Working papers series

WP ECON 25.03

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David Cuberes
Maynooth University

Aitor Lacuesta
Bank of Spain

Carlos Moreno-Pérez
Bank of Spain

Daniel Oto-Peralías
Universidad Pablo de Olavide

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Department of Economics

Land concentration and large renewable energy projects*

David Cuberes[1], Aitor Lacuesta[2], Carlos Moreno-Pérez[2], Daniel Oto-Peralías[3]

[1]Department of Economics, Maynooth University, Ireland
[2]Bank of Spain, Spain
[3]Department of Economics, Universidad Pablo de Olavide, Spain

February 2025

Abstract

This paper examines the relationship between land ownership concentration and the likelihood of hosting large green energy facilities, specifically mega-photovoltaic (PV) plants, defined as those exceeding 50 hectares. Focusing on Spain, we find that municipalities with a higher proportion of agricultural land concentrated in large farms are significantly more likely to accommodate mega PV plants. This effect remains robust after accounting for key factors influencing PV deployment, including terrain ruggedness, solar potential, and proximity to transmission lines and urban centers. To further neutralize unobserved factors that jointly influence land concentration and PV plant location, we leverage cadastral (parcel) data to conduct an intra-municipal analysis at the 0.5×0.5 km grid-cell level. Our findings reveal that grid cells with larger cadastral parcels have a substantially higher probability of being part of a mega PV facility. A simple theoretical model explains this pattern by highlighting the coordination challenges faced by small landowners. Unlike large ones, fragmented landholders struggle to meet developers' land requirements, which are necessary to cover fixed project costs. Consistent with this mechanism, we also show that areas with irrigated agriculture are less likely to host mega PV plants and exhibit more unequal distributions of plant locations by land size. Finally, we provide external validity by confirming a similar positive association between mega PV plants and land concentration across U.S. counties. These findings underscore the implications of land inequality for the spatial distribution of renewable energy projects, shedding light on the limited local benefits of such investments and the growing opposition from rural communities.

Keywords: solar plants; photovoltaic plants; land concentration

JEL Codes: O13, Q40, Q15

*We thank Leticia Vega Mateos for outstanding research assistance. We benefited from the comments of seminar participants at the Bank of Spain. Daniel Oto-Peralías gratefully acknowledges financial support by Junta de Analucía through I+D+I project P20-00808 (Andalusia ERDF 2014-2020 Operational Programme).
Corresponding author: dotoper@upo.es

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1 Introduction

In response to growing concerns about climate change and global warming, the past few decades have witnessed a significant expansion of infrastructure dedicated to renewable energy production worldwide. This trend is apparent in many high-income countries, including Spain, as illustrated in Figure 1 (International Renewable Energy Agency -IRENA-, 2024). Although most of society views these infrastructure projects as necessary or beneficial, opposition is increasing among those living near the construction sites. This opposition stems from concerns about the visual impact on the landscape, environmental considerations, spillover effects on nearby properties, preferable alternative land uses such as agriculture, and the perception of limited local economic benefits (Rodríguez-Segura et al., 2023; Scherhaufer et al., 2017; Sills et al., 2020; Späth, 2018).[1]

The economies of scale associated with large renewable energy plants often drive investors to build expansive facilities that occupy vast areas of land. These massive infrastructures tend to be concentrated in specific regions, amplifying visual and environmental concerns (Rodríguez-Segura et al., 2023). However, the local benefits remain unclear. While the construction of large solar plants generates some local employment, these job opportunities decrease and lose their impact once the construction phase ends (Fabra et al., 2024). Additionally, it remains uncertain whether small landowners will see any benefit from (pre-tax) rents, or if the majority of the profits will be captured by developers or large landowners.

This paper explores whether the structure of land ownership influences the location of large photovoltaic (PV) plants, defined here as those covering at least 50 hectares (ha). We hypothesize that, all else being equal, it is more difficult for a company to construct a large PV plant in areas with many small landowners compared to regions with a few large landowners. We assume that large renewable energy plants benefit from significant economies of scale, which often lead investors to develop vast renewable energy facilities that span large areas of land. Our argument, based on Winikoff and Parker (2023), uses the premise that small landowners are at a disadvantage compared to large landowners in the bidding process to attract a developer, as they do not know the bids of other small landowners whose landholdings are necessary to cover the fix cost of the project. As a consequence, the rents generated by these large facilities will be directed to big landowners and developers. We further explore the impact of alternative land uses for different landowners on the probability

[1]The U.S., Spain, and the UK, among others, are witnessing an increasing opposition to large PV plants as has been extensively reported by the media (France 24, 2023; The Guardian, 2022a,2022b). A recent survey in Spain reveals that 56% of the population is against locating PV plants in agricultural areas (GAD3, 2024).

of building a mega PV plant. In particular, we consider two types of agricultural land: rainfed and irrigated. In the model, the key difference between these two types of agricultural land is that irrigated farming exhibits economies of scale that are smaller than those required to make solar plants profitable. In contrast, rainfed land is not subject to any type of economies of scale for farming. As a result, differences in the probability of building a mega PV plant by the size of landholdings are exacerbated in areas with irrigated farming because this new alternative increases the rents demanded by some mid-sized landowners, reducing the likelihood of securing a solar plant. For very small and very large landowners, the optimal bid remains unaffected by alternative farming uses.

We focus on the Spanish case to test these hypotheses for three reasons. First, Spain's climate is particularly well-suited for the deployment of PV plants (ESMAP, 2020), which may, at least in part, explain Spain's recent boom in PV energy development (Figure 1). Second, Spain has large areas of uninhabited land - potentially suitable to host these plants. Finally, Spain is characterized by wide variation in land concentration (Oto-Peralías and Romero-Ávila, 2017; Oto-Peralías, 2020). We construct a comprehensive local-level data set and show that municipalities where a higher share of agricultural land was concentrated in large estates (farms with 200 or more ha) in 1999 are much more likely to host a mega PV plant today. Our results indicate that moving from a municipality in the 10th percentile to the 90th percentile of land concentration increases the probability of hosting a mega plant from 2.3% to 4%, almost a two-fold increase. This relationship is robust to controlling for province fixed effects, as well as for a large array of locational, climatic and geographic factors, such as terrain ruggedness, PV output potential, and distance to transmission lines and urban centers, among others. It is also robust to using past land concentration (measured in 1982) as an instrument for our indicator of land concentration.

In order to better control for possible omitted variables that can jointly determine land concentration and the decision to locate mega PV plants, we conduct an intra-municipal analysis. To do so, we leverage on the rich cadastral data available in Spain which allows us to delimitate the boundaries of each plot of land. We divide the area of the municipalities under research into 0.5x0.5 km grid cells and show that, within municipalities, grid cells located within larger cadastral parcels are much more likely to be part of a mega plant.[2] In line with our model, we further show that areas with irrigated agriculture are less likely to host mega PV plants. This decline is led by small and mid-size landholdings. However, for large parcel sizes, the difference with respect to rainfed agriculture declines and completely disappears.

[2] A cadastre or cadaster is a comprehensive recording of the real estate or real property's metes-and-bounds of a country. It is often represented graphically in a cadastral map.

To provide external validity to our findings, we show an analogous positive relationship between land concentration and mega PV plants for U.S. counties. Our results indicate that moving from a county in the 10th percentile in land concentration to the 90th percentile increases the probability of hosting a mega plant from 3.2% to 14.6%, more than a four-fold increase.[3]

Our paper relates to three strands of the literature. First, we contribute to the evaluation of the local benefits of large renewable energy projects. In particular, we challenge one of the main local benefits typically associated with PV plants, namely the higher rents obtained by landowners, since leasing the land is generally much more profitable than cultivating it. In Spain it is certainly the case: the average rental rate per ha is 127,4 euros for land devoted to rainfed arable crops and 564,8 euros for irrigated land (Ministry of Agriculture, 2022), while the average rental rate for PV use is around 1500 euros. Our results show that mega PV plants are frequently located in large estates, so the higher rents obtained are largely concentrated in a few hands rather than broadly distributed among the population. Besides increasing inequality, the concentration of rents is likely to also reduce the local economic impact of these investments since a high percentage of big landholdings are owned by ”absentee” individuals, who arguably have less incentives to invest in projects that may stimulate the local economy. In fact, in our data set, 14.2% of landholdings larger than 200 ha are owned by business companies, while this percentage drops to 0.3% for small landholdings (less than 10 ha).

We also relate to Winikoff and Parker (2023), who document a negative relationship between fragmented landownership and wind energy installed capacity in the U.S. We differ from their analysis in two key ways. First, we focus on solar energy, which is rapidly gaining traction compared to wind energy. Globally, solar power installed capacity (MW) has increased tenfold over the past decade, compared to a threefold increase in the case of wind power. In the United States, the former has increased 11.5-fold and the latter 2.5-fold, while in Spain the increases have been 6.1 and 1.3, respectively (IRENA, 2024). Besides, solar energy requires significantly more land area compared to wind energy, meaning it has a broader and more intensive impact, influencing a larger portion of the economy. Secondly, we focus in our model on the coordination problem among landowners as the main mechanism behind the empirical findings.[4] Importantly, we examine alternative agricultural uses, both rainfed and irrigated, to develop testable implications that help us understand the

[3]This is a larger increase than in Spain, but possibly due to the different units of analysis, since the county is a larger unit than the municipality.

[4]In contrast with their paper, we do not examine the internalization of negative externalities by large landowners, as most of them do not live in the investment area and are therefore less concerned about these issues.

mechanisms linking land concentration with the location of megaplants. The model predicts that in areas with access to irrigation, some midsize landowners will opt for this alternative, leading to a higher concentration of solar plants on large landholdings. For very small and very large landowners, however, this alternative has no impact on their bidding decisions.

The conflicts associated with the construction of PV plants relate to many papers exploring the so-called 'not in my backyard' (NIMBY) phenomenon. As explained in Hubbard (2009), NIMBY is a widely used term to describe the arguments of those opposing the development of certain infrastructure projects in their vicinity, while not necessarily elsewhere. This is usually due to the fact that the community that hosts the plant absorbs most of the environmental costs, while the rest of the population enjoys the benefits of that facility (Kunreuther and Kleindorfer, 1986; Jarvis, 2021).[5] The NIMBY phenomenon is relevant since both private companies and local politicians are likely to decide the location of PV plants based, in large part, on how much resistance they face from the local communities. Germeshausen et al. (2021) study the NIMBY phenomenon in relation to the installation of wind power plants in Germany and find significant opposition to the plants by the local population. NIMBY's has also been the subject of substantial analysis in the political economy literature (Wolsink 1994; Frey et al., 1996; Kuhn and Ballard, 1998; Bellettini and Kempf, 2013).[6] In a different context, Ahlfeldt and Maennig (2012) study the case of football stadiums and argue that because of NIMBY issues, the allocation of these types of facilities is nontrivial since interest groups may influence political decision makers.

Third, the crucial explanatory variable in our study is land concentration. There is now a substantial literature on the importance of this dimension of inequality on different outcome variables. Several studies have identified a negative relationship between land inequality and economic development across and within countries (Deininger and Squire, 1998; Galor et al., 2009; Smith, 2024; Wigton-Jones; 2020). Some of these works emphasize the importance of persistence in land distribution, stressing the fact that current land inequality is often inherited from events that happened hundreds of years ago. For the Spanish case, Oto-Peralías and Romero-Ávila (2016, 2017) find that differences in land inequality that originated in medieval times are extremely persistent, still showing up today. To our knowledge, this is the first work documenting how land concentration affects the deployment of PV energy projects, hereby showing how a historically determined factor becomes unexpectedly decisive again with the arrival of new ways to produce energy. In addition, understanding the potential of this type of wealth inequality to further concentrate income with the expansion

[5]For other theoretical analysis of NIMBY see, for example, Sakai (2012), and Öztürk et al. (2014).

[6]Rand and Hoen (2017) offer a comprehensive review of several papers related to the public acceptance of the construction of wind energy plants in North America.

of renewable energy is particularly relevant in a context of raising wealth inequality across the world (Zucman, 2019; Saez and Zucman, 2020).

The rest of the paper is organized as follows. Section 2 presents a conceptual framework that helps rationalize our empirical exercise. Section 3 describes the data. Section 4 presents the municipal-level and grid-cell level analyses. Section 5 explores further implications of the model according to alternative land uses and provides some external validity for the U.S. context. Finally, Section 6 puts forward some implications and concludes the paper.

2 Conceptual framework

To investigate whether the structure of land ownership affects the location of mega photovoltaic (PV) plants, we use a simplified version of the model by Winikoff and Parker (2023). Assume an area of land L ha that is composed by N homogeneous landholdings of size S. The higher S, the higher is land concentration. If a developer builds a plant, the landowner receives a royalty r^s per ha, normalized to be in the interval $(0, R)$, where $R > 0$. The negotiation process is such that, first, the landowners decide a royalty, and then the developer chooses to build the plant if fixed costs are covered.

From the point of view of the landowner, there are two unknowns: first, which royalty $r^s \in (0, R)$ will be accepted by the developer, and, second, how much land the developer needs to have for the PV plant to cover the fixed cost $\bar{S} \in (0, L)$. Let's assume, for simplicity, that both unknowns are uniformly distributed. Under this assumption, the probability that the developer accepts the royalty suggested by landlord i, given that the developer builds the megaplant is:

$$\text{Pr(Accepting } i \text{ offer} \mid \text{plant built)} = \frac{R - r_i^s}{R} \tag{1}$$

And the probability that the developer builds the plant is given by:

$$\text{Prob(Solar plant built)} = \text{Prob}\left(\bar{S} < \sum_{i=1}^{\frac{L}{S}} \frac{S(R - r_i^s)}{R}\right) = \frac{\sum_{i=1}^{\frac{L}{S}} \frac{S(R - r_i^s)}{R}}{L} \tag{2}$$

Therefore the maximization problem for landowner becomes:

$$max_{r_i^s}\left(\text{Pr(Solar plant built)}\,\text{Pr(Accepting } i \text{ offer} \mid \text{Solar plant built)} * Sr_i^s\right)$$

or

$$\max_{r_i^s} \left(\frac{\frac{S(R-r_i^s)}{R} + \frac{\sum_{j\neq i} S(R-r_j^s)}{R}}{L} \right) \frac{R-r_i^s}{Rr_i^s} Sr_i^s \tag{3}$$

Assuming that all landowners are identical, the problem can be solved as a symmetric Cournot equilibrium, where $r_i^s = r_j^s = r^s$, and the equilibrium royalty is:

$$r^s(S) = \frac{R}{2+\frac{S}{L}} \tag{4}$$

According to this equation, royalties increase if R raises. In economic terms, royalties increase with the value of the project. This implication is important when thinking about alternative land uses that could have different returns. More interesting for our hypothesis, royalties decrease as the average size of landholdings grows. Therefore, there is an advantage for large landowners in attracting megaplants based on the lack of coordination of the bids from other landowners whose land might be required. Finally, it can be easily shown that increasing L the derivative of the royalty respect to S increases for $N > 1$. Intuitively, *ceteris paribus*, increasing L leads to a larger number of landlords and so the probability that the plant is built approaches one and scale effects become unimportant. In the limit, the royalty becomes constant at $R/2$. We will use this result when thinking about alternative uses that might have different scale economies.

Winikoff and Parker (2023) demonstrate that significant negative externalities linked to a plant may reduce the benefits of large landholdings. These externalities stem from the disutility caused by visual pollution for those living nearby. However, it is unclear whether large landowners actually reside on their properties or even within the same municipality. In fact, 14.2% of landholdings over 200 ha are owned by business companies, while this percentage drops to just 0.3% for smaller landholdings (under 10 ha). As a result, we remain neutral on how negative externalities might vary with landholding size and will focus on the first mechanism.

Next we extend the model by considering the potential use of land for agricultural purposes. This addition allows us to examine how fluctuations in land prices for alternative agricultural uses impact the concentration of plants on large landholdings. We assume that each landowner can earn an alternative return, denoted as r^c, by using the land for agriculture. Moreover, we assume that r^c is lower than the return from a solar plant and remains

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constant regardless of the landholding size. This is justified by the fact that land used for meadows, pastures, or rainfed farming requires minimal investment and does not benefit from economies of scale, unlike solar plants. In this context, the optimization problem is slightly adjusted, and the optimal bid for a solar plant should exceed the royalty that could be earned if the land were used for crops:

$$r^s(S, r^c) = \max\left(\frac{R}{2+\frac{S}{L}}, r^c\right) \tag{5}$$

Panel A in Figure 2 shows how the likelihood that a megaplant is located in big landholdings changes when a minimum return is required regardless of the size. Having an alternative usage in each area of land increases the bids for S >0.4 since the optimal bid is the envelope of the two lines. As a result, the likelihood of small landowners securing a megaplant increases, since large landowners are now less inclined to submit low bids.

Now, consider a third option that offers the greatest benefit to landowners of a certain size: land for irrigated farming. In this case, landowners can lease their land to agricultural companies in exchange for a royalty, r^i. Irrigated farming provides higher returns than rainfed agriculture but yields lower returns than solar plants. However, this option is not available to all landowners. Since irrigated farming requires a certain scale, small landowners are at a disadvantage in this alternative bidding process. Nevertheless, because economies of scale are less pronounced, the differences between small and large landowners are smaller than in the case of megaplants, as the land area needed to make irrigated farming profitable is relatively smaller. This is shown in Figure 2 Panel B. For both very large and small landowners, this third alternative does not affect the bids for solar plants. Small landowners continue to demand very high royalties, even without any alternative, while very large landowners remain unaffected due to their competitive advantage. However, for medium-sized landowners, this third option leads to significant increases in their bids. As a result, irrigated farming reduces the likelihood of the bid being accepted for medium-sized landowners (see Figure 2, Panel C). In equilibrium, in areas with irrigated farming, the location of megaplants will become more concentrated on larger landholdings. This observation can be tested empirically and may serve to validate the reliability of our mechanism.

To summarize, due to the presence of important economies of scale and the difficulty to coordinate bids for small landlords, the owners of large landholdings have a higher probability of benefiting from green investments than small ones. The inequality associated to this is exacerbated in locations with irrigated farming because medium size landlords decrease their

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likelihood to get those investments.

3 Data

3.1 Data on PV plants

We first construct a database of mega PV plants where we proceed as follows. First, we obtain the list of PV plants connected to the power grid from the Registry of Electrical Energy Production Facilities, updated to August 2023 (Ministry for the Ecological Transition, 2023). For each plant, this registry provides its name, the municipality where it is located, and its capacity (in MW). From this list, we gather the list of municipalities with plants with a power capacity of 30 MW or more. Note that this is a value lower than 50 MW, which is the threshold used by Spanish legislation to define a large plant subject to the central government's permit. We do this to avoid the existing discontinuity in PV plants at this threshold, which is caused by companies trying to avoid the more demanding national regulation, as opposed to softer regional standards (Cuberes et al., 2025).

Second, we use satellite imagery and GIS software to manually georeference all PV plants located within the boundaries of the aforementioned list of municipalities. Third, we group together PV plants within a distance of 500 meters, which -we assume- are part of the same infrastructure facility (despite sometimes being "officially" different plants to avoid the 50 MW regulatory threshold). Four, we calculate the surface area of each grouped PV plants and keep those grouped plants occupying at least 50 ha. Therefore, our definition of mega PV plant implies a plant equal to or larger than 50 ha. We focus on surface area rather than capacity because the former is mostly what matters for its impact on the local economy and local community. As of August 2023, we identify 201 mega PV plants, located in 147 municipalities and occupying a surface area of 45,524 ha. Overall, this area represents only about 0.2% of Spain's utilized agricultural area (UAA), but for affected municipalities mega PV plants account for 4.8% of their UAA on average, and in some cases as much as 20 or 30%. Figure 3 depicts the location of the 201 mega PV plants.

3.2 Municipality dataset

Our sample comprises all municipalities in the 25 provinces with at least one mega PV plant. The dependent variable is a dummy variable capturing whether there is a mega PV plant occupying at least 50 ha in a municipality. Concerning the main explanatory variable (*LandConc*), we gather data on the distribution of land in Spanish municipalities from the

1999 agricultural census (INE, 1999). We calculate the percentage of UAA in holdings equal to or greater than 200 ha of UAA. We focus on private agricultural holdings (with legal status of natural person or company), where PV plants are more likely to be installed (as it is generally not feasible in public land). This indicator is represented in the map contained in Figure 3. We also create a dummy variable measuring a high incidence of large landholdings ($latifundia$) that takes the value of 1 when large holdings occupy 50% or more of the municipality's UAA.

We collect data on a large array of relevant confounders that can simultaneously affect both the degree of land concentration and the location of PV plants. First, we calculate two topographic variables: municipality average elevation and terrain ruggedness. Second, we calculate the average PV output potential, which is measured based on the global irradiation at optimum tilt and air temperature (Global Solar Atlas 2.0). We are also able to gather data on the environmental vulnerability of the territory for the deployment of PV facilities. The Spanish Government has classified the territory according to its environmental suitability for the deployment of PV plants, ranging from 0 (lowest suitability -due to environmental protection) to 4 (highest suitability) (Ministry for the Ecological Transition, 2020). Using these data, we calculate the average suitability of each municipality. Another important variable we construct is the distance of each municipality's centroid to the nearest grid node, which is an important factor to consider when deciding where to install a facility, as energy production facilities need to pour electricity to a grid node. In addition, we calculate other variables such as municipality surface area, distance to the coast, municipality population, and urban population within 100 km.

3.3 Grid-cell level data

The grid-cell level intra-municipality analysis focuses on municipalities with mega PV plants located within them. We create a grid of 0.5x0.5 km cell-size overlapping the group of 147 municipalities. We remove parts of grid cells falling in water bodies and areas overlapping with cadastral parcels corresponding to urban areas, roads, and, in general, any parcel corresponding to public transport infrastructure and hydrography (river courses, etc.). We further remove grid cells smaller than 1,000 sq-m (i.e., 0.1 ha). All this leaves us with 152,481 cells, amounting to a total area of 3,19 million ha.

The main dependent variable is a binary indicator capturing whether a grid cell overlaps (totally or partially) with a mega PV plant, while the main independent variable is the average cadastral parcel size. The latter is calculated as the weighted average of the size of the parcels overlapping with a grid cell, where the weights are the overlapping area of each parcel. It is worth noting that the cadastral parcel size is an imperfect proxy for landholding size since the latter can consist of several parcels, but it is the best available indicator at this high spatial resolution. Moreover, there is a high correlation (of 0.64) between the average parcel size aggregated at the municipal level and our municipal-level indicator of land concentration. The correlation is even higher when aggregating at the municipal level the percentage of area in cadastral parcels equal or higher than 25 ha (0.72).[7]

Importantly, we gather historical cadastral data corresponding to the year 2005, so that our parcel size indicator precedes the massive deployment of PV plants. Figure 4 illustrates the construction of the grid cell dataset for the cadastral parcels (top two figures) and the location of mega PV plants (bottom two figures).

We construct a number of control variables for each grid cell, including i) the average altitude and its standard deviation from a raster of 100m resolution (COPERNICUS, EUDEMv1.1), ii) the percentage of cell area located in areas under temporary water or permanent wet areas (COPERNICUS, Water and Wetness, with 40 m resolution), iii) environmental suitability for the deployment of PV plants, iv) distance to the nearest power grid node, v) the percentages of cell area with irrigated land and occupied by forest vegetation (both from cadastral data), and vi) distance to the municipality town center.[8]

4 Empirical analysis

4.1 Municipality level analysis

We estimate the following regression to analyze the relationship between mega PV plants and land concentration:

$$P_{m,p} = \alpha + \beta_1 \text{LandConc}_{m,p} + \gamma' X_{m,p} + \lambda_p + \varepsilon_{m,p} \tag{6}$$

where $P_{m,p}$ is a dummy variable capturing whether there is a mega PV plant in municipality m in province p; $\text{LandConc}_{m,p}$ refers to an indicator of land concentration, $X_{m,p}$ is a vector that includes the control variables mentioned in the previous sub-section, λ_p is a set of 25 province dummies, and $\varepsilon_{m,p}$ refers to the error term. We exclude provinces without any mega PV plant.

[7]Figure A1 in the Appendix shows binned scatterplots representing these strong correlations.

[8]Table A1 in the Appendix provides additional details about the description and sources of all the variables used in the analysis, while Table A2 shows their descriptive statistics.

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Table 1 reports the results from estimating (6) with OLS. Column 1 shows a positive and statistically significant association between land concentration and the presence of mega plants, conditional on province fixed effects. Column 2 adds geographic factors such as PV output potential, elevation, as well as the municipality's average terrain ruggedness and its area. The coefficient on land concentration decreases but remains large and statistically significant, while the control variables carry coefficients with the expected sign: positive for PV output potential and surface area, and negative for elevation. The coefficient on terrain ruggedness is insignificant, arguably due to its high correlation with elevation.

Column 3 includes variables related to urban processes, such as distance to the coast, municipality population, and urban population within 100 km. Only the latter exerts a positive influence on the presence of mega PV plants, while our variable of interest remains unchanged. Column 4 further adds two key variables for the decision to install a mega plant, distance to the nearest grid node and environmental suitability for PV plants (as defined by the Spanish Government). The former appears as an important determinant of mega plants location, while the latter is insignificant. Finally, column 5 adds the quadratic polynomial in latitude and longitude, which the objective to prevent the spatial dimension of the data from influencing the results (Kelly, 2020). Remarkably, the coefficient on land concentration remains very robust and precisely estimated. Its magnitude of 0.0003 implies that moving from a municipality in the 10th percentile in land concentration to the 90th percentile increases the probability of hosting a mega plant from 2.3% to 4% (holding the rest of variables constant at their mean values), close to a two-fold increase. Columns 6 to 10 estimate the same regression using the binary version of the land concentration indicator. Focusing on the most saturated model in column 10, municipalities where more than 50% of agricultural land is in large estates are more than twice as likely to have a mega plant than the rest of municipalities (5.3 vs 2.5%).

While we include a large vector of control variables, one may still be concerned about the possibility that some omitted variables could be driving the results. To get further reassurance, we employ Oster's approach to bound the possible bias from unobservables, based upon the assumption that selection on observables is proportional to selection on unobservables (Oster, 2019). When we do that, we find that the estimated intervals of the coefficients on land concentration and its binary version always exclude zero ((0.000054-0.0003) and (0.020-0.028), respectively), suggesting that the results are robust to omitted variables bias.

We have also checked that our results are robust when using the logistic regression, which might be advisable in this context given the low proportion of observations with mega PV

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plants. The regression coefficients are reported in Table A3. The exponentiated coefficient (i.e., odds ratio) in column 5 indicates that, holding the rest of variables constant, a one-percentage-point increase in land concentration leads to 1.36% increase in the odds of a mega PV plant within the municipality ($e^{0.0135} - 1$). Considering column 10, having more than 50% of land in large farms implies a 117% increase in the odds of hosting a mega PV plant ($e^{0.7746} - 1$).

These results indicate a positive relationship between the presence of large estates and the location of mega PV plants. This relationship is arguably causal since we control for the main relevant confounders and reverse causality is highly unlikely, as land concentration is measured well before the deployment of PV facilities. Table A4 further shows that using land concentration in 1982 (measured analogously) as an instrument for our indicator of land concentration increases the magnitude of the effect. This is arguably because the instrument helps mitigate measurement errors to actually measure land *ownership* concentration, since with the Agricultural Census we can only observe the concentration of land in farms.

4.2 Intra-municipality grid-cell level analysis

This section provides additional evidence that corroborates the causal positive effect of land concentration on the location of mega PV plants. To do so, we conduct an intra-municipality analysis which, by design, holds constant all distinctive features of each municipality. More specifically, we analyze whether mega PV plants are located in large cadastral parcels.

We estimate the following equation through OLS to analyze the effect of cadastral parcel size on the location of mega PV plants:

$$P_{i,m} = \alpha + \beta \text{Size}_{i,m} + \gamma' X_{i,m} + \lambda_m + \varepsilon_{i,m} \tag{7}$$

where $P_{i,m}$ is a binary variable capturing whether there is a mega PV plant in grid cell i in municipality m; $\text{Size}_{i,m}$ stands for the average parcel size, $X_{i,m}$ is a vector of control variables described above, λ_m denotes a set of municipality dummies, and $\varepsilon_{i,m}$ is the error term. As mentioned earlier, we focus on the sample of 147 municipalities with mega PV plants.

Table 2 shows the results of estimating (7), which again indicate a strong and positive association between land concentration and the presence of mega PV facilities. According to column 1, for example, a 10% increase in the average parcel size leads to an increase in the percentage of cells with mega plants of about 0.04 percentage points, a sizable effect given that only 2.93% of cells contain mega plants. However, this coefficient is likely to be downward-biased as plots tend to be larger in the most mountainous areas of municipalities, where PV plants are far less common.

When we introduce in column 2 elevation, terrain ruggedness, and the percentage of the grid-cell in wet areas, with irrigated land, and with forest vegetation, the coefficient on parcel size more than doubles: a 10% increase in parcel size leads to an increase in the percentage of cells with mega plants of about 0.1 percentage points. As expected, most of the control variables (terrain ruggedness, wetness, and forestland) act as deterrents to the presence of PV facilities, displaying large and statistically significant negative coefficients. Altitude appears insignificant probably because it is highly correlated with ruggedness, which exerts a stronger negative effect. Interestingly and consistent with our model, areas devoted to irrigated agriculture are less prone to be turned into PV facilities.

Column 3 further includes distance to the nearest grid node, distance to the municipality town center, and a set of dummy variables for the five categories of environmental suitability for PV deployment (being the category 'most unsuitable' omitted -in the reference group). The first control carries a strong negative coefficient (as in the municipality level analysis), the second a positive one, while the two most suitable categories carry strong positive coefficients. Column 4 adds the latitude and longitude quadratic polynomial term. Remarkably, the coefficient on average parcel area remains fairly stable in both columns. The conditional relationship between parcel size and the presence of mega PV plants is depicted using a binned scatter plot in Figure 5.[9] Columns 5 to 8 redo the analysis using a set of parcel size dummies as independent variables, rather than a single continuous variable. Parcels between 10 and 25 ha are much more likely to be part of a mega PV plant than smaller ones. Similarly, parcels of 25-50 ha and of 50-100 ha in size are more likely to host a PV plant than the previous groups. However, a further increase in parcel size does not rise the probability of being part of a mega plant. Regarding the latter, it is worth noting that 50-100 ha is a parcel size large enough to accommodate a mega plant (defined as having 50 or more ha). Moreover, a landholding is typically divided into several cadastral parcels, so parcels of 25 or 30 ha are already of significant size. Besides, many of the largest parcels are government-owned estates and/or in mountainous and forested areas, which are not generally feasible for PV plants.

The coefficients on these binary indicators of cadastral parcel size are large in magnitude. Considering the most saturated model in column 8, parcels of 50-100 ha are 4.2 percentage

[9]Moving from a municipality in the 10th percentile in log cadastral parcel size to the 90th percentile increases the probability of hosting a mega plant from 0.5% to 5% (holding the rest of variables constant at the mean values), a ten-fold increase.

points more likely to be part of a mega PV plant than those smaller than 10 ha. We have checked that using the logistic regression does not alter the results (reported in Table A5). We also redo the analysis removing grid cells with an altitude higher than the maximum altitude of grid cells with mega PV plants within each municipality. The rationale for doing this is to focus on grid cells located in areas where the installation of such facilities is feasible (as evidenced by the existent PV plants built). Table A6 reports the results, where the coefficient on parcel size is again highly statistically significant and now larger in size. The latter is because the existence of larger parcels in the most mountainous areas where mega PV plants are unfeasible creates a downward bias. By focusing on areas with lower altitude we largely remove this bias. However, to be conservative, we focus on the results reported in Table 2.

5 Mechanisms and robustness checks

5.1 Alternative land uses

The bidding process of landowners to attract a developer that wants to install a solar plant may depend at least on two other potential uses of the land. First, rainfed farming, which is available to any landholding. Second, irrigation farming, which requires an amount of land to cover fixed costs, although less than that required in solar plants. The model predicts that in those areas where irrigation is available, some midsize owners choose that option and, as a consequence, solar plants will be more concentrated into large landholdings. For very small and very large landowners this alternative option does not make any difference in their bidding process.

To test whether the evidence gives support to these predictions of the model, we introduce the interaction between parcel size (in the continuous and binary versions) and the percentage of area with irrigated agriculture. We estimate:

$$P_{i,m} = \alpha + \beta_1 \text{Size}_{i,m} + \beta_2 \text{Size}_{i,m} * PercIrrigated_{i,m} + \gamma' X_{i,m} + \lambda_m + \varepsilon_{i,m} \tag{8}$$

Table 3 reports the results of estimating (8). The coefficients in columns 1 to 4 indicate that for low values of parcel size, areas with irrigated agriculture have much less probability of having a mega PV plant than those with rainfed agriculture, but for high values of parcel size, the difference of probability substantially narrows down. The binary version of the parcel size variables in columns 5 to 8 allows a clearer interpretation. The interaction terms between the parcel size dummies and the percentage of irrigated area are negative for intermediate levels of parcel size, but the interaction is insignificant for large parcels. Figure 6 depicts the predicted probability of a mega plant for each parcel size dummy, comparing the 10th and 90th percentiles in irrigated area (%). We can clearly observe that the difference in probability between both alternative land uses is smaller or inexistent for large and very large parcel sizes.

Overall, these results suggest that the relative probability of installing mega PV plants is the highest for large landholdings with irrigated agriculture. In addition, their consistency with the hypotheses of the model concerning alternative land uses provides additional support for the proposed mechanism.

5.2 External validity: U.S. county analysis

We examine the external validity of our results by focusing on the U.S. case. We get data on the location and characteristics of PV plants from the U.S. Large-Scale Solar Photovoltaic Database (USPVDB), developed by Fujita et al. (2023). This dataset provides information of all ground-mounted PV facilities with capacity of at least 1 MW. It contains 3,699 facilities that became operational before 2022. Most of them (99%) started to operate after 2010. Facility locations and their geographic boundaries are visually verified using high-resolution aerial imagery. We define a mega PV plant as a facility occupying at least 50 ha, as in the previous analysis. On average, producing 1 MW (direct current) requires on average 1.7 ha, with 90% of the distribution of plants requiring between 1 and 3 ha per MW.

Using this georeferenced dataset of PV plants, we create a dummy variable capturing whether there is a mega PV plant in a county. We do this by overlapping the layer of mega PV plants with the geographic layer of county boundaries. The variable takes the value of 1 if a mega PV plant occupies at least 50 ha (so that, on average, produces about 29.4 MW) in a county and 0 otherwise. As of December 2021, we identify 487 mega PV plants distributed across 227 counties in 33 states and occupying a surface area of 99,500 ha. In general, this area represents 0.08% of the US cropland area in 2002, but for affected counties, mega photovoltaic plants represent on average 4% of their agricultural area and in some cases as much as 30%.

Data on land concentration comes from the 2002 Agricultural Census, sourced from Haines and ICPSR (2010). The year of measurement is well before the massive deployment of PV plants, which took place after 2010, as mentioned above. We use two indicators, the percentage of harvested cropland in farms of 500 or more acres ($\sim$200 ha), and a binary variable equal to 1 if this percentage is higher than 50, indicating a high incidence of large estates. Figure 7 depicts the spatial distribution of the land concentration indicator, as well as the location of mega PV plants. A visual inspection of the within-state variation in both variables suggests a positive correlation between them. Indeed, counties where land concentration is higher than 50% are much more likely to host a mega PV plant (9.1% of them have one in contrast to an incidence of 3.9% for the rest of the counties).

Regarding control variables, we compute the average altitude of each county and its standard deviation from a raster of 100 m resolution (Geological Survey, 2012). Second, we calculate the average PV output potential (Global Solar Atlas 2.0). Third, we also calculate the total urban population (in logs) within 100 km from the county's centroid, for which we consider the population residing in Census populated places. We also construct and control for additional variables including the distance to the coast, log of the county surface area, the county's population in 2020 (in logs), and a quadratic polynomial of latitude and longitude.

We estimate an equation analogous to Eq. 6 for counties located in the contiguous United States. Table 4 reports the results, with standard errors clustered at the state level. Column 1 shows a positive and statistically significant association between land concentration and the presence of mega plants, conditional on state fixed-effects. Column 2 adds geographic factors such as the PV output potential, elevation, as well as the county's average terrain ruggedness and its area. The coefficient on land concentration slightly decreases, but remains large and statistically significant, while the control variables carry coefficients with the expected sign: positive for PV output potential and surface area, and negative for elevation. The coefficient on terrain ruggedness is insignificant, arguably due to its high correlation with elevation. Column 3 further includes distance to the coast, urban population within 100 km and the county's population, while column 4 adds the quadratic polynomial in latitude and longitude. Remarkably, the coefficient on land concentration remains very robust and precisely estimated. Its magnitude of 0.0015 implies that moving from a county in the 10th percentile in land concentration to the 90th percentile increases the probability of hosting a mega plant from 3.2% to 14.6% (holding the rest of variables constant at their mean values).

Columns 5 to 8 estimate the same regression using the binary version of the land concentration indicator. Focusing on the most saturated model in column 8, the coefficient of 0.071 indicates that counties where more than 50% of agricultural land belongs to farms larger than 500 acres are more than twice as likely to have a mega plant than the rest of counties (12.1% vs 5%).[10]

[10]We have also checked that our results are robust when using the logistic regression. The regression coefficients are reported in Table A7. The exponentiated coefficient (i.e., odds ratio) in column 4 indicates that, holding the rest of the variables constant, a one-percentage-point increase in land concentration leads to 2.5% increase in the odds of a mega PV plant within the county ($e^{0.0249-1}$). Considering column 8,

6 Concluding remarks

The large-scale deployment of solar energy through photovoltaic (PV) plants is a critical step toward achieving a more sustainable and less carbon-dependent economy. However, economies of scale incentivize investors to develop large facilities, often occupying extensive tracts of agricultural land. This trend has sparked resistance from local communities, primarily due to concerns over job losses in agriculture, landscape alterations, and potential negative effects on biodiversity. A comprehensive understanding of the benefits and distributional consequences of mega PV plants is therefore essential for assessing their broader social and economic impact.

This study examines the relationship between land ownership concentration and the location of mega PV plants, focusing on the Spanish context. First, we find that Spanish municipalities where more than 50% of agricultural land is concentrated in farms larger than 200 hectares are approximately twice as likely to host a mega PV plant compared to municipalities with lower land concentration. Second, within municipalities that host mega PV plants, we analyze their precise location and show that these facilities are significantly more likely to be situated on larger cadastral parcels. This finding highlights a key mechanism driving the observed pattern: for developers, securing land for large-scale PV projects is considerably easier when dealing with a single large landowner rather than negotiating with numerous small landowners, where any individual owner may refuse to lease their land or demand excessively high rents.

Additionally, our results indicate that the likelihood of a mega PV plant being established is lower in irrigated areas, where agriculture is more profitable. This effect is primarily driven by medium-sized landholdings, which increase inequality in the distribution of these plants. To assess the external validity of our findings, we extend our analysis to the United States and confirm a similar pattern: counties where large farms (exceeding 500 acres) dominate the agricultural landscape are approximately twice as likely to host a mega PV plant.

Our findings suggest that mega PV plants tend to concentrate in areas with high land ownership concentration, which has important implications for the distribution of local economic benefits. In such regions, lease payments from PV projects are likely to be concentrated among a small number of large landowners or developers, many of whom do not reside in the host communities. As a result, the indirect positive economic effects on local populations may be limited. These insights highlight the need for a more thorough evaluation

having more than 50% of land in large farms implies a 227% increase in the odds of hosting a mega PV plant ($e^{1.1855-1}$).

of the spatial concentration of mega PV projects and call for policy measures that ensure a fairer distribution of benefits. Potential strategies include facilitating coordination among small landowners to attract investment or designing fiscal policies that redistribute income to the local communities hosting these projects.

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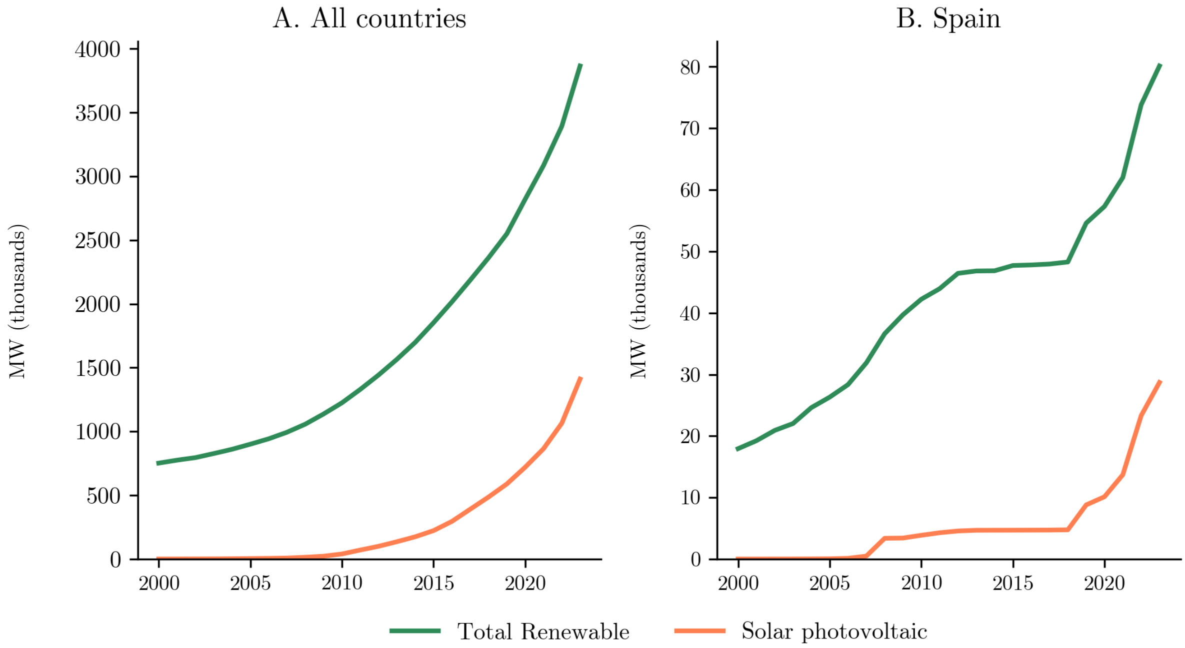
Figure 1. Total Renewable and Photovoltaic Solar Energy

Electricity Installed Capacity



Source: IRENA – International Renewable Energy Agency

Figure 2: Conceptual framework

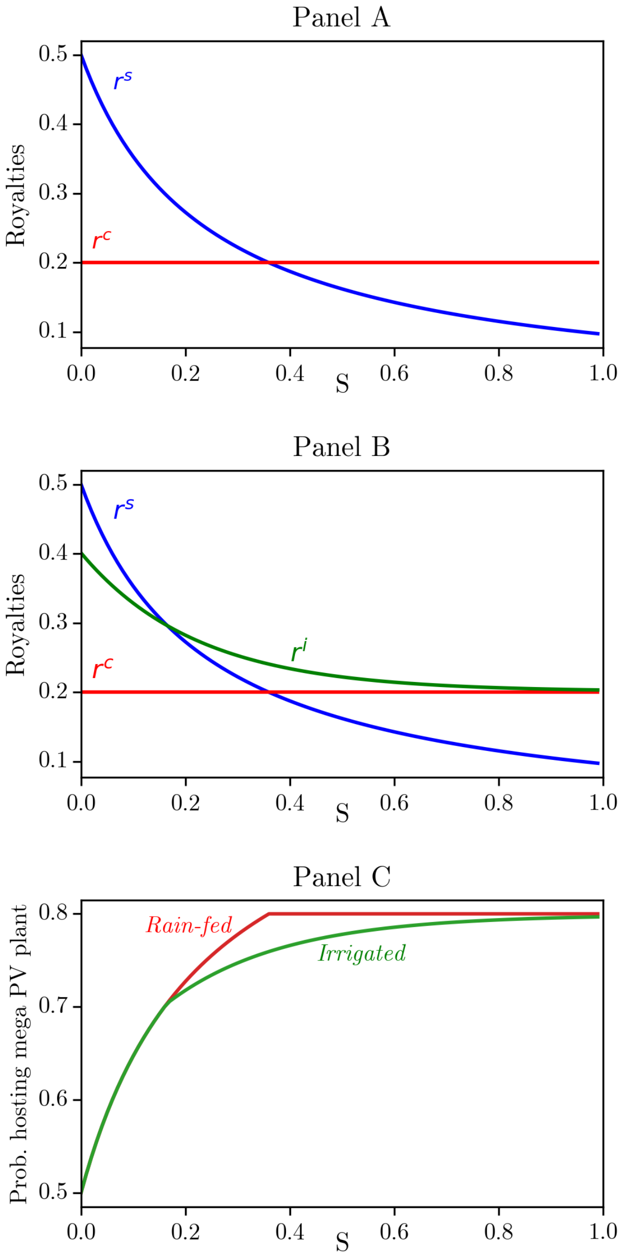


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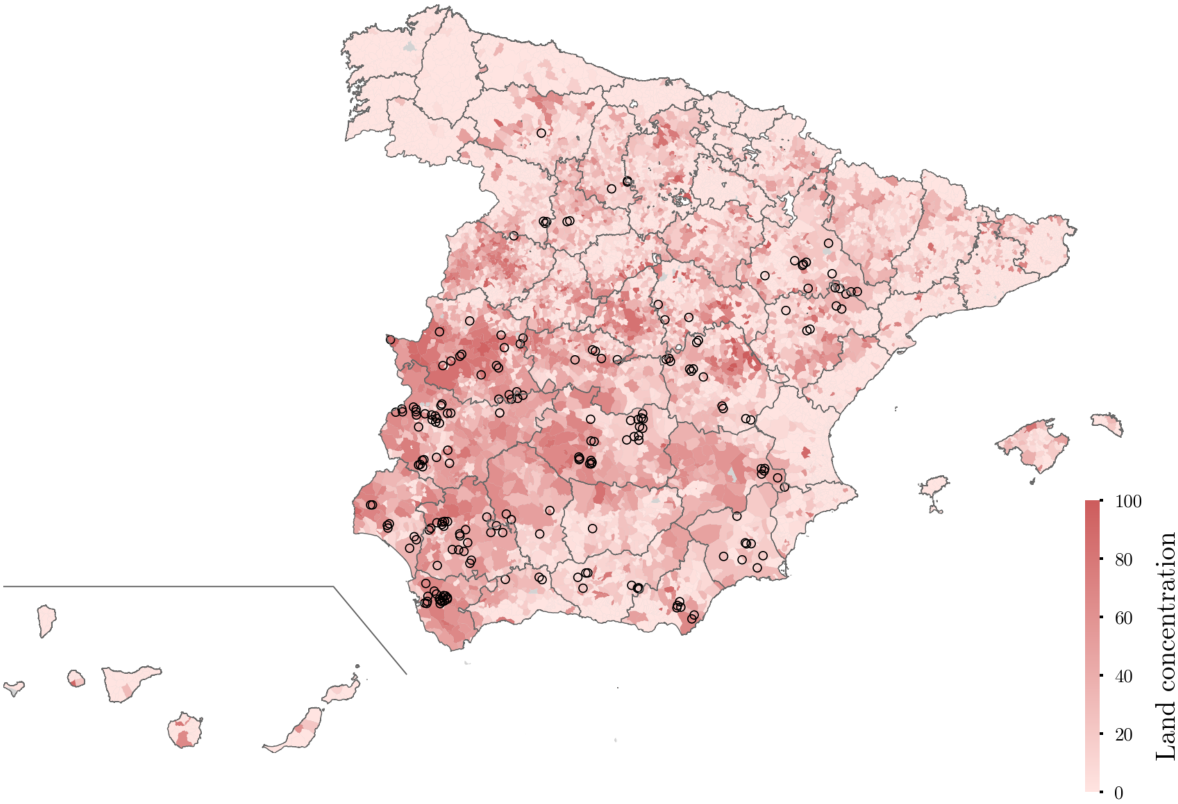
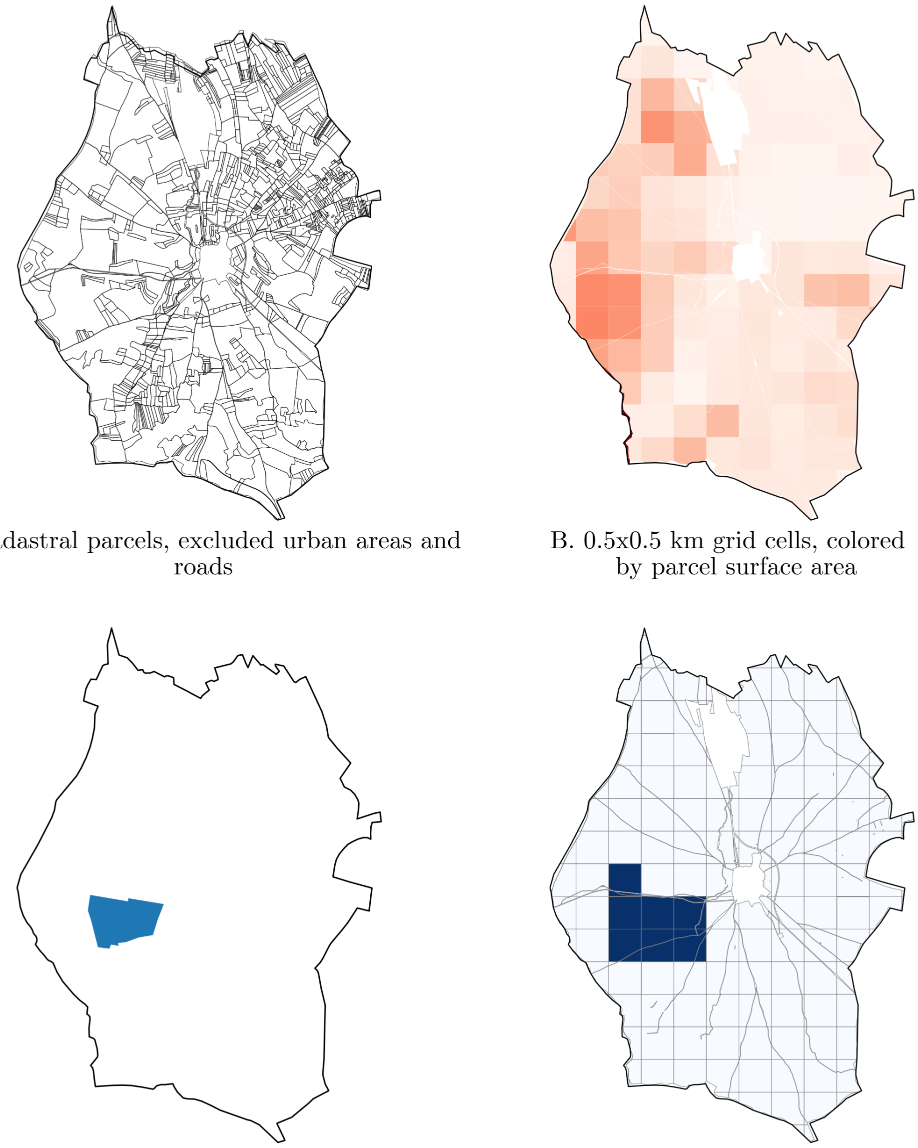
Figure 3. Land concentration and mega PV plants in Spain



Notes: The map represents the variable land concentration, which measures the percentage of agricultural land in farms larger than 200 ha. The circles represent the location of PV plants of 50 or more ha. operating in 2023. Sources: Own elaboration and 1999 Agricultural Census (INE).

Figure 4. Construction of the grid-cell level dataset



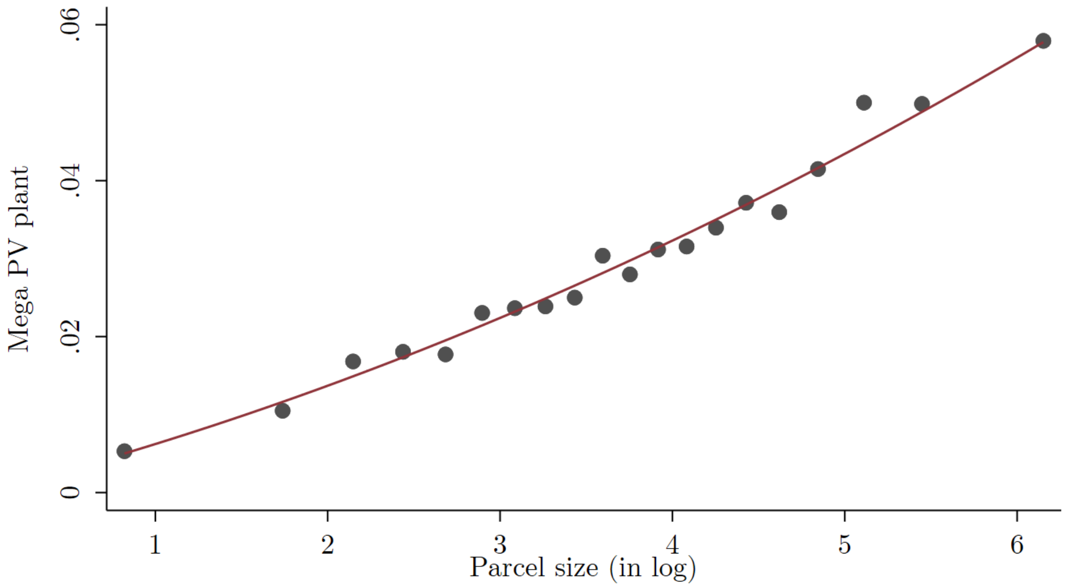
A. Cadastral parcels, excluded urban areas and roads

B. 0.5x0.5 km grid cells, colored by parcel surface area

C. Mega PV plants, georeferenced from satellite imagery

D. 0.5x0.5 km grid cells, colored by mega PV plants

Figure 5: Cadastral parcel size and mega PV plants



Notes: Binned scatterplot showing the within-municipality relationship between cadastral parcel size (in log) and mega PV plants at the grid-cell level in Spain, conditional to the control set included in column 4 in Table 2.

Figure 6: Predicted probability of a mega PV plant by cadastral parcel size, depending on agricultural use

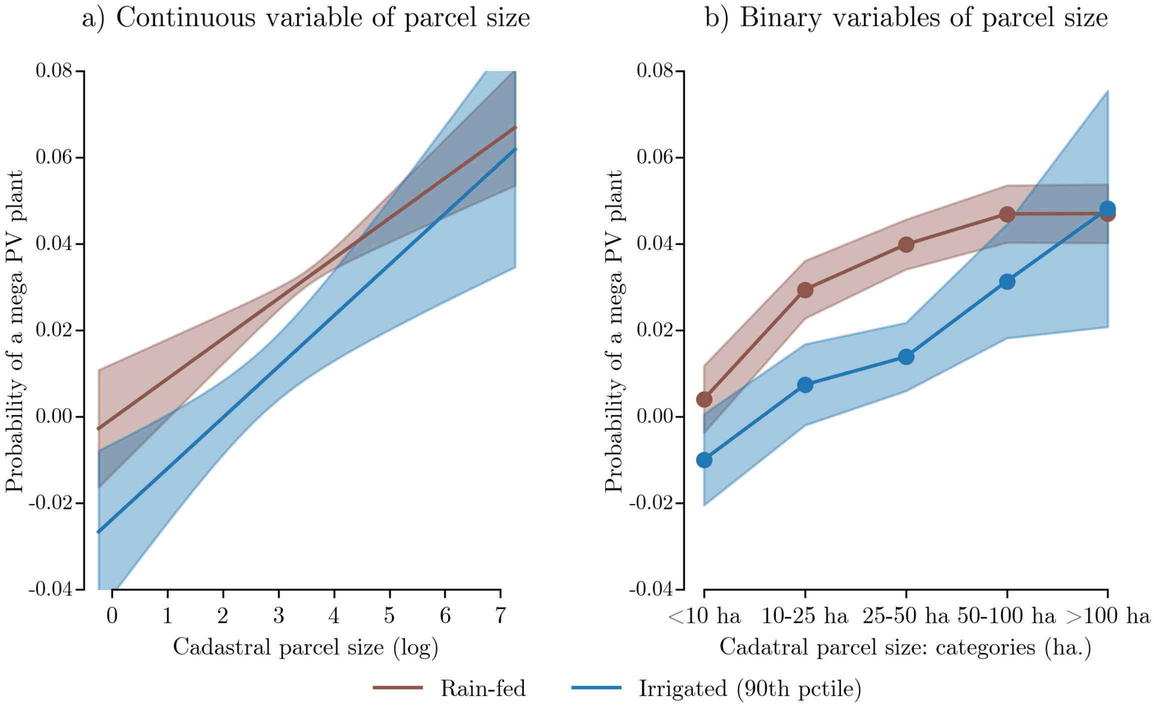
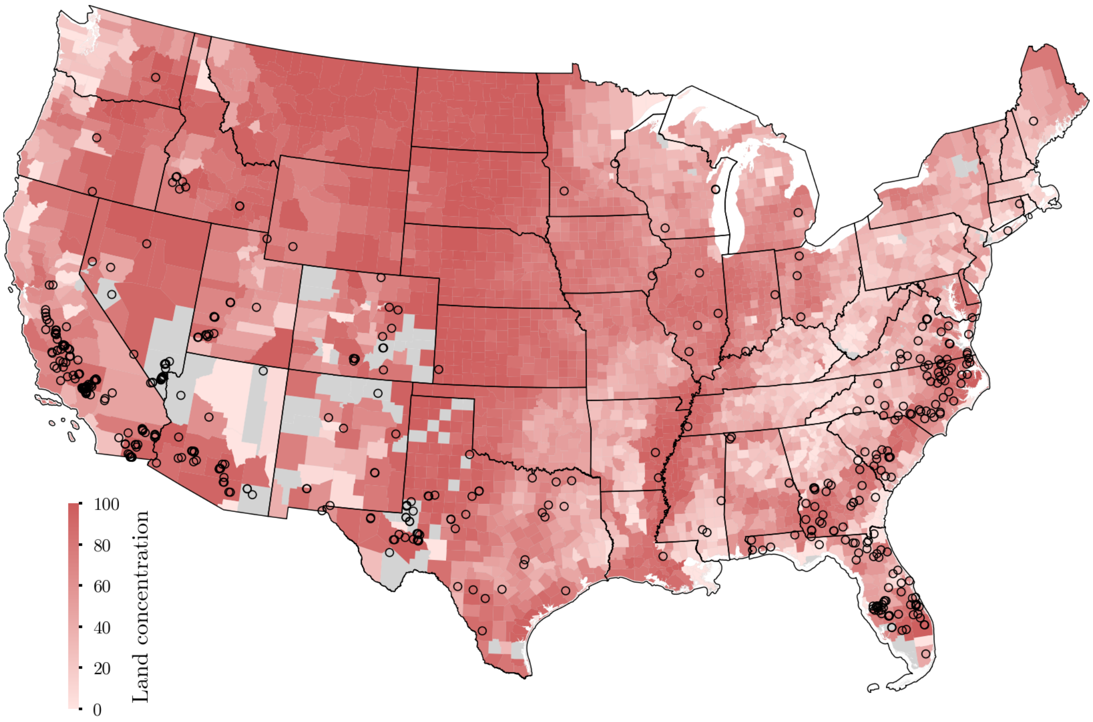


Figure 7. Land concentration and mega PV plants in the US



Notes: The map represents the variable land concentration, which measures the percentage of agricultural land in farms larger than 500 acres. Grey counties indicate missing data. The circles represent the location of PV plants of 50 or more ha. operating in 2021. Sources: US Agricultural Census 2022 (from ICPSR) and USPVDB

Table 1: Land concentration and PV plants across Spanish municipalities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Land concentration	0.0006***	0.0003**	0.0003***	0.0003**	0.0003***					
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)					
Land concent. > 50%						0.0377***	0.0263***	0.0297***	0.0276***	0.0283***
						(0.0101)	(0.01)	(0.0102)	(0.01)	(0.01)
PV output potential		0.0165***	0.0125**	0.0202***	0.0196***		0.0175***	0.0135**	0.021***	0.0209***
		(0.0043)	(0.0058)	(0.0062)	(0.0066)		(0.0043)	(0.0058)	(0.0062)	(0.0066)
Average elevation		-0.0065***	-0.0043***	-0.0017	-0.0007		-0.0065***	-0.0043***	-0.0016	-0.0008
		(0.0014)	(0.0015)	(0.0015)	(0.0016)		(0.0014)	(0.0015)	(0.0015)	(0.0016)
Terrain ruggedness		-0.0045	-0.0078*	-0.0088**	-0.0099**		-0.0046	-0.0081*	-0.0089**	-0.0099**
		(0.0044)	(0.0045)	(0.0045)	(0.0048)		(0.0044)	(0.0045)	(0.0045)	(0.0049)
Municip. area (logs)		0.0304***	0.026***	0.0288***	0.0283***		0.031***	0.0269***	0.0293***	0.0289***
		(0.004)	(0.0041)	(0.0041)	(0.0042)		(0.004)	(0.0041)	(0.0042)	(0.0042)
Distance to the coast			0	0.0001	0.0003**			0	0.0001	0.0003**
			(0.0001)	(0.0001)	(0.0002)			(0.0001)	(0.0001)	(0.0002)
Municip. pop. (logs)			0.0064**	0.0039	0.0041			0.0064**	0.0041	0.0042
			(0.0026)	(0.0026)	(0.0027)			(0.0027)	(0.0026)	(0.0027)
Urban pop. 100km (logs)			0.0109***	0.0024	0.0027			0.0114***	0.0028	0.003
			(0.0042)	(0.0043)	(0.0046)			(0.0042)	(0.0043)	(0.0046)
Dist. nearest grid node				-0.0016***	-0.0017***				-0.0016***	-0.0017***
				(0.0002)	(0.0002)				(0.0002)	(0.0002)
Environ. suitability				-0.0013	-0.0011				-0.0012	-0.001
				(0.0018)	(0.0019)				(0.0018)	(0.0019)
Quadratic polyn. lat/lon.					Yes					Yes
Province fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.04	0.07	0.08	0.09	0.09	0.04	0.07	0.08	0.09	0.09
Observations	4,380	4,379	4,379	4,379	4,379	4,380	4,379	4,379	4,379	4,379

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Heteroscedasticity robust standard errors are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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Table 2: Intra-municipality grid-cell level analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cadastre area (log)	0.0043***	0.0096***	0.0099***	0.0099***				
	(0.0013)	(0.0018)	(0.0017)	(0.0017)				
Parcel 10 - 24.99 ha					0.0184***	0.0235***	0.0226***	0.0221***
					(0.0032)	(0.0035)	(0.0035)	(0.0036)
Parcel 25 - 49.99 ha					0.0239***	0.0333***	0.033***	0.0325***
					(0.0044)	(0.005)	(0.0048)	(0.0049)
Parcel 50 - 99.99 ha					0.0284***	0.0419***	0.0426***	0.0421***
					(0.0054)	(0.0064)	(0.0062)	(0.0062)
Parcel > 100 ha					0.0214***	0.043***	0.0446***	0.0443***
					(0.0054)	(0.0069)	(0.0066)	(0.0067)
Average elevation		-0.0022	-0.0008	-0.001		-0.002	-0.0005	-0.0006
		(0.0017)	(0.002)	(0.0018)		(0.0016)	(0.002)	(0.0018)
Terrain ruggedness		-0.0015***	-0.0014***	-0.0013***		-0.0015***	-0.0013***	-0.0013***
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0002)	(0.0003)
Wetness (%)		-0.0011***	-0.0009***	-0.0009***		-0.0011***	-0.0009***	-0.0009***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Irrigation (%)		-0.0258***	-0.0305***	-0.0311***		-0.0256***	-0.0303***	-0.0308***
		(0.0063)	(0.0073)	(0.0076)		(0.0065)	(0.0075)	(0.0078)
Forest (%)		-0.0511***	-0.0442***	-0.0447***		-0.0516***	-0.0454***	-0.0457***
		(0.0077)	(0.008)	(0.0075)		(0.0078)	(0.0079)	(0.0075)
Distance to nearest grid node			-0.0025***	-0.0026***			-0.0025***	-0.0026***
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
Distance to municipality capital			0.0008**	0.001***			0.0009**	0.0011***
			(0.0004)	(0.0004)			(0.0004)	(0.0003)
Env. suitability 1			0.0072	0.0071			0.0066	0.0066
			(0.0097)	(0.0096)			(0.0098)	(0.0097)
Env. suitability 2			0.0088*	0.0082			0.0087*	0.0082
			(0.0051)	(0.0052)			(0.0051)	(0.0052)
Env. suitability 3			0.0297***	0.0294***			0.0299***	0.0296***
			(0.0062)	(0.0064)			(0.0063)	(0.0064)
Env. suitability 4			0.0305***	0.0297***			0.0315***	0.0308***
			(0.0062)	(0.0064)			(0.0062)	(0.0064)
Quadratic polyn. in lat. and long.				Yes				Yes
Municipality fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.06	0.07	0.07	0.05	0.06	0.07	0.07
Observations	152,481	148,373	148,373	148,373	152,481	148,373	148,373	148,373

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Standard errors clustered at the municipality level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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Table 3: Alternative land uses: irrigated vs rainfed agriculture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cadastre area (log)	0.0029**	0.0087***	0.0093***	0.0094***				
	(0.0013)	(0.0019)	(0.0018)	(0.0018)				
Cadastre area (log) x Irrigation (%)	0.0112**	0.0071	0.0046	0.0041				
	(0.0048)	(0.0049)	(0.0054)	(0.0054)				
Parcel 10 - 24.99 ha					0.0209***	0.0258***	0.0254***	0.0251***
					(0.0037)	(0.0039)	(0.0039)	(0.004)
Parcel 25 - 49.99 ha					0.0244***	0.0352***	0.0358***	0.0356***
					(0.0049)	(0.0055)	(0.0054)	(0.0054)
Parcel 50 - 99.99 ha					0.0259***	0.0413***	0.0429***	0.0427***
					(0.0059)	(0.0068)	(0.0066)	(0.0067)
Parcel > 100 ha					0.0168***	0.0408***	0.0429***	0.0431***
					(0.0054)	(0.0069)	(0.0067)	(0.0068)
Parcel 10 - 24.99 ha x Irrigation (%)					-0.0129*	-0.0116	-0.0148*	-0.0162*
					(0.0071)	(0.0076)	(0.0086)	(0.0082)
Parcel 25 - 49.99 ha x Irrigation (%)					-0.0104	-0.0154	-0.0221**	-0.0236**
					(0.0098)	(0.0098)	(0.0104)	(0.0104)
Parcel 50 - 99.99 ha x Irrigation (%)					0.0134	0.0046	-0.0029	-0.0044
					(0.0162)	(0.016)	(0.0166)	(0.0169)
Parcel > 100 ha x Irrigation (%)					0.0535**	0.0335	0.0279	0.026
					(0.0265)	(0.0261)	(0.0275)	(0.028)
Irrigation (%)	-0.0396***	-0.0456***	-0.0429***	-0.0418***	-0.0122	-0.025***	-0.0258***	-0.0253***
	(0.0129)	(0.0133)	(0.0145)	(0.0145)	(0.0079)	(0.0082)	(0.0085)	(0.0085)
Additional controls 1		Yes	Yes	Yes		Yes	Yes	Yes
Additional controls 2			Yes	Yes			Yes	Yes
Additional controls 3				Yes				Yes
Municipality fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.06	0.07	0.07	0.05	0.06	0.07	0.07
Observations	152,481	148,373	148,373	148,373	152,481	148,373	148,373	148,373

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Additional controls 1 include elevation, terrain ruggedness, wetlands (%), forestland (%). Add. controls 2 include distance to the nearest grid node, distance to the municipality town center, and a set of dummy variables for the five categories of environmental suitability for PV deployment. Add. controls 3 include a quadratic polynomial in latitude and longitude. Standard errors clustered at the municipality level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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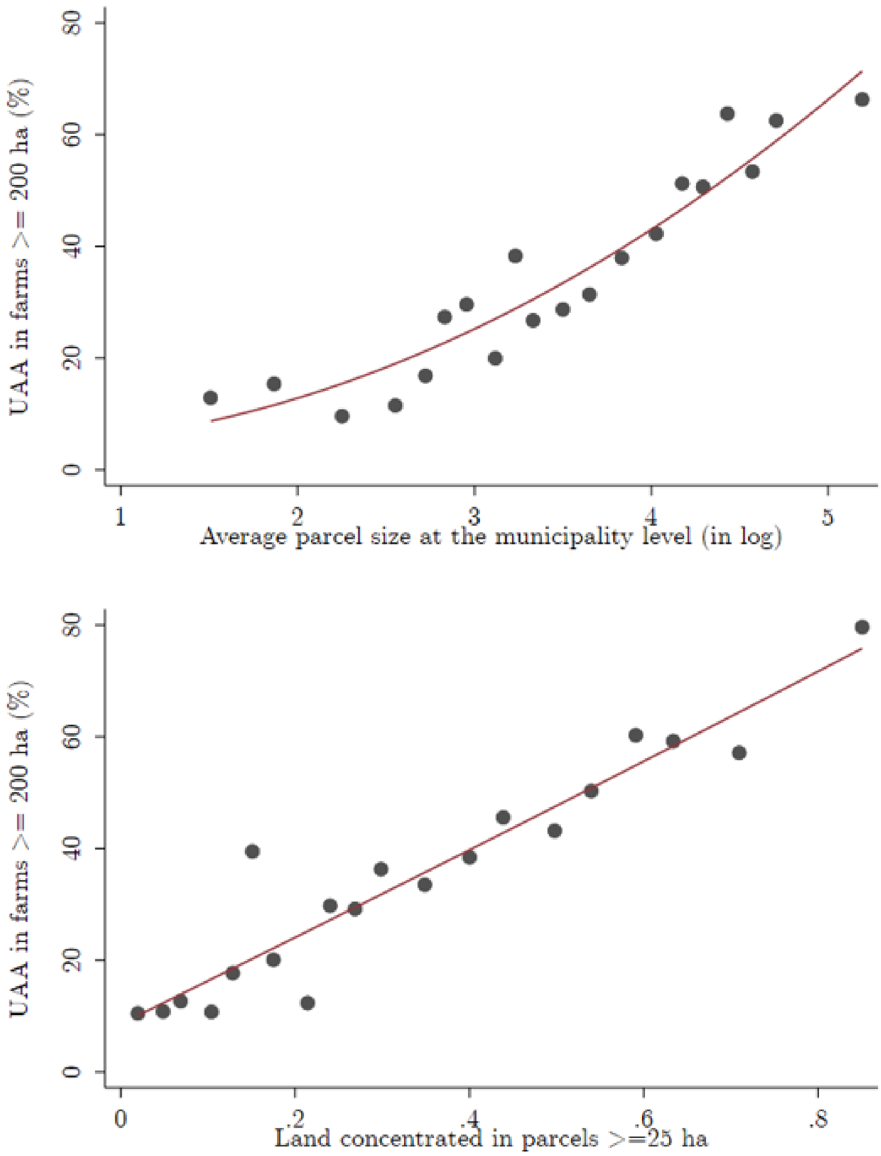
Table 4: Land concentration and PV plants across U.S. counties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Land concentration	0.0022***	0.0012**	0.0015**	0.0015***				
	(0.0006)	(0.0005)	(0.0005)	(0.0005)				
Land concentration > 50%					0.114***	0.0632***	0.0685***	0.0708***
					(0.0293)	(0.0228)	(0.0238)	(0.0237)
PV output potential		0.0007***	0.0008***	0.0004*		0.0007***	0.0008***	0.0004**
		(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)
Average elevation		-0.0002***	-0.0002***	-0.0001**		-0.0002***	-0.0002***	-0.0001**
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Terrain ruggedness		0	0	-0.0001		-0.0001	-0.0001	-0.0002
		(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)
County surface area (log)		0.0891***	0.09***	0.0909***		0.0933***	0.0972***	0.0977***
		(0.0214)	(0.0235)	(0.0223)		(0.0212)	(0.0233)	(0.0224)
Distance to the coast			-0.0001	0			0	0.0001
			(0.0001)	(0.0001)			(0.0001)	(0.0001)
County population (log)			0.0111	0.0104			0.0085	0.0077
			(0.0077)	(0.0074)			(0.0077)	(0.0073)
Urban pop. within 100 km (log)			0.0119	0.0094			0.012	0.0098
			(0.008)	(0.008)			(0.0079)	(0.0078)
Quadratic polynomial in lattitude and longitude				Yes				Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.22	0.23	0.23	0.17	0.22	0.22	0.23
Observations	2,238	2,235	2,227	2,227	2,238	2,235	2,227	2,227

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Standard errors clustered at the state level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

Appendices



The y axis represents the percentage of utilized agricultural area (UAA) in farms with 200 ha or more, at the municipality level. The x axis represents either the average cadastral parcel size aggregated at the municipal level (above) or the percentage of land in cadastres of 25 or more ha (below). To calculate the latter two variables, we focus on grid cells with at least 50% of its surface area devoted to rainfed agriculture or at least 10% devoted to irrigated agriculture.

Figure A1: Cadastral parcel size and land concentration

Table A1. Description and sources of variables

Variable name	Description	Source
Spain municipality analysis		
Mega PV plant	Binary variable equal to 1 if there is a PV facility occupying at least 50 ha in the municipality.	Own elaboration using GIS software and manually processed satellite imagery (Sentinel, Google Earth).
Land concentration	Percentage the percentage of utilized agricultural area (UAA) in holdings equal to or greater than 200 hectares (ha) of UAA.	Own elaboration using data from the 1999 Spanish agricultural census (INE, 1999).
Binary: Land concentration > 50%	Binary variable equal to 1 if the percentage of utilized agricultural area (UAA) in holdings equal to or greater than 200 hectares (ha) of UAA is higher than 50.	Own elaboration using data from the 1999 Spanish agricultural census (INE, 1999).
PV output potential	Average PV output potential of the municipality surface area. The PV output potential is calculated based on the global irradiation at optimum tilt and air temperature.	Own elaboration using data from the Global Solar Atlas 2.0.
Average elevation	Average altitude of the surface area of the municipality (in hundreds of meters).	Own elaboration using data from the GTOPO30 (U.S. Geological Survey).
Terrain ruggedness	Standard deviation of the altitude of the municipality's territory (in hundreds of meters).	Own elaboration using data from the GTOPO30 (U.S. Geological Survey).
Municipality surface area (logs)	Logarithm of the surface area of the municipality, in km.	Own elaboration using GIS software.
Distance to the coast	Distance between the centroid of the municipality and the nearest point of the coast (in km).	Own elaboration using GIS software.
Municipality population (logs)	Total population of the municipality in 2005, in logarithm.	Spanish Statistical Office (INE, Padrón Municipal).
Urban pop. within 100 km (in logs)	Total urban population (in logarithm) within 100 km from the municipality centroid, for which we consider the population residing in the main town (capital) of municipalities in 2022.	Own elaboration using GIS software and data from Nomenclátor Geográfico de Municipios y Entidades de Población (IGN)
Distance to nearest grid node	Distance between the centroid of the municipality and the nearest grid node, in kilometers.	Own elaboration using GIS software and data from Red Eléctrica de España (Informe sobre Capacidad de acceso disponible y ocupada).
Environmental suitability	Average value of the environmental suitability of the territory for the deployment of PV plants, ranging from 0 (the lowest suitability -due to environmental protection) to 4 (the highest suitability)	Own elaboration using GIS software and data from the Ministry for the Ecological Transition (2020).
Latitude	Latitude of the county centroid, in degrees.	Own elaboration using GIS software.
Longitude	Longitude of the county centroid, in degrees.	Own elaboration using GIS software.
Spain grid-cell level analysis		
Mega PV plant	Binary indicator capturing whether a grid cell overlaps (totally or partially) with a mega PV plant	Own elaboration using GIS software and manually processed satellite imagery (Sentinel, Google Earth).
Cadatral parcel area (log)	Logarithm of the average cadastral parcel size in 2005, in hectares. It is calculated as the weighted average of the size of the parcels overlapping with a grid cell, where the weights are the overlapping area of each parcel.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Parcel 10 - 24.99 ha	Binary variable equal to 1 if the average parcel size is equal to or higher than 10 and lower than 25 ha.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Parcel 25 - 49.99 ha	Binary variable equal to 1 if the average parcel size is equal to or higher than 25 and lower than 50 ha.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Parcel 50 - 99.99 ha	Binary variable equal to 1 if the average parcel size is equal to or higher than 50 and lower than 100 ha.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Parcel ≥ 100 ha	Binary variable equal to 1 if the average parcel size is equal to or higher than 100 ha.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).

Table A1. Description and sources of variables *(continued)*		
Variable name	**Description**	**Source**
Average elevation	Average altitude of the grid cell, computed using a raster of 100 m resolution.	Own elaboration using data from COPERNICUS, EUDEMv1.1.
Terrain ruggedness	Standard deviation of the elevation of the grid cell, computed using a raster of 100 m resolution.	Own elaboration using data from COPERNICUS, EUDEMv1.1.
Wetness (%)	Percentage of cell area in temporary water or permanent wet.	Own elaboration using data from COPERNICUS, Water and Wetness.
Irrigation (%)	Percentage of cell area with irrigated land in 2005.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Forest (%)	Percentage of cell area occupied by forest vegetation in 2005.	Own elaboration using GIS software and data from the Spanish Cadastral Office (*Cartografía Catastral Histórica*).
Distance to nearest grid node	Distance between the centroid of the grid cell and the nearest grid node, in kilometers.	Own elaboration using GIS software and data from Red Eléctrica de España (Informe sobre Capacidad de acceso disponible y ocupada).
Distance to municipality capital	Distance from the grid cell centroid to the town center of the municipality.	Own elaboration using GIS software.
Environmental suitability	Binary variables for each of the 5 categories of the classification of the territory according to the environmental suitability for the deployment of PV plants, ranging from 0 (the lowest suitability -due to environmental protection) to 4 (the highest suitability)	Own elaboration using GIS software and data from the Ministry for the Ecological Transition (2020).
US county analysis		
Mega PV plant	Binary variable equal to 1 if there is a PV facility occupying at least 50 ha in the county.	Own elaboration using data from USPVDB.
Land concentration	Percentage of harvested cropland in farms of 500 or more acres (~200 ha).	2002 US Agricultural Census, from Haines and ICPSR (2010).
Binary: Land concentration > 50%	Binary variable equal to 1 if the percentage of harvested cropland in farms of 500 or more acres (~200 ha) is higher than 50.	2002 US Agricultural Census, from Haines and ICPSR (2010).
PV output potential	Average PV output potential of the county surface area. The PV output potential is calculated based on the global irradiation at optimum tilt and air temperature.	Own elaboration using data from the Global Solar Atlas 2.0.
Average elevation	Average altitude of the county, computed using a raster of 100 m resolution.	Own elaboration using data from the Geological Survey (2012).
Terrain ruggedness	Standard deviation of the elevation of the county, computed using a raster of 100 m resolution.	Own elaboration using data from the Geological Survey (2012).
County surface area (log)	Logarithm of the surface area of the county, in meters.	Own elaboration using data from NHGIS (Adams et al., 2004).
Distance to the coast	Distance (in km) from the county representative point (i.e.,centroid) to the nearest point of the shoreline.	Own elaboration using data from NHGIS (Adams et al., 2004) and NOAA's Medium Resolution Digital Vector Shoreline .
County population (log)	Population of the county in 2020, in logarithm.	U.S. Census Bureau, Population Division. : Annual Resident Population Estimates, 2023.
Urban pop. within 100 km (log)	Total urban population (in logarithm) within 100 km from the county centroid, for which we consider the population residing in 2020 U.S. Census populated places.	Own elaboration using data from NHGIS (Adams et al., 2004) and USA Census Populated Place Points (Esri; U.S. Department of Commerce, Census Bureau).
Latitude	Latitude of the county centroid, in meters.	Own elaboration using data from NHGIS (Adams et al., 2004).
Longitude	Longitude of the county centroid, in meters.	Own elaboration using data from NHGIS (Adams et al., 2004).

References not included in the main text:

John S. Adams, William C. Block, Mark Lindberg, Robert McMaster, Steven Ruggles, and Wendy Thomas, National Historical Geographic Information System: Pre-release Version 0.1, Minneapolis: Minnesota Population Center, University of Minnesota, 2004.

Table A2: Descriptive statistics: Spain municipality analysis

Variable name	Obs	Mean	Std. Dev.	Min	Max
Mega PV plant	4,380	0.029	0.17	0.00	1.00
Land concentration	4,380	19.39	24.18	0.00	100.00
Binary: Land concentration > 50%	4,380	0.14	0.35	0.00	1.00
PV output potential	4,380	16.25	0.73	11.97	18.12
Average elevation	4,379	7.47	3.15	0.05	24.06
Terrain ruggedness	4,379	0.74	0.80	0.00	8.61
Municipality surface area (logs)	4,380	3.77	0.99	-0.02	7.47
Distance to the coast	4,380	154.29	80.99	0.44	358.63
Municipality population (logs)	4,380	6.34	1.70	1.95	13.46
Urban pop. within 100 km (in logs)	4,380	13.92	0.78	11.37	15.80
Distance to nearest grid node	4,380	23.1	15.01	0	92
Environmental suitability	4,380	2.4	1.25	0	4
Latitude	4,380	40.21	1.76	36.11	43.16
Longitude	4,380	-3.93	1.88	-7.48	0.32
Spain grid-cell level analysis					
Mega PV plant	152,481	0.03	0.17	0.00	1.00
Cadatral parcel area (log)	152,481	3.62	1.73	-3.05	8.37
Parcel 10 - 24.99 ha	152,481	0.15	0.35	0.00	1.00
Parcel 25 - 49.99 ha	152,481	0.13	0.34	0.00	1.00
Parcel 50 - 99.99 ha	152,481	0.16	0.36	0.00	1.00
Parcel > 100 ha	152,481	0.32	0.47	0.00	1.00
Average elevation	148,373	4.21	2.94	-0.01	26.91
Terrain ruggedness	148,373	7.70	9.33	0.00	132.37
Wetness (%)	152,481	0.08	2.33	0.00	99.87
Irrigation (%)	152,481	0.13	0.27	0.00	1.00
Forest (%)	152,481	0.16	0.29	0.00	1.00
Distance to nearest grid node	152,481	15.27	9.12	0.03	51.26
Distance to municipality capital	152,481	12.15	9.39	0.03	61.66
Env. suitability 0	152,481	0.28	0.45	0.00	1.00
Env. suitability 1	152,481	0.05	0.21	0.00	1.00
Env. suitability 2	152,481	0.17	0.38	0.00	1.00
Env. suitability 3	152,481	0.18	0.38	0.00	1.00
Env. suitability 4	152,481	0.33	0.47	0.00	1.00

Table A2: Descriptive statistics (continued): U.S. counties

Variable name	Obs	Mean	Std. Dev.	Min	Max
Mega PV plant	2,997	0.07	0.26	0.00	1.00
Land concentration	2,997	57.69	28.93	0.00	100.00
Binary: Land concentration > 50%	2,997	0.61	0.49	0.00	1.00
PV output potential	2,994	1,515.63	125.49	1,109.70	1,982.25
Average elevation	2,994	405.15	408.17	0.08	1,628.25
Terrain ruggedness	2,994	67.82	89.74	0.50	344.61
County surface area (log)	2,996	21.31	0.72	17.90	24.69
Distance to the coast	2,994	353.87	303.19	0.00	1,309.33
County population (log)	2,988	10.28	1.47	5.59	16.12
Urban pop. within 100 km (log)	2,994	13.17	1.42	6.41	16.82
Latitude	2,996	158,731	562,603	-1,263,667	1,519,304
Longitude	2,996	386,597	952,313	-2,303,825	2,199,191

Notes: Variables' descriptions are provided in Table A1.

Table A3: Land concentration and PV plants across Spanish municipalities: Logistic regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Land concentration	0.019***	0.0132***	0.0164***	0.0131**	0.0135**					
	(0.003)	(0.0048)	(0.005)	(0.0054)	(0.0057)					
Land concentration > 50%						0.9024***	0.6711***	0.7946***	0.7436***	0.7746***
						(0.1982)	(0.2499)	(0.2504)	(0.2788)	(0.286)
PV output potential		1.8594***	1.5578***	2.0536***	1.8551***		1.8692***	1.6036***	2.1494***	1.9713***
		(0.44)	(0.4391)	(0.5008)	(0.5305)		(0.4334)	(0.4386)	(0.5084)	(0.5362)
Average elevation		-0.2586***	-0.1997***	-0.1414*	-0.0934		-0.2552***	-0.207***	-0.1546*	-0.1081
		(0.0624)	(0.0679)	(0.0854)	(0.1006)		(0.0619)	(0.0681)	(0.0848)	(0.1008)
Terrain ruggedness		-0.2977	-0.3681	-0.3268	-0.3112		-0.3109	-0.3727	-0.3188	-0.2992
		(0.3078)	(0.3167)	(0.3151)	(0.3264)		(0.3096)	(0.3193)	(0.3124)	(0.3281)
Municip. area (logs)		0.8652***	0.699***	1.2118***	1.1741***		0.9113***	0.7817***	1.2707***	1.2348***
		(0.1143)	(0.1295)	(0.1659)	(0.1714)		(0.1114)	(0.1285)	(0.1591)	(0.162)
Distance to the coast			0.0049	0.0102**	0.0222***			0.0056*	0.0109***	0.0227***
			(0.0033)	(0.004)	(0.0083)			(0.0033)	(0.004)	(0.0083)
Municip. pop. (logs)			0.2003**	-0.0669	-0.0435			0.1743*	-0.0856	-0.063
			(0.0875)	(0.1022)	(0.1022)			(0.0895)	(0.1015)	(0.1011)
Urban pop. 100km (in logs)			0.4896**	0.1084	0.243			0.4746**	0.089	0.2302
			(0.2054)	(0.2258)	(0.2311)			(0.2064)	(0.2286)	(0.2363)
Dist. nearest grid node				-0.1148***	-0.1175***				-0.1161***	-0.1188***
				(0.0154)	(0.0158)				(0.0153)	(0.0156)
Environ, suitability				0.2876**	0.3187***				0.2851**	0.318***
				(0.1114)	(0.1155)				(0.1115)	(0.1154)
Quadratic polyn. lat/long.					Yes					Yes
Province fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.15	0.26	0.27	0.36	0.37	0.14	0.26	0.27	0.36	0.37
Observations	4,380	4,379	4,379	4,379	4,379	4,380	4,379	4,379	4,379	4,379

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Heteroscedasticity robust standard errors are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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Table A4: Land concentration and PV plants across Spanish municipalities: 2SLS

	(1)	(2)	(3)	(4)	(5)
Land concentration	0.0018***	0.0011***	0.0013***	0.0012***	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
PV output potential		0.0173***	0.0128**	0.0192***	0.0184***
		(0.0044)	(0.0059)	(0.0062)	(0.0068)
Average elevation		-0.0074***	-0.0042***	-0.0018	-0.0021
		(0.0014)	(0.0015)	(0.0015)	(0.0015)
Terrain ruggedness		-0.0014	-0.0053	-0.0061	-0.0055
		(0.0044)	(0.0046)	(0.0045)	(0.0046)
Municipality surface area (logs)		0.0229***	0.0143***	0.0181***	0.0177***
		(0.0045)	(0.0051)	(0.0051)	(0.0051)
Distance to the coast			0.000	0.0001	0.0001
			(0.0001)	(0.0001)	(0.0001)
Municipality population (logs)			0.0102***	0.0076***	0.0074***
			(0.0028)	(0.0028)	(0.0028)
Urban pop. within 100 km (in logs)			0.0118***	0.0037	0.0022
			(0.0042)	(0.0043)	(0.0044)
Distance to nearest grid node				-0.0015***	-0.0016***
				(0.0002)	(0.0002)
Environmental suitability				-0.0001	-0.0002
				(0.0019)	(0.0019)
Latitude, longitude and its interaction					Yes
First stage (Dep. var: Land conc. 1999)	955.7	645.3	561.4	549.4	895.9
Land conc. 1982: Partial R-sq.	0.247	0.194	0.178	0.175	0.172
Province fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	4,342	4,341	4,341	4,341	4,341

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Heteroscedasticity robust standard errors are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

Table A5: Intra-municipality grid-cell level analysis: logistic regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cadastre area (log)	0.1733***	0.4052***	0.472***	0.484***				
	(0.0487)	(0.0527)	(0.0524)	(0.0527)				
Parcel [10 - 25 ha)					0.7546***	1.0164***	1.0402***	1.059***
					(0.127)	(0.1299)	(0.1202)	(0.1197)
Parcel [25 - 50 ha)					0.9559***	1.4256***	1.4978***	1.5202***
					(0.161)	(0.1593)	(0.1495)	(0.1453)
Parcel [50 - 100 ha)					1.1153***	1.7459***	1.8875***	1.9131***
					(0.1892)	(0.1818)	(0.1773)	(0.1768)
Parcel [> 100 ha]					0.8989***	1.7889***	2.0094***	2.0463***
					(0.2207)	(0.2186)	(0.2133)	(0.2153)
Average elevation		-0.329**	-0.3068**	-0.3266**		-0.313**	-0.297**	-0.3144**
		(0.1291)	(0.1467)	(0.1466)		(0.1315)	(0.1478)	(0.1481)
Terrain ruggedness		-0.1594***	-0.1607***	-0.1611***		-0.1581***	-0.1587***	-0.1591***
		(0.0191)	(0.0198)	(0.0195)		(0.0196)	(0.0205)	(0.0202)
Wetness (%)		-0.4361	-0.3026	-0.3052		-0.4284	-0.2795	-0.2804
		(0.3034)	(0.222)	(0.2241)		(0.2992)	(0.2124)	(0.2128)
Irrigation (%)		-1.3193***	-1.5893***	-1.5449***		-1.3498***	-1.6229***	-1.5823***
		(0.2668)	(0.3613)	(0.3332)		(0.2678)	(0.3609)	(0.3307)
Forest (%)		-3.6759***	-3.4642***	-3.3786***		-3.6504***	-3.4396***	-3.3584***
		(0.3362)	(0.3534)	(0.3616)		(0.3249)	(0.3357)	(0.3417)
Distance to nearest grid node			-0.1598***	-0.1623***			-0.1568***	-0.1595***
			(0.0218)	(0.0219)			(0.0223)	(0.0221)
Distance to municipality capital			0.0097	-0.0002			0.014	0.0039
			(0.02)	(0.0194)			(0.0194)	(0.0189)
Environ. suitability 2			0.9743**	1**			0.9578**	0.9833**
			(0.4404)	(0.4293)			(0.4437)	(0.4363)
Environ. suitability 3			0.9032***	0.9567***			0.9197***	0.9678***
			(0.3069)	(0.3086)			(0.3072)	(0.3104)
Environ. suitability 4			1.6182***	1.6138***			1.6334***	1.6197***
			(0.2902)	(0.2849)			(0.2915)	(0.2872)
Environ. suitability 5			1.7627***	1.7661***			1.7781***	1.7778***
			(0.3058)	(0.3079)			(0.3036)	(0.3067)
Quadratic polyn. lat/lon				Yes				Yes
Municipality fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.13	0.22	0.28	0.28	0.14	0.23	0.28	0.28
Observations	152,481	148,373	148,373	148,373	152,481	148,373	148,373	148,373

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Standard errors clustered at the state level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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Table A6: Intra-municipality grid-cell level analysis: removing grid cells above an altitude for which there is no grid-cells with mega PV plants in the municipality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cadastre area (log)	0.0108***	0.0147***	0.0145***	0.015***				
	(0.0025)	(0.003)	(0.0031)	(0.003)				
Parcel [10 - 25 ha)					0.0293***	0.0333***	0.0313***	0.0309***
					(0.005)	(0.0055)	(0.0056)	(0.0056)
Parcel [25 - 50 ha)					0.0432***	0.0491***	0.0477***	0.0472***
					(0.0071)	(0.0078)	(0.0078)	(0.0078)
Parcel [50 - 100 ha)					0.0523***	0.0613***	0.0608***	0.0606***
					(0.0084)	(0.0094)	(0.0095)	(0.0094)
Parcel [> 100 ha]					0.0504***	0.0673***	0.0674***	0.0682***
					(0.0093)	(0.0108)	(0.011)	(0.0109)
Average elevation		0.0389***	0.032***	0.0329***		0.038***	0.0318***	0.0328***
		(0.0104)	(0.0092)	(0.0095)		(0.0102)	(0.009)	(0.0093)
Terrain ruggedness		-0.0036***	-0.0034***	-0.0034***		-0.0035***	-0.0033***	-0.0034***
		(0.0007)	(0.0007)	(0.0007)		(0.0007)	(0.0007)	(0.0007)
Wetness (%)		-0.0012***	-0.0008***	-0.0009***		-0.0012***	-0.0008***	-0.0009***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Irrigation (%)		-0.039***	-0.0455***	-0.0467***		-0.0387***	-0.0449***	-0.046***
		(0.009)	(0.0105)	(0.0111)		(0.0092)	(0.0109)	(0.0113)
Forest (%)		-0.0759***	-0.0658***	-0.0689***		-0.0778***	-0.0686***	-0.0711***
		(0.0159)	(0.016)	(0.0146)		(0.0158)	(0.0156)	(0.0146)
Distance to nearest grid node			-0.0035***	-0.0036***			-0.0035***	-0.0036***
			(0.0008)	(0.0007)			(0.0008)	(0.0007)
Distance to municipality capital			0.0016**	0.0016***			0.0018***	0.0018***
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
Environ. suitability 2			0.0095	0.0099			0.009	0.0095
			(0.0134)	(0.0142)			(0.0136)	(0.0144)
Environ. suitability 3			0.0147*	0.014*			0.015*	0.0144*
			(0.0077)	(0.0079)			(0.0079)	(0.0081)
Environ. suitability 4			0.0444***	0.0451***			0.0452***	0.0458***
			(0.0085)	(0.0087)			(0.0086)	(0.0088)
Environ. suitability 5			0.046***	0.0452***			0.0481***	0.0473***
			(0.0087)	(0.0085)			(0.0086)	(0.0085)
Quadratic polyn, lat/lon				Yes				Yes
Municipality fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.07	0.09	0.11	0.11	0.07	0.1	0.11	0.11
Observations	91,102	91,102	91,102	91,102	91,102	91,102	91,102	91,102

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Standard errors clustered at the state level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.

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Table A7: Land concentration and PV plants across U.S. counties: Logistic regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Land concentration	0.0281***	0.0182***	0.0222***	0.0249***				
	(0.004)	(0.0042)	(0.0049)	(0.0052)				
Land concentration > 50%					1.5291***	0.9803***	1.102***	1.1855***
					(0.2236)	(0.224)	(0.2531)	(0.2755)
PV output potential		0.0098***	0.0106***	0.0051		0.0102***	0.011***	0.006
		(0.0024)	(0.0027)	(0.0041)		(0.0022)	(0.0026)	(0.0039)
Average elevation		-0.0027***	-0.002**	-0.0013		-0.0026***	-0.0021**	-0.0014
		(0.0007)	(0.0009)	(0.0009)		(0.0007)	(0.0009)	(0.0009)
Terrain ruggedness		-0.0013	-0.0014	-0.0032		-0.0019	-0.0021	-0.0039*
		(0.0021)	(0.0023)	(0.0023)		(0.002)	(0.0021)	(0.0021)
County surface area (logs)		1.1596***	1.1872***	1.2564***		1.1727***	1.236***	1.2957***
		(0.2561)	(0.3118)	(0.3195)		(0.2555)	(0.3002)	(0.3097)
Dist. to coast			-0.0007	-0.0007			-0.0005	-0.0003
			(0.0012)	(0.0015)			(0.0012)	(0.0014)
County pop. (logs)			0.1318	0.1286			0.0935	0.0871
			(0.101)	(0.1026)			(0.0995)	(0.1006)
Urban pop. 100km (in logs)			0.222*	0.2388*			0.212*	0.2256*
			(0.1273)	(0.127)			(0.1155)	(0.1156)
Quadratic polyn. lat/lon				Yes				Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.24	0.3	0.31	0.32	0.24	0.3	0.31	0.32
Observations	2,238	2,235	2,227	2,227	2,238	2,235	2,227	2,227

Notes: The dependent variable is the mega PV plant dummy. Variables' descriptions are provided in Table A1. All the regressions include a constant term which is omitted for space considerations. Standard errors clustered at the state level are in parentheses. *,**,*** denote statistical significance at the 10, 5, and 1% levels, respectively.