudes of local governments.

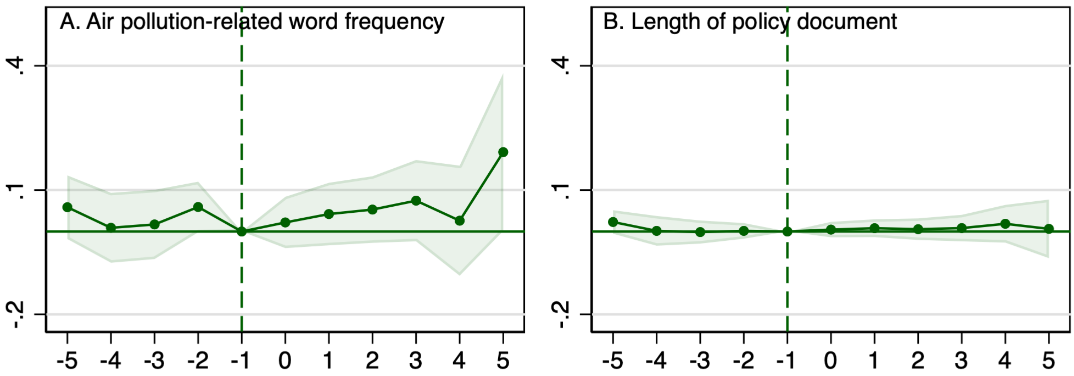

FIGURE 7 Robustness checks: Environmental attitudes

Notes: This figure addresses the potential confounding effects of government's environmental attitudes. The dependent variable in Panel A is the natural log of the frequency of air-pollution-related words in government annual reports, and the dependent variable in Panel B is the natural log of the total word counts of environmental policy documents. Standard errors are clustered at the city level. The shaded areas denote the 95% confidence intervals.

Spatial spillover effects. Another concern involves the potential for spatial spillover effects. Counties may share economic resources, labor markets, and air quality with neighboring counties, resulting in the propagation of the impacts of solar energy development over space. To more precisely estimate the localized economic impacts, we incorporate the solar energy developments of neighboring counties into our regression model. This approach helps mitigate potential omitted variable bias, ensuring that our estimated effects are not confounded by contemporaneous solar installations in adjacent areas. Specifically, as presented in Appendix B, we additionally control for the solar power installation of bordering counties, counties within 50km, and counties within 100km of the focal county, respectively, in the DID model Equation (7). The resulting estimates remain consistent across specifications.

5.3 Mechanism

This subsection investigates the underlying mechanisms of the negative economic impacts of solar energy development.

5.3.1 Land competition effect

Solar farms typically require substantial land for photovoltaic panels and related infrastructure. According to the United States National Renewable Energy Laboratory, solar farms require approximately 3.5 acres per gigawatt-hour per year, or 2.5-2.8 acres per megawatt of installed capacity (Ong et al., 2013). As a comparison, coal power plants require only about 10% of the land needed for solar farms (Mitavachan and Srinivasan, 2012). As a result, solar farms often occupy land that could have been used for other purposes. If these alternative uses could have generated higher returns, solar farm installation could diminish economic performance.

Figure 8 displays the distribution of land types used for solar farms. As detailed in subsection 4.1, we calculate the share of nine major land types based on land use data before the construction of solar farms. We find that croplands account for 45.2% of the total, followed by impervious surfaces at 21.3% and grasslands at 17.1%. Forests cover 9.7%, and barren lands and water bodies make up the remaining 6.7%. Impervious surfaces, made of hard, non-porous materials, often represents high-value land with active economic activities in a county. Using impervious surfaces for solar farms imposes much higher opportunity cost, as it sacrifices land that could be used for other, potentially more valuable economic activities.

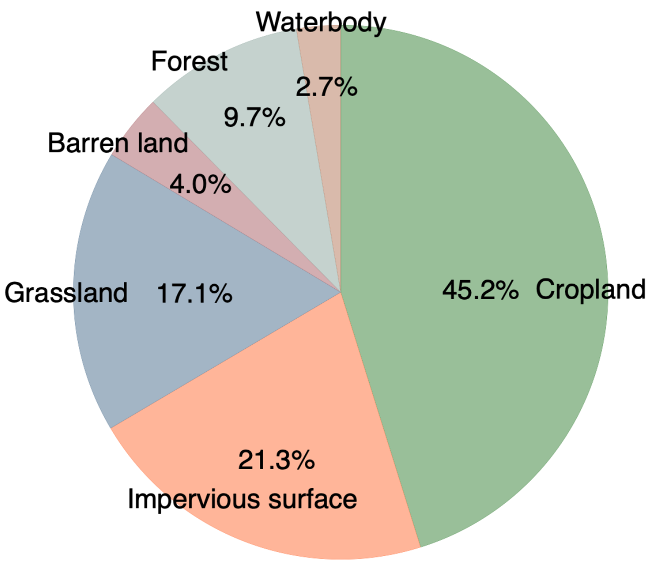

FIGURE 8 Land used for solar farms by land type

Notes: This figure presents the share of each land type used for solar farms. Calculation details are provided in subsection 4.1.

If the land competition effect contributes to the observed negative economic impact of solar farms, we would expect a stronger negative impact in counties where more solar farms were built on impervious surfaces. To empirically examine this, we employ a model where we interact the DID term with the share of each type of land used for solar farm installation in each county:

$$GDP_{i,t} = \beta Treated_i * Post_{i,t} + \delta Treated_i * Post_{i,t} * Land_i + \theta_i + \theta_t + \epsilon_{i,t} \quad (11)$$

where $Land_i$ denotes the share of a specific type of land type used for solar farms in county i. Other variables are the same as the baseline model.

Table 2 presents the estimated effects across six distinct land types. A statistically significant negative interaction effect is observed solely for impervious surfaces, as shown in Column (3). This finding suggests that the negative economic impact is more pronounced when solar farms are constructed on impervious surfaces. Quantitatively, a 1% increase in impervious surfaces utilized for solar farms corresponds to a 0.21% reduction in GDP per capita. Given that 21% of solar farms are situated on impervious surfaces, this result indicates that competition for high-value land is a primary driver of the negative economic impact associated with solar power installations.

Notably, the interaction effects for forest and water body land types are statistically significant and positive. As shown in Columns (5) and (7) of Table 2, a 1% increase in the share of forest and water body areas utilized for solar farms corresponds to increases in GDP per capita of 0.12% and 0.30%, respectively. These findings further corroborate the land competition hypothesis, suggesting that the economic impacts can be positive when solar farms are situated on lands with lower economic value. This result also underscores a critical policy implication: the negative economic impacts of solar farm installations could potentially be mitigated or even reversed by prioritizing their placement on low-value lands. However, it is important to note that the relatively small proportions of forest (9.7%) and water body (2.7%) currently used for solar farms indicate that the negative effects from occupying impervious surfaces remain dominant in the overall economic impact. To further investigate the mechanism behind the land competition effect, we decompose GDP into its sectoral components—agricultural, industrial, and service GDP. The results show that land competition with high-value land (i.e., impervious surfaces) negatively impacts all three sectors. See Appendix C for detailed results.

TABLE 2 Mechanism: Land competition

	(1)	(2)	(3)	(4)
		Interaction with land shares		
	Baseline	Cropland	Impervious surface	Grassland
$Treated_i * Post_{i,t}$	-0.027*	-0.035	0.013	-0.037**
	(0.014)	(0.022)	(0.016)	(0.017)
$Treated_i * Post_{i,t} * Land_i$		0.018	-0.215***	0.051
		(0.041)	(0.046)	(0.049)
Mean of $Land_i$		0.45	0.21	0.17
Observations	33,701	33,701	33,701	33,701
R-squared	0.950	0.950	0.950	0.950

	(1)	(5)	(6)	(7)
		Interaction with land shares		
	Baseline	Forest	Barren land	Water body
$Treated_i * Post_{i,t}$	-0.027*	-0.037**	-0.025*	-0.033**
	(0.014)	(0.016)	(0.015)	(0.014)
$Treated_i * Post_{i,t} * Land_i$		0.115**	-0.019	0.296***
		(0.046)	(0.080)	(0.120)
Mean of $Land_i$		0.09	0.04	0.03
Observations	33,701	33,701	33,701	33,701
R-squared	0.950	0.959	0.950	0.950

Notes: The dependent variable in all columns is the natural log of the real GDP per capita. Column (1) replicates the baseline DID estimates to facilitate comparison. Columns (2)–(7) present the estimates of Equation (11), which interacts the DID term with the share of each type of land used for solar farms. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

To further examine the land competition effect, we apply the event study model to analyze the effects of solar farm installations on land sales. If solar farm installations indeed reduce economic growth by occupying high-value land, we would expect a decline in land transactions for high-return economic activities. Figure 9 presents the estimated dynamic effects of solar farm installations on the natural log of area of land sold, revenue from land sales, and the number of land transactions, across both residential and industrial & commercial land. The results indicate a decrease in the area sold for both residential and industrial & commercial land in counties with solar farms relative to control counties. Moreover, we also observe a decline in government revenue from residential land sales. An alternative hypothesis for the observed decline in residential land transactions and sales revenue is that proximity to solar farms might deter potential residents, thereby reducing housing demand. However, our subsequent analysis reveals increases in both local population and housing prices, which contradicts this demand-driven explanation.

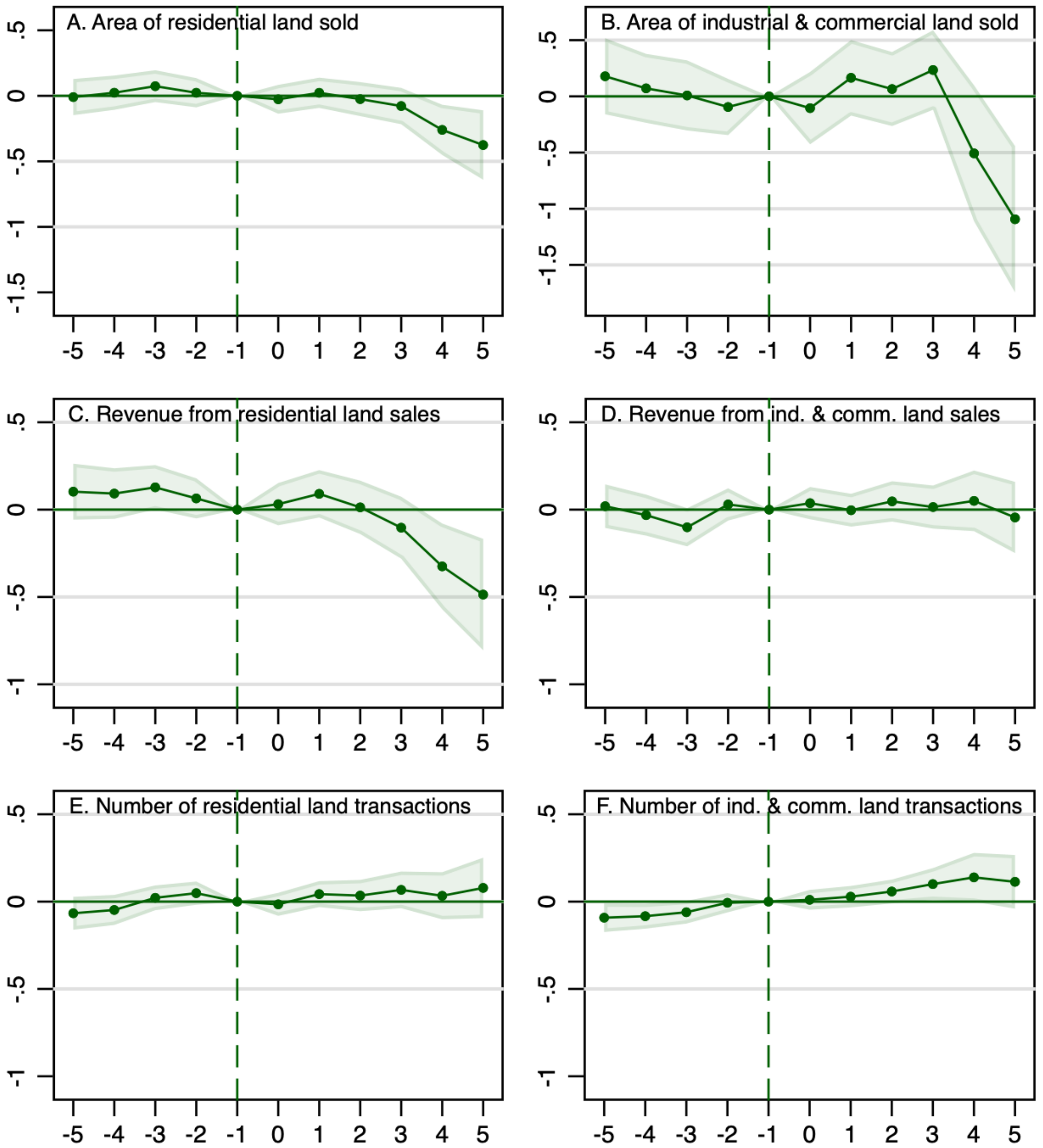

FIGURE 9 Mechanism: Effects on land sales

Notes: The dependent variables in Panels A–F are the natural logs of area size of residential and industrial & commercial land sold, revenue from residential and industrial & commercial land sales, and the number of residential and industrial & commercial land transactions, respectively. The shaded area denotes the 95% confidence intervals constructed based on standard errors clustered at the city level.

Solar farm requires large land areas, and owners typically choose to lease the land to reduce risks and protect cash flow, resulting in lower immediate government income compared to selling the land outright. During our study period, the average unit price of residential land parcels was significantly higher than that of industrial and commercial land parcels (He et al., 2022; Henderson et al., 2022). Consequently, revenue from residential land sales plays a vital role in local economic growth (Mo, 2018). The loss of revenue from residential land sales thus represents a key reason for the observed GDP decline. To validate the idea that the decline in residential land sales revenue is a primary explanation for the GDP decline, we provide a brief calculation here. While revenue from land sales does not directly contribute to local GDP, it is a crucial income source, accounting for over 40% of local government revenue (Gyourko et al., 2022). This income then becomes government spending, a significant driver of local GDP growth in China, representing about 35% to 40% of GDP (Liu, 2020). Taking these numbers combined, we can infer that revenue of residential land sales indirectly contributes to about 14% of local GDP. Therefore, on average, the roughly 20% observed decrease in land revenue would result in an approximately 2.8% decline in GDP, *ceteris paribus*, which closely matches our estimates for the effects on GDP.

5.3.2 Productivity effects

Solar farms are typically established on leased land through contracts spanning 30 to 35 years, resulting in long-term commitments that effectively immobilize large tracts of land. These extended commitments constrain local governments' capacity to generate revenue through land sales and invest in productivity-enhancing infrastructure. Consequently, this reduction in government investment can lead to a deterioration of local productivity, which diminishes the region's attractiveness to businesses.[11] Figure 10 presents the decline in total factor productivity (TFP) following solar power installation, a result that is robust across different TFP estimation methods. Through this mechanism, the land competition effect propagates beyond a mere reduction in government revenue, potentially triggering broader negative economic consequences that can persist for longer periods.

11. The literature on fiscal multipliers in China emphasizes the critical role of government spending in stimulating local economic activity. Guo et al. (2016) estimate that each RMB of county government expenditure can generate a 1.2 RMB increase in intra-county investment.

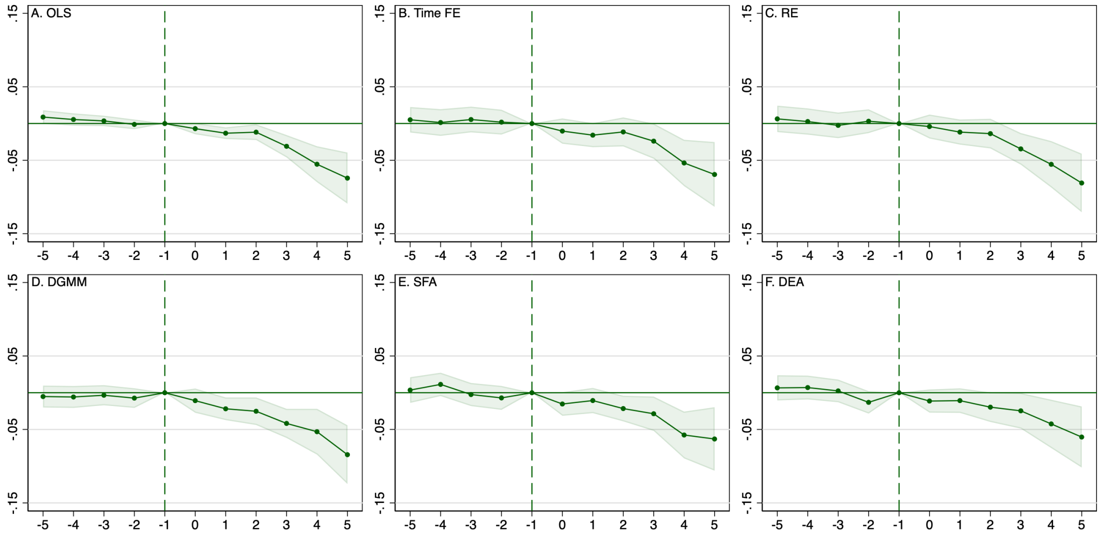

FIGURE 10 Mechanism: Effects on total factor productivity

Notes: This figure presents the estimates from Equation (9) with county-level total factor productivity (TFP) as the dependent variable. Panels A–F display the results using different methods to estimate the TFP: OLS, time fixed effects, random effects, dynamic generalized method of moments, stochastic frontier analysis, and Malmquist Index through data envelopment analysis, respectively. The shaded area denotes the 95% confidence intervals constructed based on standard errors clustered at the city level.

To shed light on the cascading economic consequences, we examine the effects of solar energy development on firm entry. Panel A of Figure 11 illustrates a decline in the total number of firm entries following solar farm installations. This result helps further explain the observed GDP declines. Specifically, Panels C and D reveal decreases in the entry of agricultural and service firms, while Panel B indicates that industrial firm entry remains relatively stable. The diminished entry of agricultural and service firms suggests two possible explanations. These firms may be more reliant on robust infrastructure and high productivity levels, which could be compromised by solar farm development. Additionally, as many of these firms are small businesses that operate within or near residential areas, their reduced entry may directly stem from the decrease in available residential land. The productivity effect is also evidenced by the change in firm exits, as shown in Appendix D.

The conceptual model suggests that solar energy development enhances local energy supply. While we document that solar energy development has indeed boosted local energy supply in Appendix E, increasing total electricity consumption by 7.9%, these benefits have not translated into sufficient economic gains to counterbalance the adverse effects of land allocation for solar farms.

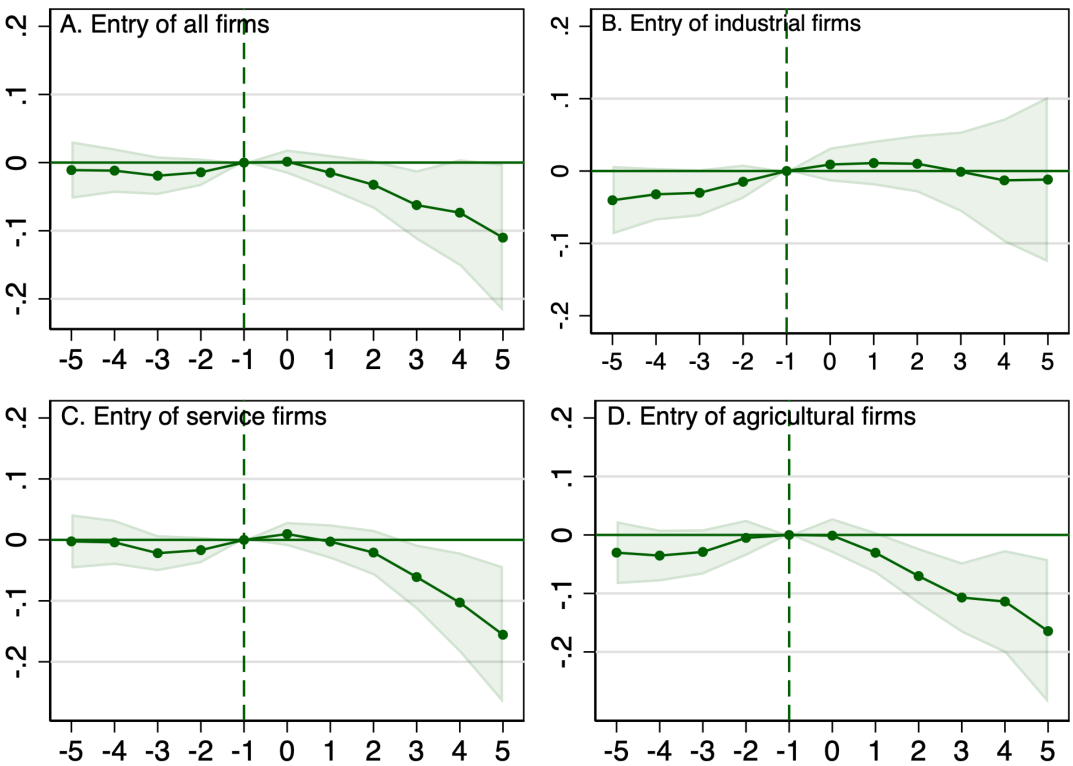

FIGURE 11 Mechanism: Effects on firm entry

Notes: This figure presents the estimates from Equation (9) using different dependent variables. The dependent variables in Panels A–D are the log of the total number of firm entries, the log of industrial firms entries, the log of service firm entries, and the log of agricultural firm entries, respectively. The shaded area denotes the 95% confidence intervals constructed based on standard errors clustered at the city level.

5.4 Heterogeneity

The results presented thus far focus on the average treatment effects of solar farm installation. We expect these effects to vary across counties with different geographical suitability for solar farms, economic levels, and urbanization rates. These factors influence the opportunity costs and benefits of solar farm installation.

We employ a DID specification to examine the heterogeneous effects of solar farms, with the results shown in Table 3. Panel A reports the heterogeneous effects across counties with different geographical features, focusing on counties' slope (Column 2) and elevation (Column 3). Counties with higher average slope experience smaller negative impacts on output, as the coefficient for the interaction term between solar installation and slope is significantly positive. This finding aligns with the proposed mechanism that the opportunity cost of allocating land to solar farms is lower in counties with steeper slopes, which are less suitable for other economic activities. Elevation has insignificant impacts, as the interaction coefficient between solar installation and elevation is statistically indistinguishable from zero. This suggests that while slope matters, differences in elevation alone do not significantly moderate the negative relationship between solar energy development and GDP.

Panel B focuses on economic heterogeneity by adding interaction terms between the DID variable and key economic indicators: natural log of real GDP per capita, industrial share in GDP, service share in GDP, and agricultural share in GDP. These economic variables are calculated using the 2005-2008 averages, prior to the installation of the national first solar farm, to avoid endogeneity issues. The findings in Panel B show that the interaction terms for log GDP per capita (Column 4) and industrial share in GDP (Column 5) are significantly negative. This suggests that the negative economic impacts of solar farms are more pronounced in counties with higher GDP per capita or a larger industrial sector. In China, a high industrial share typically correlates with a higher economic level, which increases the opportunity cost of land. Conversely, the interaction terms for service share (Column 6) and agricultural share (Column 7) are significantly positive, with the agricultural share having the largest effect. The lower opportunity costs of using agricultural land for solar farms may explain this.

Panel C examines heterogeneity related to urbanization. We measure urbanization rate using the proportion of urban land area, rather than the share of population residing in urban areas. This metric aligns more closely with our study's focus on land use dynamics. The results indicate that counties with higher urbanization levels in 2005, as well as those experiencing substantial urban growth between 2000 and 2005, face more pronounced negative economic impacts from solar energy development. These findings reinforce our land competition hypothesis. Both a high initial urbanization rate and rapid urban growth (prior to the establishment of the first solar farm) signify high opportunity costs of land use. Consequently, the installation of solar farms in such counties likely displaces or precludes higher-value economic activities, resulting in more substantial economic trade-offs.[12]

12. In China, the average urbanization rate, measured by the share of urban land, was just about 1% during 2000–2005. Thus, while urbanization rates in 2005 were relatively high in certain counties than in other counties, they remained low in absolute terms. These counties were still undergoing urbanization and required significant land for future economic activities, unlike in some developed countries where a high urbanization rate might indicate a largely completed urbanization process.

TABLE 3 Heterogeneity

Panel A: Geographical heterogeneity (log GDP per capita as dependent variable)

	(1)	(2)	(3)
		Interaction with geographical variables	
	Baseline	Log slope	Log elevation
$Treated_i * Post_t$	-0.027*	-0.020	-0.027*
	(0.014)	(0.014)	(0.014)
$Treated_i * Post_t * Intera_i$		0.049*	0.005
		(0.026)	(0.008)
Observations	33,701	33,642	33,627
R-squared	0.950	0.947	0.946

Panel B: Economic heterogeneity (log GDP per capita as dependent variable)

	(1)	(4)	(5)	(6)	(7)
		Interaction with economic variables			
	Baseline	Log GDP per capita	Industrial share	Service share	Agricultural share
$Treated_i * Post_t$	-0.027*	-0.017	-0.020	-0.019	-0.028*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$Treated_i * Post_t * Intera_i$		-0.129***	-0.566***	0.487***	0.582***
		(0.023)	(0.062)	(0.116)	(0.081)
Observations	33,701	33,141	33,087	33,087	33,014
R-squared	0.950	0.950	0.950	0.949	0.950

Panel C: Urbanization heterogeneity (log GDP per capita as dependent variable)

	(1)	(8)	(9)
		Interaction with urbanization variables	
	Baseline	Urbanization in 2005	Change in urbanization during 2000-2005
$Treated_i * Post_t$	-0.027*	-0.016	-0.019
	(0.014)	(0.015)	(0.014)
$Treated_i * Post_t * Intera_i$		-0.025***	-0.004***
		(0.008)	(0.001)
Observations	33,701	33,701	33,701
R-squared	0.950	0.950	0.950

Notes: The dependent variable in all columns is the log of real GDP per capita. Column (1) replicates the baseline DID estimates to facilitate comparison. Columns (2)–(9) present the estimates of Equation (11) with new interaction terms. Panel A examines the mediating effects of geographic variables by interacting the DID term with county average slope and elevation. Panel B focuses on economic variables, interacting the DID term with log GDP per capita and the shares of industry, services, and agriculture in GDP. The interaction terms in columns (4)–(7) use 2005-2008 averages, predating China's solar energy development to avoid endogeneity. Panel C assesses urbanization effects, interacting the DID term with county urbanization rates in 2005 and changes from 2000 to 2005, similarly chosen to predate the sample period. All the $Intera_i$ variables are de-meaned. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

6 Effects on Residential Welfare

Although GDP reflects economic output, it may not provide a complete picture of local welfare. Our conceptual model suggests that population change better reflects the net welfare effect of solar energy development, as people "vote with their feet," migrating to places where their overall well-being improves.

Panel A of Figure 12 demonstrates a local population increase of up to 2% following the initial installation of a solar farm, suggesting an improvement in residential welfare. Panels B and C reveal approximately a 5% decline in wage rates and a comparable increase in housing prices, respectively. The wage rate decline can be partially attributed to reduced local productivity, and the housing price increase reflects the decreased residential land availability. More importantly, these patterns indicate a substantial enhancement in local amenities, despite our inability to fully observe them directly. The net welfare change depends on the relative magnitudes of changes in wage rates, housing prices, and local amenities. In this context, the observed population growth, coupled with declining wages and rising housing prices, suggests that residents are willing to accept lower labor compensation and higher living expenses in exchange for improved amenities.

We provide empirical evidence suggesting that the observed population growth can be attributed to improvements in the local environment, particularly enhanced air quality. Panels D and E of Figure 12 demonstrate reductions in CO and SO_2 concentrations, respectively–the primary pollutants emitted by fossil fuel-based power plants. Furthermore, Panel F illustrates that counties experience a decline in incumbent electricity generation firms, primarily fossil-based generators, following the installation of solar farms.

Appendix F presents additional results for other air pollutants, including O_3, NO_2, and $PM_{2.5}$. These pollutants did not exhibit a downward trend following solar farm installations. This lack of change aligns with their primary sources being non-energy related, such as transportation, or their nature as secondary pollutants, rendering them less responsive to shifts in energy generation composition. The absence of significant changes in these pollutants serves as a placebo test, reinforcing the robustness of our main findings. It suggests that the observed effects of solar power deployment on GDP are not confounded by omitted variables such as government environmental regulatory stringency. Had such confounding factors been present, we would expect to observe concurrent declines in O_3, NO_2, and $PM_{2.5}$.

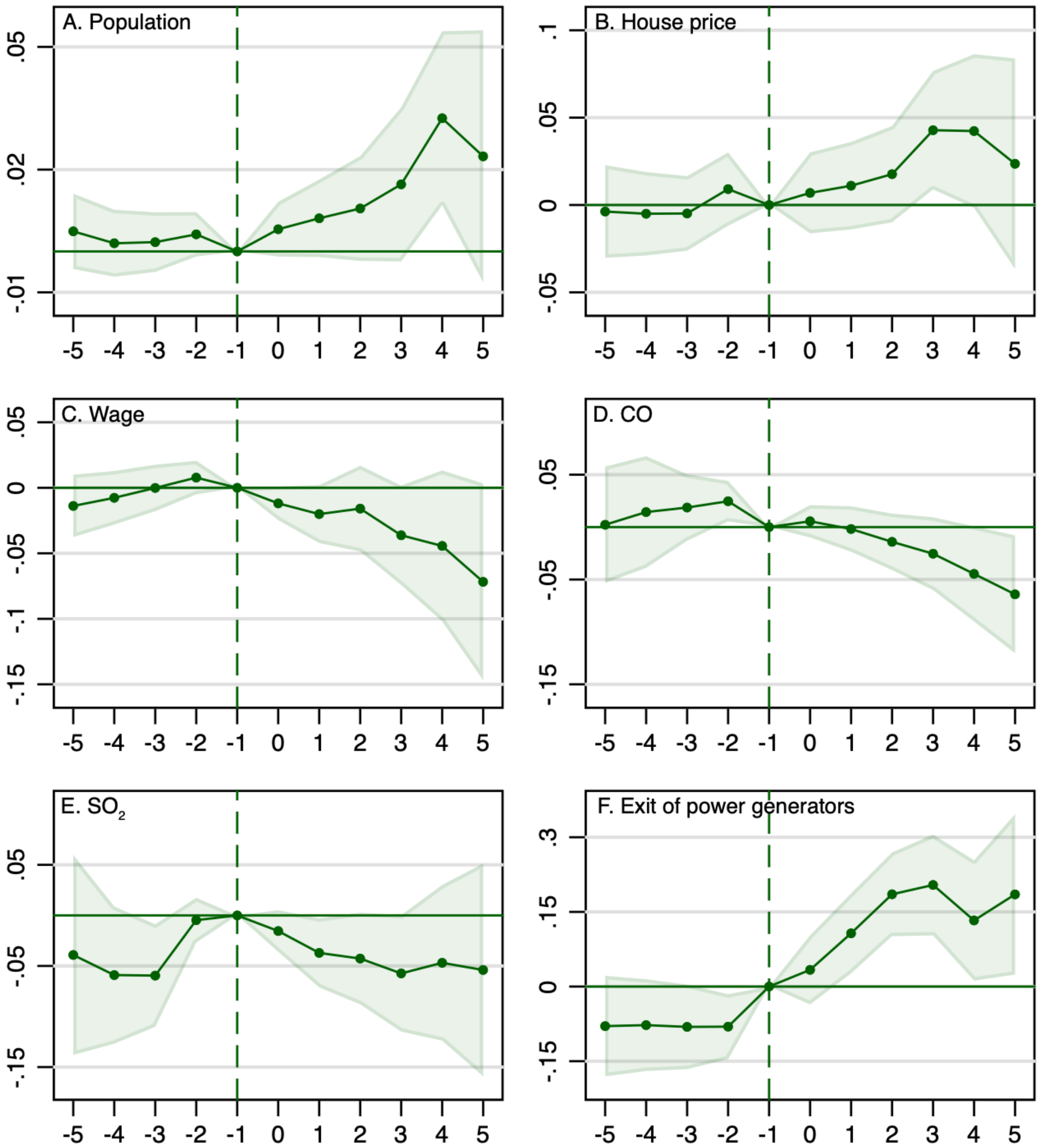

FIGURE 12 Effects on residential welfare

Notes: This figure presents the estimates from Equation (9) using different dependent variables. The dependent variables in Panels A–F are the log of total population, the log of housing price, the log of wage per capita, the log of CO concentration, the log of SO_2 concentration, and the log of the exit of electricity generation firms, respectively. The shaded area denotes the 95% confidence intervals constructed based on standard errors clustered at the city level.

7 Conclusion

The impact of resource abundance on economic growth has been a subject of longstanding debate, traditionally centered on fossil fuels. Solar energy, however, presents distinct characteristics: it is renewable, clean, and requires substantial land for infrastructure. These unique attributes suggest that solar energy may have different economic and welfare implications compared to conventional energy sources. Given the rapid expansion of solar energy in China and globally, understanding these implications is crucial. Our research investigates the effects of solar energy development, highlighting the complex dynamics of land use and the associated challenges and benefits to local economies.

Our analysis is grounded in a conceptual model that evaluates the economic and welfare impacts of solar energy development within a locational equilibrium framework. The model demonstrates how solar farm installations imposes substantial economic costs through intensified land competition, which reduces local government revenue from land sales and impairs its capacity to invest in productivity-enhancing infrastructure. Simultaneously, the model employs population changes as a revealed preference measure of changes in residential welfare, taking into account the net effect of changes in wage rates, housing prices, and local amenities.

Exploiting the spatio-temporal variation in solar farm installations, our empirical analysis yields two primary findings. First, we identify an average decline in GDP per capita of approximately 2.7%. This negative impact is more pronounced in counties where land has higher opportunity costs. Our detailed mechanism analysis suggests that land competition, particularly for impervious surfaces with the potential for more economically productive uses, significantly contributes to this adverse economic outcome. Conversely, when solar farms utilize low-economic-value lands, the economic effects of solar energy expansion can even be positive. This land competition also crowds out residential land sales revenue, further impeding local economic growth by dampening new firm entries. While counties with solar energy development experience increased electricity utilization, the associated economic benefits appear insufficient to offset the losses due to land competition.

Second, there is evidence of enhanced local amenities, particularly improvements in environmental quality, as we observe declines in the concentration of certain air pollutants and the phasing-out of fossil fuel-based electricity generators. We find a 2% increase in local population, despite a 5% decline in wage rates and a 5% increase in housing prices. This population growth, in the face of seemingly adverse economic conditions, suggests that the benefits of improved local amenities may outweigh the economic drawbacks. Such a pattern is consistent with an overall increase in local residential welfare, as residents appear willing to accept lower wages and higher living costs in exchange for enhanced environmental quality.

Solar power deployment is widely recognized as a critical pathway for countries to achieve clean electricity grids and transition towards low-carbon economies. Our findings underscore the importance of strategic solar farm siting decisions, which should carefully consider the complex interplay between land use opportunity costs and residential welfare. *Ceteris paribus*, policymakers should prioritize avoiding high-value or potentially productive land for solar installations, particularly in regions experiencing rapid urbanization.

There are several caveats in our study that warrant future considerations. First, the emergence of solar energy in China began only around 2009, limiting our observation to short-to-medium-term economic and welfare impacts within a decade or so. In the long term, solar farms may yield economic benefits through sustained renewable energy production, reduced reliance on imported fossil fuels, technological advancements in solar efficiency, and possible population agglomerations. Second, the economic benefits of improved air quality, such as health improvements and enhancements in human capital can be substantial and may outweigh the economic costs in the long term. Third, the economic impacts of other renewable energy sources may differ from those of solar energy, necessitating future research.

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Appendix

A Model details

Given the model setup and assumptions outlined in the main text, the local government's maximization problem can be characterized as to allocating a share L^S of land for solar farms, a share of L^Y for production facilities, with the remaining $(1-L^S-L^Y)$ share designated for residential development. The first-order condition of this optimization problem can be expressed as:

$$\frac{d\Omega}{dL^S} = \frac{\partial\Omega}{\partial Y}\frac{dY}{dL^S} + \frac{\partial\Omega}{\partial V}\frac{dV}{dL^S} \geq 0 \tag{A.1}$$

For brevity, we omit the county subscript c in subsequent equations.

The derivative of the social objective function with respect to L^S is non-negative. While we assume that the objective function strictly increases in its components ($\frac{\partial\Omega}{\partial Y} > 0$ and $\frac{\partial\Omega}{\partial V} > 0$), the signs of $\frac{dY}{dL^S}$ and $\frac{dV}{dL^S}$ are ambiguous. If solar expansion enhances both economic performance and residential welfare until solar capacity reaches its optimal level, the overall sign of the derivative is positive. Alternatively, further solar expansion might increase the value of the social objective function by improving economic performance at the expense of residential welfare, or vice versa. However, the derivative of the social objective function with respect to L^S cannot be negative. This non-negativity constraint stems from the optimization principle: if increasing L^S were to decrease the value of the objective function, it would not be optimal for the local government to increase L^S any further.

According to Equation (3), the derivative of the production function with respect to land allocated for solar farm construction can be expressed as:

$$\begin{aligned}
\frac{dY}{dL^S} &= \frac{d\phi}{dL^S}Q(\cdot) + \frac{dQ(\cdot)}{dL^S}\phi \\
&= \frac{d\phi}{d\Pi}\left(L^R\frac{dP^R}{dL^S} + P^R\frac{dL^R}{dL^S} + L^Y\frac{dP^Y}{dL^S} + P^Y\frac{dL^Y}{dL^S}\right)Q(\cdot) \\
&\quad + \left(\frac{\partial Q}{\partial N}\frac{dN}{dL^S} + \frac{\partial Q}{\partial L^Y}\frac{dL^Y}{dL^S} + \frac{\partial Q}{\partial E}\frac{dE}{dL^S}\right)\phi
\end{aligned} \tag{A.2}$$

where $\Pi = L^R P^R + L^Y P^Y$ represents the revenue from residential and production (industrial and commercial) land sales. This expression demonstrates that allocating land for solar farms impacts aggregate output through two main channels. First, as more land is allocated to solar construction, land sale revenue are likely to decrease. Since land sales revenue is used to support production infrastructure in China, this change affects aggregate output by influencing the total factor productivity. Second, the allocation of land to solar farms can alter the levels of factor inputs of production, specifically labor (N), land (L^Y), and energy (E).

By rearranging the terms, we can express these effects in the form of elasticities:

$$\theta_{Y,L^S} = \theta_{\phi,\pi}\theta_{\pi,L^S} + (\theta_{Q,N}\theta_{N,L^S} + \theta_{Q,Y^S}\theta_{L^Y,L^S} + \theta_{Q,E}\theta_{E,L^S}) \tag{A.3}$$

where $\theta_{\phi,\pi}$ is the elasticity of total factor productivity with respect to land sales revenue. $\theta_{\pi,L^S} = \theta_{P^R,L^S} + \theta_{L^R,L^S} + \theta_{P^Y,L^S} + \theta_{L^Y,L^S}$ decomposes the elasticity of land sales revenue with respect to solar land into its components: the elasticities of residential and production land prices and quantities with respect to solar land, respectively. $\theta_{Q,N}$, θ_{Q,L^Y} and $\theta_{Q,E}$ represent the output elasticities with respect to labor, land, and energy inputs. θ_{N,L^S}, θ_{L^Y,L^S} and θ_{E,L^S} denote the elasticities of labor, land, and energy with respect to solar land.

By assumption, $\theta_{\phi,\pi} > 0$. We expect that $\theta_{P^R,L^S} \geq 0$ and $\theta_{L^R,L^S} < 0$, as increased land allocation for solar construction could reduce available residential land, potentially driving up residential land prices due to scarcity. We also expect θ_{P^Y,L^S} and θ_{L^Y,L^S} to be negligible as local governments in China collect land sales revenue primarily from residential land. Consequently, the first term in Equation (A.3) could be either positive or negative. Regarding the second term, $\theta_{Q,N}$, θ_{Q,L^Y} and $\theta_{Q,E}$ are positive based on the Cobb-Douglas production function. We anticipate $\theta_{E,L^S} \geq 0$, as more land allocated to solar construction should increase local electricity utilization. θ_{L^Y,L^S} can be either positive or negative. Solar farms may compete for land resources, yet local governments might also increase production land allocation to complement solar energy development. In addition, the sign of θ_{N,L^S} is indeterminate, depending on whether solar energy development attracts more people to settle in the county. Considering these factors collectively, the overall impact of allocating land to solar construction on local aggregate output θ_{Y,L^S} is ambiguous.

We now examine how the expansion of solar farms affects residential utility. The total derivative of utility (V) with respect to land allocated to solar (L^S) is given by:

$$\frac{dV}{dL^S} = \frac{\partial V}{\partial w}\frac{dw}{dL^S} + \frac{\partial V}{\partial r}\frac{dr}{dL^S} + \frac{\partial V}{\partial A}\frac{dA}{dL^S} \tag{A.4}$$

This equation decomposes the overall impact of solar land allocation on residential utility into three channels. The first term captures how solar expansion affects utility through changes in wage rate, the second through changes in housing prices, and the third through changes in local amenities.

Building on Equations (4) and (5), we can derive the following expressions:

$$\frac{dw}{dL^S} = \tilde{w}(\cdot)\frac{d\phi}{dL^S} + \phi(\frac{\partial \tilde{w}}{\partial N}\frac{dN}{dL^S} + \frac{\partial \tilde{w}}{\partial L^Y}\frac{dL^Y}{dL^S} + \frac{\partial \tilde{w}}{\partial E}\frac{dE}{dL^S}) \tag{A.5}$$

and

$$\frac{dr}{dL^S} = \frac{\partial r}{\partial P^R}\frac{dP^R}{dL^S} + \frac{\partial r}{\partial N}\frac{dN}{dL^S} \tag{A.6}$$

Equation (A.5) decomposes the effect of solar land allocation on wage into productivity-driven and factor-driven (population, production land, and energy) components. Similarly, Equation (A.6) breaks down the impact on housing prices into effects from changes in residential land prices and population (as a proxy for local aggregate demand).

Furthermore, we can establish a relationship between the utility level and population distribution. Note that $\bar{N}$ represent the total population and λ the proportion settling in the county. This yields:

$$N = \lambda \bar{N} = \frac{V}{V + \bar{V}}\bar{N} \tag{A.7}$$

For simplicity, we assume $\bar{N} = \bar{V} = 1$. Under these conditions, we can show that N and V move in tandem for a marginal change in L^S:

$$\frac{dN}{dL^S} = \frac{1}{(V+1)^2}\frac{dV}{dL^S} \tag{A.8}$$

Combining these equations yields:

$$\theta_{V,L^S} = \frac{\theta_{V,w}(\theta_{\phi,\pi}\theta_{\pi,L^S} + \theta_{\tilde{w},L^Y}\theta_{L^Y,L^S} + \theta_{\tilde{w},E}\theta_{E,L^S}) + \theta_{V,r}\theta_{r,P^R}\theta_{P^R,L^S} + \theta_{V,A}\theta_{A,L^S}}{1 - \frac{\theta_{V,w}\theta_{\tilde{w},N} + \theta_{V,r}\theta_{r,N}}{V+1}} \tag{A.9}$$

where θ_{V,L^S} is the elasticity of residential utility with respect to solar land allocation. The numerator represents the effects of wage rate, housing prices, and amenity changes due to the allocation of land to solar construction on residential utility. The denominator adjusts for this utility change due to the equilibrium population feedback.

The numerator of θ_{V,L^S} consists of three key components. The first component is the combined effect of productivity change and land and energy input change, where productivity change is likely negative based on our previous discussion, while energy input change may be positive and land input is indeterminate. The second component is the change in housing prices, which is probably non-positive as increased solar land typically reduces residential land and raises housing prices. The third component is the shift in local amenities accompanying solar land allocation, which could be positive – for example, if solar farms reduce pollution. The denominator is positive due to its negative second term, reflecting how a positive population change lowers wages and increases housing prices and vice versa. Given these factors, the overall sign of θ_{V,L^S} is also ambiguous. However, if a positive population effect is observed in the county along with a decline in nominal wage and increased housing prices – both of which are hypotheses we can test empirically – it is likely due to the improvement in local amenities.

B Additional robustness

TABLE B.1 Effects of solar farms on GDP per capita using Callaway and Sant'Anna DID method

	(1)	(2)	(3)	(4)
	Baseline	Simple weighted ATE	Calendar time effects	Group-specific effects
$Treated_i * Post_{i,t}$	-0.027***	-0.039**	-0.030***	-0.032*
	(0.005)	(0.017)	(0.009)	(0.017)
Observations	33,701	33,701	33,701	33,701

Notes: The dependent variable is the natural log of the real GDP per capita. Columns 1 presents the DID estimates based on Equation (7). Columns 2-4 present the DID estimates based on Callaway and Sant'Anna DID. Column 2 displays the overall average treatment effect (ATE) across all treated units and time periods, with using the size of each group as weights. Column 3 estimates the average treatment effect for each calendar year, which are then combined into an overall average. Column 4 computes the treatment effect for each cohort, where a cohort is defined by the year it first received treatment, which is then averaged. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE B.2 Effects of solar farms on GDP per capita: controlling for spillover effects

	(1)	(2)	(3)	(4)
$Treat_i * Post_t$	-0.027***	-0.018***	-0.019***	-0.024***
	(0.005)	(0.005)	(0.005)	(0.005)
$Treat_i * Post_t$(bordering counties)		-0.043***		
		(0.004)		
$Treat_i * Post_t$(counties within 50km)			-0.079***	
			(0.005)	
$Treat_i * Post_t$(counties within 100km)				-0.050***
				(0.004)
Observations	33,701	32,321	27,234	31,781
R-squared	0.953	0.954	0.954	0.955

Notes: Column 1 replicates the baseline estimates. Column 2 additionally controls for bordering counties' solar farms, and columns 3 and 4 control for solar farms of counties within 50km and 100km, respectively, of the centroid of the county. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

C Additional results for land competition effects

TABLE C.1 Impacts on agricultural GDP across land types

	(1)	(2)	(3)	(4)
		Interaction with land shares		
	Baseline	Cropland	Impervious surface	Grassland
$Treated_i * Post_{i,t}$	0.013	0.037*	0.051***	-0.014
	(0.014)	(0.020)	(0.016)	(0.015)
$Treated_i * Post_{i,t} * Land_i$		-0.054	-0.209***	0.138***
		(0.034)	(0.046)	(0.037)
Mean of $Land_i$		0.45	0.21	0.17
Observations	33,256	33,256	33,256	33,256
R-squared	0.931	0.931	0.932	0.932

	(1)	(5)	(6)	(7)
		Interaction with land shares		
	Baseline	Forest	Barren land	Water body
$Treated_i * Post_{i,t}$	0.013	0.009	0.004	0.015
	(0.014)	(0.014)	(0.015)	(0.014)
$Treated_i * Post_{i,t} * Land_i$		0.059	0.099**	-0.093
		(0.066)	(0.048)	(0.105)
Mean of $Land_i$		0.09	0.04	0.03
Observations	33,256	33,256	33,256	33,256
R-squared	0.931	0.931	0.931	0.931

Notes: The dependent variable in all columns is the natural log of the real agricultural GDP per capita. Column (1) replicates the baseline DID estimates to facilitate comparison. Columns (2)–(7) present the estimates of Equation (11), which interacts the DID term with the share of each type of land used for solar farms. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

TABLE C.2 Impacts on industrial GDP across land types

	(1)	(2)	(3)	(4)
		Interaction with land shares		
	Baseline	Cropland	Impervious surface	Grassland
$Treated_i * Post_{i,t}$	-0.034	-0.007	0.039	-0.073**
	(0.024)	(0.042)	(0.028)	(0.029)
$Treated_i * Post_{i,t} * Land_i$		-0.061	-0.399***	0.201**
		(0.078)	(0.076)	(0.090)
Mean of $Land_i$		0.45	0.21	0.17
Observations	33,407	33,407	33,407	33,407
R-squared	0.921	0.921	0.922	0.921

	(1)	(5)	(6)	(7)
		Interaction with land shares		
	Baseline	Forest	Barren land	Water body
$Treated_i * Post_{i,t}$	-0.034	-0.036	-0.048*	-0.044*
	(0.024)	(0.024)	(0.027)	(0.025)
$Treated_i * Post_{i,t} * Land_i$		0.044	0.168**	0.469**
		(0.158)	(0.081)	(0.188)
Mean of $Land_i$		0.09	0.04	0.03
Observations	33,407	33,407	33,407	33,407
R-squared	0.921	0.921	0.921	0.921

Notes: The dependent variable in all columns is the natural log of the real industrial GDP per capita. Column (1) replicates the baseline DID estimates to facilitate comparison. Columns (2)–(7) present the estimates of Equation (11), which interacts the DID term with the share of each type of land used for solar farms. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

TABLE C.3 Impacts on service GDP across land types

	(1)	(2)	(3)	(4)
		Interaction with land shares		
	Baseline	Cropland	Impervious surface	Grassland
$Treated_i * Post_{i,t}$	-0.012	-0.047***	0.008	0.001
	(0.013)	(0.017)	(0.015)	(0.015)
$Treated_i * Post_{i,t} * Land_i$		0.077**	-0.114**	-0.070**
		(0.031)	(0.050)	(0.035)
Mean of $Land_i$		0.45	0.21	0.17
Observations	33,310	33,310	33,310	33,310
R-squared	0.961	0.961	0.961	0.961

	(1)	(5)	(6)	(7)
		Interaction with land shares		
	Baseline	Forest	Barren land	Water body
$Treated_i * Post_{i,t}$	-0.012	-0.013	-0.020	-0.016
	(0.013)	(0.014)	(0.015)	(0.013)
$Treated_i * Post_{i,t} * Land_i$		0.015	0.082**	0.175
		(0.047)	(0.039)	(0.133)
Mean of $Land_i$		0.09	0.04	0.03
Observations	33,310	33,310	33,310	33,310
R-squared	0.961	0.961	0.961	0.961

Notes: The dependent variable in all columns is the natural log of the real service GDP per capita. Column (1) replicates the baseline DID estimates to facilitate comparison. Columns (2)–(7) present the estimates of Equation (11), which interacts the DID term with the share of each type of land used for solar farms. Standard errors reported in parentheses are clustered at the city level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

D Additional results for productivity effects

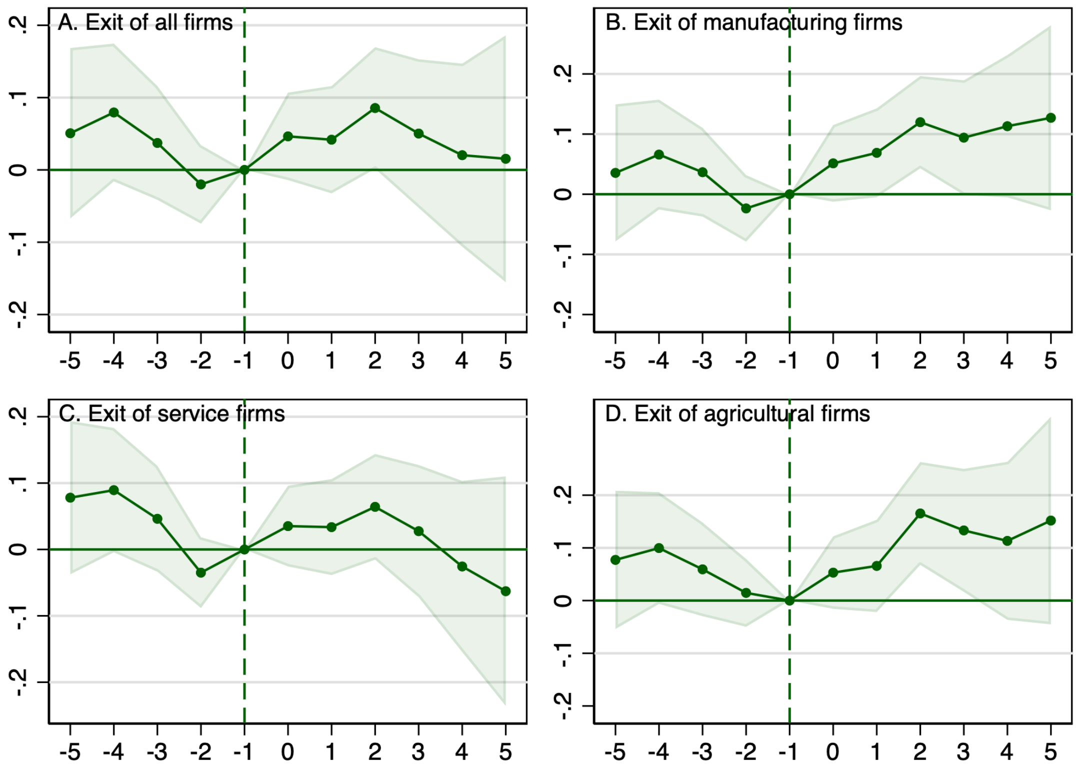

FIGURE D.1 Effects of solar farms on firm exits

This figure presents the estimates of Equation (9) using the number of firm exits across sectors as the dependent variables. The shaded areas denote the 95% confidence intervals constructed based on standard errors clustered at the city level.

E Energy supply effects

Our conceptual framework posits that solar energy development enhances local energy supply, potentially improving access to electricity. Figure E.1 illustrates the impact of solar installations on electricity consumption. Following the establishment of solar farm in a county, total electricity consumption increases by approximately 7.9% (Panel A). This growth is primarily driven by a 15.1% average annual increase in industrial electricity consumption (Panel C), with no discernible change in residential electricity consumption (Panel B). We also observe a significant increase in agricultural machinery power (Panel D), suggesting that part of the additional electricity is utilized in the agricultural sector. Note that the net damage of solar farms on GDP per capita suggests that despite this increased electricity input in production, the economic gains from enhanced electricity access have not been sufficient to counterbalance the losses resulting from land allocation to solar farms.

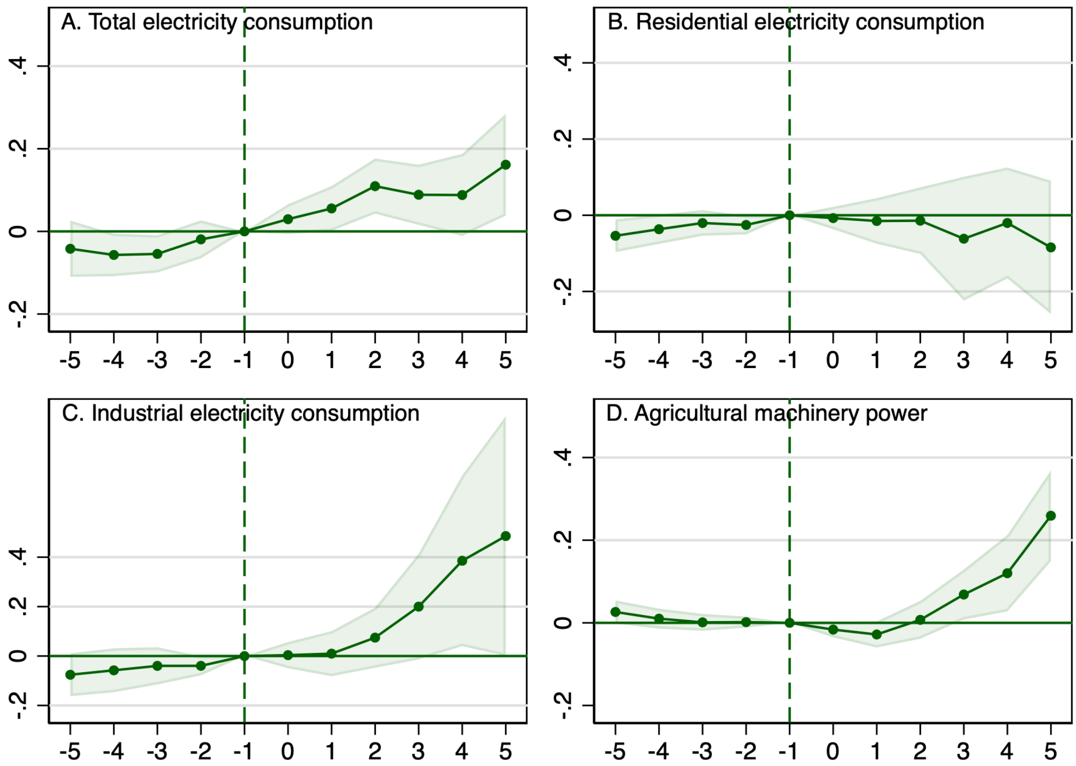

FIGURE E.1 Mechanism: Effects on electricity consumption

Notes: This figure presents the estimates from Equation (9) using different dependent variables. The dependent variables in Panels A–D are the log of total electricity consumption, the log of residential electricity consumption, the log of industrial electricity consumption, and the log of agricultural machinery power, respectively. The shaded area denotes the 95% confidence intervals constructed based on standard errors clustered at the city level.

Another potential explanation for the observed GDP decline relates to the intermittency of solar-generated electricity. The variable nature of solar power generation, coupled with inadequate storage and transmission infrastructure, has posed significant challenges for grid integration. This has resulted in historically high curtailment rates of solar energy in China, leading to substantial wastage of generated power. In 2015 alone, China curtailed 4.65 million MWh of solar power, with the curtailment rate reaching 12.6%.[13] This issue has been particularly severe in northwestern provinces like Gansu, Qinghai, Xinjiang, and Ningxia, where curtailment rates exceeded 40% in 2016.[14] These high curtailment rates suggest that a significant portion of the potential economic benefits from solar power generation may be unrealized.

However, we present suggestive evidence that solar power intermittency is not a primary driver of the observed GDP decline in our study context. Specifically, we examine the correlation between solar capacity and electricity stability at the city level. Appendix Figure E.2 illustrates the relationship between solar energy capacity and both the average number and duration of outages per user. This result does not support the hypothesis that solar energy development negatively impacts the local economy by compromising grid stability.

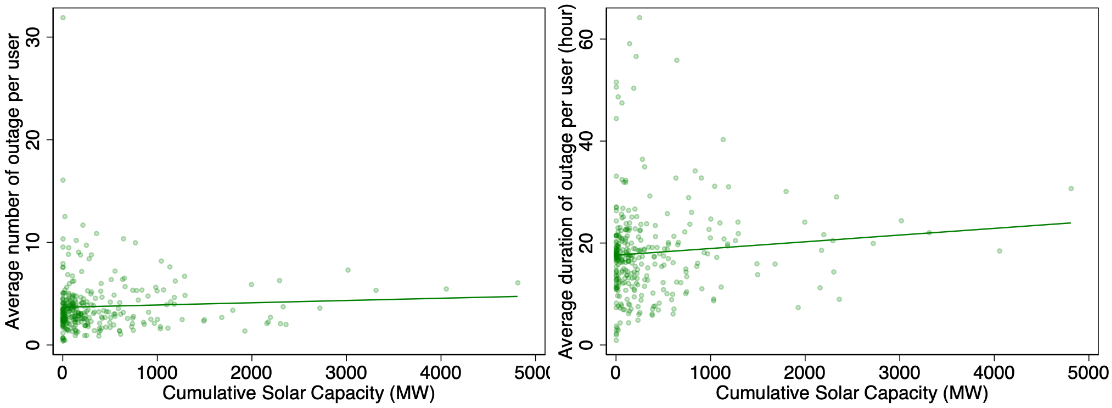

FIGURE E.2 Power outage and solar power capacity

The left subfigure presents a two-way scatter plot illustrating the relationship between the city-level average number of outages per user and the city-level cumulative solar capacity, with a solid line representing the linear fit. The right subfigure similarly depicts a two-way scatter plot of the city-level average outage duration per user (in hours) against the city-level cumulative solar capacity. Both figures indicate that neither the frequency nor the duration of outages increases with solar capacity.

13. https://chinafocus.ucsd.edu/2021/02/16/solar-energy-in-china-the-past-present-and-future/

14. https://www.nea.gov.cn/2017-01/19/c_135996630.htm

F Impacts on air pollution

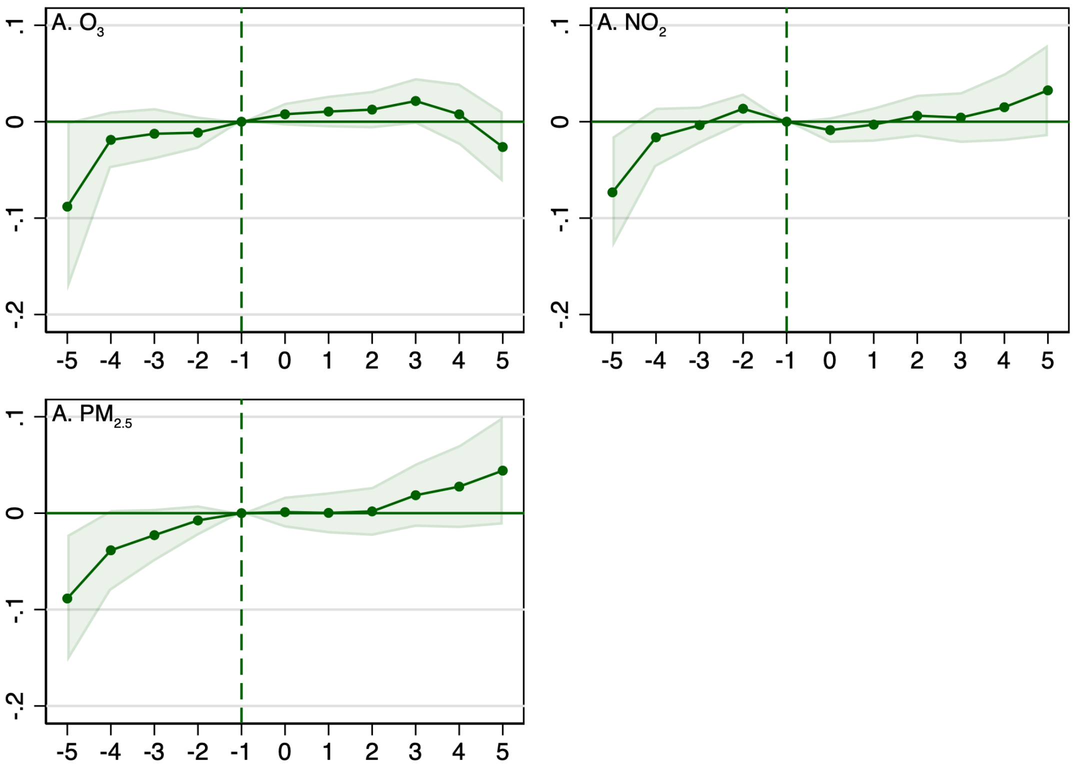

FIGURE F.1 Effects of solar farms on other air pollutants

This figure presents the estimates of Equation (9) using different air pollution measures as the dependent variables. The dependent variables in Panel A–C are the log of O_3, NO_2, and $PM_{2.5}$ concentrations, respectively. The shaded areas denote the 95% confidence intervals constructed based on standard errors clustered at the city level.