

Land concentration and large renewable energy projects*

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Abstract

This paper examines how land ownership concentration shapes the deployment of large-scale renewable energy projects across six European countries (Spain, Germany, France, Italy, Belgium, and the Netherlands). Using a 5×5 km grid-cell framework with cadastral parcel data, we show that cells with a higher share of area in large parcels (≥ 10 ha) are substantially more likely to host mega photovoltaic (PV) plants (≥ 50 ha), with a standardized semi-elasticity of 68% in the pooled sample, consistent across all six countries. Land concentration also drives aggregate solar deployment: a one-standard-deviation increase raises expected PV hectares within a grid cell by 62%, an effect driven almost entirely by the mega-plant margin. By contrast, the effect on wind parks is weaker and heterogeneous, consistent with wind requiring less contiguous land assembly than solar. A specificity test and decomposition analysis corroborate that the assembly mechanism operates specifically at the mega-plant margin, and a horse-race between cadastral concentration and farm operational size establishes that ownership, not farming scale, is the operative mechanism. A finer 500 m grid within-municipality analysis corroborates the effect of land concentration on mega PV plants and further reveals that it is attenuated in irrigated areas, where higher agricultural rents raise landowner reservation values. We rationalize these patterns with a conceptual framework in which solar assembly requires unanimous consent from a set of landowners whose number falls with parcel size, while wind requires only a subset. Our findings reveal that land ownership structure is a decisive factor in the energy transition: fragmentation impedes large-scale deployment, while concentration enables it but channels its benefits toward a few large landowners, potentially deepening rural grievances and local opposition.

Keywords: solar plants; photovoltaic plants; land concentration; energy transition; renewable projects

JEL Codes: O13, Q40, Q15

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1 Introduction

The global energy transition is reshaping landscapes at an unprecedented scale. Driven by ambitious climate targets and falling technology costs, total renewable installed capacity nearly tripled worldwide over the past decade, with solar photovoltaic (PV) experiencing an astonishing tenfold expansion (Figure 1; IRENASTAT 2026). A key driver of this expansion is economies of scale: larger facilities generate electricity at substantially lower unit costs, pushing investors toward large installations that occupy vast tracts of land. The recent acceleration of PV installed capacity is largely driven by large (utility-scale) installations, which accounted for more than two-thirds of new capacity additions in 2024 (Masson et al., 2025).

Yet this same logic of scale creates a deep territorial tension. Large installations tend to cluster in specific regions, concentrating their negative externalities in the communities that host them, while the benefits flow largely elsewhere. Thus, although most of society views these energy infrastructures as necessary or beneficial, rural opposition is significant fueled by concerns over landscape alteration, environmental impact, loss of agricultural land, and the perception that host communities bear the costs while benefits flow elsewhere (Scherhauer et al., 2017; Sills et al., 2020; Späth, 2018; Rodríguez-Segura et al., 2023; Elmallah et al., 2023; Carattini et al., 2024).¹ Understanding what drives the spatial distribution of these facilities — where they are built and why — is therefore of first-order importance, both for the pace of the energy transition and for its social sustainability.

A factor that has received little attention in this debate is land ownership structure. Utility-scale solar installations are land-intensive by nature: a single mega PV plant covering 50 hectares or more must sit on a compact, contiguous block of land, typically assembled from multiple privately owned parcels. This geometric requirement makes the deployment of large-scale solar fundamentally different from most other infrastructure investments — it is not enough to find a suitable location; a developer must also secure the consent of every landowner whose parcel falls within the project footprint. Where land is fragmented among many small owners, the probability that all owners accept the developer’s offer falls mechanically, since each owner independently weighs the offer against their own reservation value — the income from alternative land uses and the cost of relinquishing their land. Where land is concentrated in few hands, the same assembly problem dissolves — fewer consenting owners are required. Land ownership structure may therefore be a decisive factor

¹The U.S. and Europe, among other regions, are witnessing a significant opposition to large renewable energy facilities as has been extensively reported by the media (France24, 2023; The Guardian, 2022b,a). A recent survey in Spain reveals that 56% of the population is against locating PV plants in agricultural areas (GAD3, 2024).

in determining both the pace of the energy transition and the associated territorial tensions.

This paper provides the first systematic evidence on this mechanism, examining how land concentration shapes the location of mega PV plants (≥ 50 ha) across six European countries: Spain, Germany, France, Italy, Belgium, and the Netherlands. Europe is the world’s second-largest PV market after China, with 406 GW of cumulative installed capacity at end-2025 — ahead of the United States (268 GW) — and added 66 GW of new capacity in 2025 alone (de l’Epine et al., 2026). Crucially, the six countries in our sample span a wide range of land ownership structures, from the fragmented smallholder landscapes of Belgium and the Netherlands to the large-estate latifundia of Spain and parts of Italy, providing the cross-sectional variation needed to identify the assembly mechanism. They also differ substantially in the balance between centralized utility-scale and distributed rooftop PV — Spain installs almost exclusively at utility scale, while Belgium and the Netherlands remain predominantly distributed — making the sample an unusually rich laboratory for isolating the conditions under which land ownership becomes a binding constraint on large-scale deployment.

Our analysis operates at two spatial resolutions — a 5×5 km grid covering the full six-country territory and a finer 500×500 m intra-municipal grid — and exploits rich cadastral parcel data to measure land ownership concentration. We show that land concentration is a powerful and robust predictor of mega PV deployment, with a one-standard-deviation increase in the share of land in large parcels raising megaplant probability by around 68% of its mean — an effect that is consistent across all six countries and between four and seven times larger than the corresponding effect on smaller plants. Crucially, this specificity to large-scale facilities is the signature of the assembly mechanism: the difficulty of gathering land matters precisely when many parcels must be assembled together, not when a single small parcel suffices. In contrast, wind parks, whose more irregular and discontinuous spatial footprint requires less contiguous land assembly than solar, show a weaker overall relationship with land concentration and heterogeneous pattern across countries (positive effect for France, Germany and BENL; insignificant for Spain; negative for Italy).

We further show that the contribution of land concentration to aggregate solar deployment is large: a one-standard-deviation increase in land concentration raises expected PV hectares within a grid cell by 62%. Decomposing this effect, it is almost entirely driven by mega installations — the corresponding semi-elasticity is 96% for mega-plant hectares but only 8% for smaller plants. A mediation analysis further reveals that more than half of the total effect on solar area operates through the presence of a megaplant, confirming that land concentration shapes aggregate renewable deployment primarily by enabling large-scale facilities.

A horse-race between cadastral concentration and farm operational size further confirms

that it is ownership, not farming scale, that drives the result for solar. When entered jointly, cadastral concentration retains its full predictive power (standardized semi-elasticity of 65%) while farm size shrinks to less than a fifth of its standalone effect and loses statistical significance. This is consistent with our argument that the binding constraint for developers is the number of landowners whose consent must be secured, not the number of farm operators — a distinction that matters because in Europe land is frequently farmed by tenants rather than its owners.

We also employ a more granular 500×500 m grid to conduct a more demanding analysis that focuses on within-municipal variation, absorbing with municipality fixed effects all factors that are constant across cells of the same municipality. The results confirm the baseline finding: a one-standard-deviation increase in land concentration raises megaplant probability by 59% of its mean across the six-country sample, with positive and significant effects in Spain, Germany, Italy, and France individually. The wind counterpart reproduces the asymmetry observed at the coarser scale — a pooled semi-elasticity of 12%, positive and significant in Spain, Germany, and France, but null in Italy and BENL. The specificity of the assembly mechanism is equally apparent: land concentration strongly predicts megaplant presence (59%) but is essentially unrelated or negatively related to small-plant presence (-10%), while for wind the contrast between large and small facilities is less pronounced. Finally, exploiting heterogeneity between irrigated and rain-fed agriculture in Spain, we find that the positive effect of land concentration on PV deployment is significantly attenuated in irrigated areas, suggesting that the value of alternative agricultural uses moderates the assembly mechanism. Crucially, this interaction is absent for wind, confirming that it operates through the land assembly channel rather than through any general correlation between land structure and agricultural profitability.

The main analysis is conducted with current cadastral data. One may wonder whether reverse causation is an issue. This concern is mitigated by the way land is accessed for energy infrastructure. Developers typically enter into long-term lease agreements with landowners (International Finance Corporation, 2015; Purcell et al., 2025) — the preferred strategy to avoid the high upfront costs of outright land acquisition (Purcell et al., 2025) — without incurring property transactions. Cadastral boundaries therefore remain stable after the installation of a large plant. We verify this directly using historical cadastral data for France (2017) and Spain (2005): the presence of a mega plant neither increases land concentration nor the average parcel size within a cell. Results are also unchanged when replacing current with historical land concentration measures to predict the presence of large renewable energy facilities.²

²A previous version of the paper included an external validity check for our findings for U.S. counties,

Our finding that land concentration is shaping the geography of the energy future, determining what territories host large renewable facilities, relates to three strands of the literature. First, we contribute to the evaluation of the local benefits of large renewable energy projects (see, e.g., Rivera et al., 2024; Fabra et al., 2020; Serra-Sala, 2024). In particular, we challenge one of the main local benefits typically associated with PV plants, namely, the higher rents obtained by landowners —as leasing the land is generally much more profitable than cultivating it.³ 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 big landholdings are often owned by "absentee" individuals, who arguably have less incentives to invest in projects that may stimulate the local economy.

We also relate to Winikoff and Parker (2024), who document a negative relationship between fragmented landownership and wind energy installed capacity in the U.S. Our analysis differs from theirs in three key respects. First, while they focus exclusively on wind, we analyze both solar and wind energy, allowing us to characterize the conditions under which the assembly mechanism is operative across technologies. This matters because solar is now the primary driver of renewable expansion globally: installed PV capacity has increased tenfold over the past decade, compared to a threefold increase for wind, and accounted for three-quarters of new capacity additions in 2025 (IRENASTAT, 2026). Second, we analyze six European countries rather than a single national context, exploiting rich cross-country variation in land ownership structures as well as in regulatory frameworks and deployment patterns. This multi-country design allows us to assess the generality of the mechanism across institutional settings. Third, we develop a conceptual framework that isolates the land assembly problem as the operative mechanism — distinct from the externality-based model in Winikoff and Parker (2024) — and generates predictions that go beyond the sign of the concentration effect. Indeed, our paper is motivated by the literature on anticommons (Heller (1998); Buchanan and Yoon (2000)). Utility-scale solar projects require the assembly of a large and contiguous land surface under fragmented private ownership. When multiple landowners hold exclusion rights over parcels that are all necessary for project completion, renewable investments may be blocked even when they generate large social gains. We provide evidence that this classic anticommons problem is quantitatively relevant for the

finding that a one-standard-deviation increase in land concentration raises the probability of hosting a mega plant by 54.5%, relative to the mean.

³In 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.

deployment of large-scale solar energy, while being much less important for wind projects, whose spatial requirements are more flexible.

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).⁴ 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).⁵ 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) and Oto-Peralías (2020) document 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 of renewable energy is particularly relevant in a context of raising wealth inequality across the world (Zucman, 2019; Saez and Zucman, 2020).

⁴For other theoretical analysis of NIMBY see, for example, Sakai (2012), and Öztürk et al. (2014).

⁵Rand 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.

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 our main results. Section 5 reports a series of robustness checks and further results, including a horse race between cadastral and farm-level concentration, a within-municipality analysis at 500m resolution, an extension to irrigation as an alternative outside option, and a historical cadastral exercise. Finally, Section 6 concludes.

2 Conceptual framework

Large renewable plants provide a particularly clean setting to study anticommons problems because project viability requires a large and continuous land surface. Unlike many investments that can be relocated or redesigned around uncooperative owners, utility-scale solar projects typically require the consent of all landowners within a compact footprint. Fragmented ownership therefore creates coordination frictions that may prevent otherwise profitable renewable investments from being implemented. Spatial requirements are more flexible for wind projects making this problem less important. With this framework in mind, we create a simple model to rationalize the effect of the structure of land ownership on the location of large PV plants and wind parks. There is one developer that requires a total land area of L to make the project viable, generating a total surplus $V > 0$ if completed. The target area is divided among landowners, each owning a parcel of size $s > 0$, so that the developer must assemble $N \equiv L/s$ landowners. Land concentration therefore enters the model through s : holding L fixed, larger parcels imply fewer landowners and a less severe assembly problem. The developer takes the initiative, identifying a target area and making simultaneous take-it-or-leave-it (TIOLI) offers of a transfer t to all N landowners.

Technology and geometry

The two technologies differ in their spatial requirements. A **solar plant** requires a contiguous rectangular footprint covering the full area L , so the developer needs *all* N landowners to accept. If even one owner refuses, the project cannot be implemented. A **wind park**, by contrast, consists of scattered turbines whose positions can be adjusted. Each turbine has a small land footprint, so the developer requires a much smaller effective area than solar, and needs only K parcels out of the N available, with $K < N$. Individual refusals can therefore be accommodated by relocating turbines to consenting owners' land. Moreover, wind turbines occupy only a small fraction $\delta \in (0, 1)$ of each parcel, so accepting a turbine lease does not require the landowner to relinquish the remaining agricultural use of their

land.⁶

Landowner preferences

Each landowner i decides whether to accept the offered transfer t . Acceptance yields t ; rejection yields the landowner's reservation value. For solar, accepting requires converting the entire parcel, so the reservation value is:

$$r_i^{\text{solar}} = v + \varepsilon_i.$$

For wind, accepting requires only a fraction δ of the parcel, leaving the remainder in agricultural use, so the reservation value is:

$$r_i^{\text{wind}} = \delta v + \varepsilon_i,$$

where $v \geq 0$ is the *agricultural rent*, common to all landowners in the area, and $\varepsilon_i \stackrel{\text{iid}}{\sim} U[0, \bar{\varepsilon}]$ is an idiosyncratic shock with fixed dispersion $\bar{\varepsilon} > 0$ capturing heterogeneity in attachment to the land – some landowners may place high intrinsic value on retaining control of their plot due to tradition, community ties, or avoidance of social disapproval. Each landowner accepts if and only if $t \geq r_i$.

Since v is common within an area, solar reservation values are i.i.d. with $r_i^{\text{solar}} \sim U[v, v + \bar{\varepsilon}]$, and the individual acceptance probability under offer t is:

$$p(t) \equiv \Pr(r_i^{\text{solar}} \leq t) = \frac{t - v}{\bar{\varepsilon}}, \quad t \in [v, v + \bar{\varepsilon}].$$

Notice that $p(t)$ does not depend on s : parcel size affects the developer's problem only through the number of landowners $N = L/s$ that must be contacted, not through any individual owner's willingness to accept a given offer.⁷

⁶For a solar plant, unanimity should be understood as a simplification of quasi-unanimous consent. In practice, a developer may retain limited flexibility to exclude a holdout parcel at the edge of the footprint by redrawing its boundary. The qualitative results are unchanged as long as the developer requires the consent of nearly all owners within an essentially fixed contiguous area, in sharp contrast to wind, where only $K \ll L/s$ owners are needed and turbines can be relocated to any consenting parcel.

⁷The model could be extended to allow attachment costs to vary with parcel size, e.g. $r_i^{\text{solar}} = v + \phi(s) + \varepsilon_i$ with $\phi(s) \geq 0$ decreasing in s ($\phi'(s) < 0$), capturing the idea that small landowners face a higher, non-random attachment cost to their plot. Such a term would shift the location of the reservation-value distribution downward as s rises, reinforcing the mechanical channel described below. We omit it from the baseline model for parsimony, since it does not affect the sign of any testable prediction: the qualitative results are driven entirely by the number of landowners $N = L/s$ the developer must persuade, independently of whether reservation values also shift deterministically with s .

Solar plant

The developer needs all N owners to accept. Given i.i.d. acceptance probabilities, the probability of completing the project under offer t is:

$$P_{\text{solar}}(t, s) = p(t)^N = \left(\frac{t - v}{\bar{\varepsilon}} \right)^N.$$

If the plant is built the developer earns $V - Nt$; otherwise it earns zero. The developer maximizes expected profit:

$$\max_t (V - Nt) \left(\frac{t - v}{\bar{\varepsilon}} \right)^N.$$

The first-order condition yields the optimal offer:

$$t^*(s) = \frac{V + v}{N + 1},$$

with equilibrium success probability:

$$P_{\text{solar}}^*(s) = \left(\frac{V - vN}{(N + 1)\bar{\varepsilon}} \right)^N, \quad N = \frac{L}{s}.^8$$

The probability of solar plant construction is increasing in parcel size s through the number of landowners the developer must persuade. Each landowner draws an idiosyncratic shock $\varepsilon_i \sim U[0, \bar{\varepsilon}]$, so even under the optimal offer $t^*(s)$, any landowner whose realized ε_i is sufficiently high will refuse. Because $P_{\text{solar}}^*(s) = p(t^*)^N$ raises a probability strictly less than one to the power N , the chance that all N independent draws fall below the offer shrinks mechanically as N grows. Since $N = L/s$ falls as parcels grow larger, fewer signatures are required and the probability of unanimous acceptance rises. This generates the core empirical prediction: locations with more fragmented land ownership — smaller s , larger N — are less likely to host a mega solar plant: assembling contiguous land from more independent owners mechanically lowers the probability that all of them accept.

Wind park

For wind, the developer requires only K consenting landowners out of the N available, with $K < N$, and makes the same take-it-or-leave-it offer t to all of them simultaneously. The project succeeds as long as at least K owners accept. Since each landowner forfeits only a

⁸We assume parameter values such that $vN < V$ throughout the relevant range of s (equivalently $s > vL/V$), which guarantees $t^*(s) \in (v, v + \bar{\varepsilon})$ and rules out corner solutions in which the developer either abandons the project or offers a transfer that guarantees acceptance with certainty.

fraction δ of their agricultural use, the individual acceptance probability under offer t is:

$$p^\delta(t) \equiv \Pr(\delta v + \varepsilon_i \leq t) = \frac{t - \delta v}{\bar{\varepsilon}}, \quad t \in [\delta v, \delta v + \bar{\varepsilon}],$$

which exceeds the solar acceptance probability $p(t)$ for any given t , since $\delta < 1$. With i.i.d. r_i^{wind} , the probability of assembling at least K consenting owners out of N under offer t is the upper tail of a Binomial($N, p^\delta(t)$) distribution:

$$P_{\text{wind}}(t, s) = \sum_{j=K}^N \binom{N}{j} p^\delta(t)^j (1 - p^\delta(t))^{N-j}.$$

If the project succeeds the developer earns $V - Kt$, paying only the K landowners whose parcels are used; otherwise it earns zero. The developer chooses t to maximize $(V - Kt) P_{\text{wind}}(t, s)$. Unlike the solar case, the resulting first-order condition has no closed-form solution for t^* , since P_{wind} is a sum of binomial terms rather than a single power function; we characterize t^* implicitly and assume parameter values such that an interior solution $t^* \in (\delta v, \delta v + \bar{\varepsilon})$ exists.⁹ What matters for the comparative statics is the behavior of $P_{\text{wind}}^*(s) \equiv P_{\text{wind}}(t^*, s)$ as $N = L/s$ varies. When $N \gg K$ — the empirically relevant case, since a wind park typically requires only a small number of turbine sites relative to the number of parcels in the target area — the developer retains substantial flexibility to route around uncooperative owners, and P_{wind}^* remains close to one and far less sensitive to N than P_{solar}^* , which requires the entire mass of N independent draws to fall below the offer. In the limit as $N/K \rightarrow \infty$, $P_{\text{wind}}^*(s) \rightarrow 1$ regardless of s , so land fragmentation has no effect on wind development probability.

Testable implications

1. *Land concentration increases the probability of mega solar plant installation.* Larger parcels reduce the number of landowners $N = L/s$ that must unanimously agree, mechanically raising the probability that all N idiosyncratic shocks fall below the optimal offer, and therefore raising P_{solar}^* .
2. *The effect is specific to solar and attenuated or absent for wind.* Wind requires only $K < N$ acceptances rather than unanimity, and landowners forfeit only a fraction δ of

⁹The first-order condition is $K P_{\text{wind}}(t^*, s) = (V - Kt^*) \partial P_{\text{wind}} / \partial t|_{t^*}$, where $\partial P_{\text{wind}} / \partial t$ follows from the standard identity for the derivative of a binomial tail probability with respect to the underlying success probability, $\partial P_{\text{wind}} / \partial p^\delta = N \binom{N-1}{K-1} (p^\delta)^{K-1} (1 - p^\delta)^{N-K}$, combined with the chain rule $\partial p^\delta / \partial t = 1/\bar{\varepsilon}$. As in the solar case, the interior-solution assumption rules out corner solutions in which the offer either guarantees fewer than K acceptances with certainty or induces acceptance with certainty.

their agricultural use, both of which make P_{wind} far less sensitive to N — and hence to parcel size — than P_{solar} .

3. *The fragmentation effect is increasing in project scale.* A larger required area L increases the number of landowners $N = L/s$ for any given s , amplifying the role of the most reluctant owner.

3 Data

3.1 Renewable energy installations

Our primary source for solar photovoltaic plant locations is the Transition Zero Solar Asset Monitor (TransitionZero, 2026), a global database of utility-scale PV installations derived from satellite imagery, updated to the first quarter of 2026. The dataset provides georeferenced polygons of PV panels generated using a combination of machine learning methods and human annotation. We restrict the analysis to the mainland territories of our six study countries—Spain, Germany, France, Italy, Belgium, and the Netherlands—excluding overseas departments.

We group together plant polygons lying within 500 meters of each other into what we term a *solar park*. Our definition of a *mega PV plant* is a solar park whose total footprint equals or exceeds 50 hectares. As of Q1 2026, we identify 856 mega PV plants in our six-country sample, occupying a combined footprint of approximately 264,106 ha., with Spain and Germany accounting for the majority of mega plants (56 and 22%, respectively, followed by Italy, 10%, and France, 7%). Panel B of Figure 2 shows the geographic location of these 856 mega PV plants.

Wind turbine locations come from the Global Onshore Wind Energy Resource Spatial dataset (Jung and Schindler, 2026), which provides point-level coordinates for individual onshore turbines across the world updated to July 2025. We group together turbines located within 1000 m of each other, and define a *large wind park* as a cluster of at least 10 turbines. We identify 2,128 large wind parks across the six countries, from which 42% are in Germany, 27% in Spain, 15% in France, 12% in Italy and about 4% in Belgium-Netherlands (Panel C of Figure 2).¹⁰

¹⁰500 and 1000 m are reasonable cutoffs to group PV plants and wind turbines, respectively. The larger distance for turbines reflects minimum spacing requirements to avoid aerodynamic wake losses. In terms of installed capacity, 50 ha of PV panels and 10 turbines are roughly comparable. A utility-scale PV installation achieves approximately 0.5-0.6 MW per hectare of footprint—consistent with the mean power density of 0.58 MW/ha we compute from the Transition Zero data—yielding around 25-30 MW for a 50 ha plant. On the wind side, the fleet average capacity of existing onshore turbines in our study countries is substantially below

3.2 Units of analysis: 5 km and 500 m grids

Our main analysis uses a regular 5×5 km grid covering the mainland territory of the six study countries. To each grid cell, we assign the country and NUTS region where the centroid of the cell is located. In order to have NUTS regions of similar size, we use NUTS-3 for France and Spain and NUTS-2 for the rest. Belgium and the Netherlands are treated as a single country when reporting the results. The German state of Bavaria is excluded as their cadastral parcel data is not publicly available. We remove grid cells with 25% or more of their surface area located in urban fabric or falling in water (using Copernicus Corine Land Cover –CLC– 2012’s classification, European Environment Agency (2012)). The resulting sample size is 64,984 cells.

For a more granular within-municipality analysis we construct a 500×500 m reference grid, restricted to municipalities (LAU in Eurostat’s terms) hosting at least one large renewable energy installation—specifically, those where a mega PV plant overlaps the municipal territory by at least one hectare, or where a large wind park (10 or more turbines) is present. We remove grid cells with no data on cadastral parcels, and those with 10% or more of their surface area located in urban fabric or falling in water. This yields a sample of 2292 municipalities and 836,711 grid cells at the 500m resolution.¹¹

3.3 Cadastral parcel data and land concentration measure

The core explanatory variable is constructed from cadastral parcel data, which record the boundaries of individually registered land parcels and thus provide a direct spatial measure of land holding structure. We assemble data for all six countries from their respective national cadastral registries, harmonized to a common format and projection.

Ideally, we would observe the ownership dimension of cadastral data — joining parcels by registered owner to measure landownership concentration directly. This information is, however, confidential in all six countries of our sample. We therefore rely on parcel size concentration as a proxy. The approximation is well grounded because parcel size provides a logical lower bound on property size: a large parcel can only belong to a large property, so areas with a high share of land in large parcels necessarily have concentrated ownership. In addition, because we include region and municipality fixed effects, any systematic tendency for properties in a given area to be split into more cadastral parcels than elsewhere is absorbed

the 4–5 MW of machines installed in 2024 (WindEurope, 2025), since large-scale deployment accelerated in the early 2000s with 1.5–2.5 MW machines. A conservative fleet average of 2–3 MW implies that 10 turbines represent roughly 20–30 MW.

¹¹All spatial computations are performed in the ETRS89 Lambert Azimuthal Equal-Area projection (EPSG:3035), which provides equal-area cells and metric distances suited to pan-European analysis.

and does not confound our estimates.

Data sources. For Spain we use two vintages of the Catastro (Dirección General del Catastro): the current cadastre (52 provinces) and a historical extract of rural parcels (*parcelas rústicas*) corresponding to approximately 2005 (48 provinces; the Basque Country and Navarra are excluded as they maintain independent registries). For France we use the 2017 and 2025 editions of the Plan Cadastral Informatisé (PCI) Vecteur IGN from cadastre.gouv.fr (96 metropolitan departments in each case). For Germany we use ALKIS (Official Real Estate Cadastre Information System), one GeoPackage per *Bundesland* (15 states; Bavaria excluded), updated to February 2026. For Italy data come from the Catasto terreni (Agenzia delle Entrate), one file per province corresponding to February 2026; the autonomous provinces of Bolzano and Trento are excluded. For Belgium we use the CadMap dataset (SPF Finances) at the arrondissement level (43 units), updated to August 2025. For the Netherlands data come from the *Nationaal georegister* Kadastrale Percelen (INSPIRE geharmoniseerd) as a single national file, updated to March 2026.

Filtering pipeline. All raw cadastral files pass through a standardized three-stage filter before spatial intersection with the 5 km and 500 m grids. First, we discard parcels smaller than 250 m², which removes cadastral slivers, boundary artefacts, and many small urban parcels. Second, we apply a shape filter to identify and remove parcels corresponding to roads, railways, and rivers, which appear in cadastral layers of all countries. We compute parcel compactness $C = 4\pi A/P^2$ (where A is area and P perimeter) and remove parcels with $C < 0.02$; for the borderline range $0.02 \leq C < 0.05$ we additionally compute solidity $S = A/A_{\text{conv}}$ and remove parcels with $S < 0.5$. Third, using the Copernicus CLC 2012 raster with 100 m resolution (European Environment Agency, 2012), we discard parcels whose centroid falls on urban fabric (CLC classes 1–2) or water bodies (CLC classes 40–44). After filtering, parcel areas are capped at 500 ha to limit the leverage of very large (mostly public) estates. The resulting dataset comprises 261 million cadastral parcels.

Grid-cell variables. For each grid cell we perform a spatial intersection of filtered parcel polygons with the cell geometry, yielding the overlap area a_{ij} for every (cell, parcel) pair. The main land concentration indicator (**landconc**) is the percentage of the cell’s total covered area lying within parcels of at least 10 hectares: $\sum_{j: s_j \geq 10 \text{ ha}} a_{ij} / \sum_j a_{ij} \times 100$. We also compute the area-weighted mean parcel size (**AREA.av** = $\sum_j s_j a_{ij} / \sum_j a_{ij}$). We prefer the measure of land concentration (**landconc**) over average parcel size because it directly captures the fraction of land available in blocks large enough to assemble a utility-scale plant without requiring

many separate parcels, making the land assembly problem faced by a developer substantially less severe.¹² Figure 2 (Panel A) maps the main land concentration indicator across the 5×5 km grid for the six-country sample.

3.4 Control variables

For both grid resolutions we include control variables capturing the main geographic, environmental, and infrastructural factors that may simultaneously affect renewable energy infrastructure and the historical distribution of land holdings. Average elevation and terrain ruggedness (std. dev. of elevation within each cell) come from the Copernicus EU-DEM v1.1 raster (100 m resolution). Average PV output potential (kWh/kW_p/year at optimum tilt) is drawn from the Global Solar Atlas 2.0; an analogous wind resource variable is included for the wind analysis (Global Wind Atlas). We also control for the distribution of CLC 2012 land-cover classes within each cell (Copernicus), population (JRC–Eurostat 2021 Census Population Grid), distance to the nearest electricity transmission network node (PyPSA-Eur, Xiong et al. (2025)), and coverage by Natura 2000 protected areas (European Environment Agency, EEA). Finally, for the horse-race exercise against farm operational scale, we draw on newly released geospatial data by EUROSTAT from agricultural census on European scale. Unlike our cadastral measure—which captures registered land parcels each with a single legal owner—the census measures the operational unit, which frequently differs from the ownership unit in Europe because land is widely farmed under tenancy arrangements. Appendix A provides the descriptive statistics of all the variables used in the analysis.

4 Main Results

4.1 Empirical specification

We estimate variants of the following linear probability model:

$$Y_{c,r} = \alpha + \beta \text{LandConc}_{c,r} + \gamma' X_{c,r} + \lambda_r + \varepsilon_{c,r} \quad (1)$$

where $Y_{c,r}$ is a binary outcome for grid cell c in NUTS region r — either the presence of a mega PV plant (≥ 50 ha) or a mega wind park (≥ 10 turbines); $\text{LandConc}_{c,r}$ is the share

¹²Table 8 in Section 4.4 shows that this measure predicts megaplant location significantly better than log average parcel size.

of cell area in cadastral parcels of at least 10 ha, our primary measure of land ownership concentration; $X_{c,r}$ is a vector of control variables; and λ_r is a set of NUTS-region fixed effects that absorb time-invariant regional differences in regulation, grid infrastructure, and local energy policy. Standard errors are clustered by NUTS region to account for spatial correlation within administrative units. We estimate (1) using the Stata command `reghdfe` (Correia and Constantine, 2014).

The vector $X_{c,r}$ includes three groups of controls. The first group captures renewable energy resource potential and physical geography: PV output potential (annual irradiation) and wind power density (100m hub-height wind power density), which ensure that land concentration is not proxying for differences in resource endowment; mean elevation and its standard deviation (terrain ruggedness), which proxy for engineering feasibility and construction costs. The second group controls for land cover and environmental constraints using CLC 2012 shares for agricultural land, forest and semi-natural areas, wetlands, and water bodies — with artificial surfaces omitted — and a categorical variable for Natura 2000 protection intensity, which captures regulatory restrictions on land use. The third group accounts for market access and urban pressure: log distance to the nearest high-voltage transmission line, log distance to the nearest population center, and cell population entered as a categorical variable. All specifications also include a quadratic polynomial in latitude and longitude (Kelly, 2020) to absorb smooth spatial trends not captured by the NUTS fixed effects.

For the aggregate deployment analysis, the outcome is continuous — total renewable energy output in hectares or turbine counts — and we employ Poisson Pseudo-Maximum Likelihood (PPML), estimated through the command `ppmlhdfc` (Correia et al., 2019)), which handles the heavy right skew and zero-inflation in the outcome distribution without requiring ad hoc transformations.

Throughout, we report standardized semi-elasticities at the bottom of each table: $(\hat{\beta} \cdot \text{SD}(X)/\bar{Y}) \times 100$ for LPM specifications and $(\exp(\hat{\beta} \cdot \text{SD}(X)) - 1) \times 100$ for PPML specifications.

4.2 Baseline results

Table 1 reports estimates of equation (1) for both mega PV plants and mega wind parks across progressively saturated specifications. Columns 1–3 focus on solar; columns 4–6 focus on wind.

Column 1 shows a positive and highly significant association between land concentration and the probability of hosting a mega PV plant, conditional on NUTS-region fixed effects

only. The coefficient of 0.017 implies that moving from a fully fragmented cell to a fully concentrated one raises the megaplant probability by 1.7 percentage points — a large effect relative to the sample mean of approximately 1%. Evaluated at a more empirically relevant margin, a one-standard-deviation increase in land concentration leads to a 32.4% increase relative to the mean, as reported at the bottom of the table. Column 2 adds land cover shares and basic geographic controls. The coefficient increases to 0.039, reflecting omitted-variable bias in column 1 that runs against the effect of interest: more forested and mountainous cells tend to have larger parcels but are unfavorable for solar development. The land cover controls correct for this confound. Column 3, our preferred specification, adds distance to the nearest high-voltage transmission line, population density categories, distance to the nearest population center, and Natura 2000 protection intensity, as well as a quadratic polynomial in latitude and longitude (Kelly, 2020). The coefficient on land concentration remains stable at 0.036, with a standardized semi-elasticity of 67.6%, as reported at the bottom.

The control variables carry coefficients broadly consistent with expectations. Elevation is negatively associated with megaplant presence, as mountainous terrain imposes engineering and grid-access costs. Distance to the high-voltage grid is also negative and strongly significant, reflecting the importance of transmission access for the economics of large-scale projects. Cells with greater Natura 2000 coverage are less likely to host plants, consistent with environmental protection constraints. Distance to the NUTS population center decreases the probability of a mega plant, but urbanized cells are less likely to host them.

The contrast with wind is informative. Columns 4–6 repeat the specification for mega wind parks. The pooled coefficient on land concentration is small (-0.021 in the basic specification) and statistically insignificant in the full specification, with the standardized semi-elasticity essentially zero in column 6. This absence of a positive association for wind is consistent with our conceptual framework: assembling contiguous land parcels is not a binding constraint for wind development, which requires only a subset of landowners to agree rather than unanimous consent across the entire footprint. Cadastral fragmentation therefore does not generate the same assembly friction for wind as it does for solar, and the land concentration measure consequently has weak predictive power.

By-country results. Table 2 disaggregates the full-specification coefficient by country for solar. The coefficient is positive and significant in all five countries individually, with standardized semi-elasticities ranging from 54.9% (Italy) to 115.7% (Belgium and the Netherlands). The consistency across countries with very different institutional frameworks, land markets, and solar irradiation levels strengthens confidence that the result reflects a common land assembly mechanism rather than a country-specific effect.

The wind results by country (Table 3) show a more mixed picture: the coefficient is positive and significant for Germany, France and Belgium-Netherlands, negative and significant for Italy, and statistically indistinguishable from zero for Spain. Taken together, these cross-country differences support the interpretation that the positive PV–concentration link is specific to a technology with a hard assembly requirement, while the wind results are heterogeneous and lack the clean directional prediction that solar exhibits. Moreover, in every country the magnitude of the effect is substantially larger for solar than for wind.

Figures 3 and 4 display binned scatterplots of the conditional relationship between land concentration and megaplant probability for the four largest countries (within-NUTS-region residuals), confirming that the positive association for solar is approximately linear and present in each country individually. For wind, the relationship is flat for Spain, negative for Italy, and positive for France and Germany, mirroring the heterogeneity of the by-country regression results.

4.3 Specificity and aggregate deployment

Specificity by plant size. A key implication of the land assembly mechanism is that the positive effect of concentration should be larger for larger plants, which require assembling more parcels. Table 4, tests this by estimating equation (1) separately for three size categories of solar installations: small (≤ 10 ha), medium (10–50 ha), and mega (≥ 50 ha). The coefficient is positive and significant for all three categories, but the standardized semi-elasticity rises sharply with plant size: 9.0% for small, 15.6% for medium, and 67.6% for mega plants. The pattern is clear: concentration matters proportionally more as the required footprint grows.

Table 5 repeats the exercise for wind, categorized as single turbines, medium parks (2–10 turbines), and mega parks (≥ 10 turbines). The pattern does not mirror solar. The coefficient is negative for single turbines (−0.010), positive for medium parks (0.027), and close to zero for mega parks (0.006), with standardized semi-elasticities of −10.9%, 9.2%, and 3.2%, respectively. Thus, there is no monotone scaling of the wind coefficients with park size, in contrast to the solar result, which further distinguishes the two technologies.

Aggregate renewable energy deployment. Table 6 examines whether land concentration shapes not just the location of megaplants but also the total volume of solar energy deployed within a region, and whether this aggregate effect operates through the megaplant channel. We estimate PPML regressions where the outcomes are (1) total PV ha., (2) total PV ha. in non-mega plants, and (3) mega PV ha. in megaplants, using only the NUTS re-

gions with at least one megaplant (to keep a homogeneous sample).¹³ Column 1 shows that land concentration exerts a strong effect on the deployment of PV energy: a one-standard-deviation increase in land concentration raises total PV ha. by 62.4%. Columns 2 and 3 reveal that the effect is highly asymmetric: non-mega solar responds modestly (8.3%), while mega solar responds strongly (95.9%). Columns 4 and 5 implement a simple mediation exercise by adding an indicator for megaplant presence to the total-effect regression: the coefficient on land concentration falls from 1.691 to 0.754, and the indirect effect — the fraction of the total effect that operates through megaplant presence — is estimated at 55.4%. Together, these results indicate that land concentration promotes aggregate solar deployment primarily by making the megaplant pathway viable, rather than by stimulating incremental, distributed generation.

Table 7 repeats the exercise for wind. The total effect of land concentration on aggregate wind output is positive but substantially smaller (semi-elasticity 17.4%), with a similar indirect effect through mega parks (56.9%). The interpretation, however, differs from the solar case. The LPM results in Table 7 show that land concentration is not a robust predictor of mega wind park location in the pooled sample. Most importantly, the overall effect is much smaller than for solar (17.4% vs. 62.4%), confirming that land concentration plays a minor role in wind deployment.

Related, it is worth noting that large wind parks account for a larger share of total wind turbines than mega plants do of total solar hectares: on average across countries, 67% of turbines are installed in mega parks versus 52% of PV capacity in mega plants, with particularly stark differences in Germany (62% vs. 28%), France (63% vs. 26%), and the Netherlands (49% vs. 27%).¹⁴ This suggests that wind deployment is inherently concentrated at the mega-park margin regardless of land ownership structure — for wind, the drivers of that concentration lie elsewhere.

4.4 Cadastral versus farm-level concentration

Table 8 presents two horse races that together speak to the operative mechanism behind the baseline results. The first compares our preferred measure — the share of cell area in parcels ≥ 10 ha — against log average parcel size, an alternative cadastral indicator. This comparison is motivated by the discussion in Section 3.3: while both variables are derived from the same cadastral source, the share in large parcels captures directly the fraction of land available

¹³The command `ppmlhdfc` drops observations from groups where the outcome is uniformly zero, since the group fixed effect is not identified in that case. Without the ex-ante restriction, column 3 would silently lose all NUTS regions without megaplants, leaving the three columns estimated on different samples.

¹⁴Spain features the highest concentration in both technologies (89% for wind and 82% for solar) while Belgium the lowest (36% vs 18%).

in blocks large enough to assemble a megaplant without combining many separate parcels, while average parcel size summarizes the full parcel size distribution without reference to any economically meaningful threshold, potentially mixing cells where land is moderately concentrated throughout with cells where a small number of very large parcels coexist with many small ones. Columns 1 and 2 of Panel A report the standalone results for each measure, where the share in large parcels dominates in magnitude (67.6% vs 54.7%), while column 4 enters them jointly. Notably, while the share in large parcels remains unchanged, average parcel size becomes essentially zero.

The second horse race, in columns 3 and 5, compares average cadastral parcel with average utilized agricultural area (UAA) per farm holding from the Eurostat geospatial agricultural census data (Eurostat, 2025).¹⁵ This comparison is conceptually crucial. As discussed in Section 3.3, the census measures the operational unit of farming, which in Europe frequently differs from the ownership unit because land is widely farmed under tenancy arrangements. The assembly problem a developer faces is a cadastral problem — it depends on the number of registered landowners whose consent must be secured, not on the number of farm operators working the land. If our results truly reflect the assembly mechanism, cadastral concentration should predict megaplant location independently of farm operational size, while the latter should add little once cadastral structure is controlled for.

The data strongly support this prediction. In column 3, log average farm size enters with a standardized semi-elasticity of 27.4%, less than half that of analogous cadastral indicator in column 2. In the joint horse race of column 5, the cadastral indicator retains a semi-elasticity of 51.1% and remains highly significant, while farm size collapses to 13.6% and loses statistical significance.

Table 9 shows the analogous results for wind: here the pattern reverses, with farm operational size entering positively and significantly (semi-elasticity 23.9%) while cadastral concentration is insignificant. This reversal further distinguishes the two technologies — for wind, where no assembly requirement binds, it is the agricultural economic landscape that correlates with deployment, not the legal structure of land parcels.

¹⁵We use the indicator of average cadastral size because land concentration measures are not available from Eurostat (2025). That is, the only available farm size indicator is average UAA per farm holding.

5 Robustness Checks and Further Results

5.1 Within-municipality analysis at 500m resolution

The analysis in Section 4 exploits variation across grid cells within NUTS regions. A potential concern is that, despite the rich set of controls and the NUTS fixed effects, unobserved sub-regional factors may jointly determine both land concentration and megaplant location. To address this, we replicate the baseline analysis at a finer spatial resolution using a 500×500 m grid, replacing NUTS fixed effects with municipality fixed effects. The estimated equation is otherwise identical to (1), with two adaptations to the outcome variables that reflect the finer resolution. At 500m, a cell is coded as hosting a megaplant if it overlaps by at least 1 ha with a PV installation whose total area is ≥ 50 ha; analogously, a cell is coded as hosting a mega wind park if it contains at least one turbine belonging to a park with ≥ 10 turbines in total. These definitions ensure that the 500m outcomes refer to the same set of large-scale installations as the 5km analysis. The main explanatory variable is the share of cell area in parcels ≥ 10 ha, and the control vector is the same as in the main analysis. By absorbing municipality fixed effects, this specification holds constant all factors uniform within a municipality — including local permitting practices, municipal land-use plans, and the identity of active developers — and identifies the effect of land concentration purely from sub-municipal variation in parcel structure. The sample is restricted to municipalities hosting at least one megaplant (for the PV outcome) or at least one mega wind park (for the wind outcome), as municipalities with no large installation provide no within-municipality variation in the outcome.

Tables 10 and 11 report the 500m baseline results for solar and wind, respectively. For solar (Table 10), the pooled coefficient is positive and highly significant, with a standardized semi-elasticity of 58.9% — somewhat below the 5km estimate of 67.6%, consistent with the more demanding within-municipality identification. By country, the effect is positive and significant for Spain (58.7%), Germany (40.9%), Italy (57.1%), and France (20.0%), and statistically indistinguishable from zero for Belgium–Netherlands (−6.0%). For wind (Table 11), the pooled semi-elasticity is 12.1%, with significant positive effects for Spain (20.3%), Germany (11.0%), and France (9.6%), a negative but insignificant coefficient for Italy (−1.4%), and a near-zero coefficient for Belgium–Netherlands (−3.3%). The solar–wind asymmetry documented at the 5km scale is therefore fully reproduced within municipalities: for the pooled sample, the effect of land concentration on mega PV plants is five times larger than on mega wind parks (58.9% vs. 12.1%), and in every country the effect is substantially larger for solar than for wind.

Table 12 replicates the specificity analysis at 500m resolution. Alongside the baseline megaplant and mega wind park columns, the table adds two new outcomes: small PV plants (any installation with total area below 50 ha overlapping the cell), estimated on municipalities selected for wind but not solar to avoid sample-selection pressure on the PV outcome; and small wind parks (any park with fewer than 10 turbines), estimated symmetrically on PV-only municipalities. The key new finding is the sign reversal for small installations. For solar, land concentration turns negative for small plants (-9.7%), in stark contrast to the strongly positive effect for megaplants (58.9%). Within municipalities, concentrated land is not merely more likely to host any solar installation — it is actively channelled toward large-scale facilities at the expense of small ones, consistent with large landowners preferentially engaging with big developers. The wind pattern is analogous: land concentration predicts small park presence negatively (-22.8%, only marginally significant), while it is positive for mega wind parks (12.1%).

5.2 Historical cadastral data

The main analysis uses cadastral parcel data from the most recent available snapshot, which for most countries in the sample is the only one available. A potential concern is reverse causality: if the installation of a mega PV plant triggers changes in land ownership structure — for instance, because developers consolidate the parcels comprising the PV facility — then current land concentration would partly reflect plant presence rather than predicting it. A key feature of the institutional context already mitigates this concern: developers access land through long-term leases rather than outright purchases (International Finance Corporation, 2015; Purcell et al., 2025), so cadastral boundaries are unaffected by plant installation. Nevertheless, we test this directly using historical cadastral data for Spain and France.

For Spain, we obtained cadastral parcel data from *Dirección General de Catastro* as of approximately 2005, well before the large-scale deployment of both PV plants and wind parks in the country. For France, the earliest available snapshot from the cadastre *étalab* is 2017, which postdates some pre-existing installations. We therefore adopt a more conservative approach for France: when testing whether historical concentration predicts plant location, we focus on plants installed from 2020 onwards, which allows sufficient time for the planning, permitting, and construction process to have commenced after the cadastral snapshot date.

The analysis proceeds in two steps. The first, reported in Table 13, tests for reverse causality directly by asking whether the presence of a megaplant predicts a subsequent *increase* in land concentration. The outcome variables are two binary indicators: whether

the share of cell area in parcels ≥ 10 ha increased by more than 1 pp. between the historical and current snapshot (Δ concentr), and whether average parcel size increased by more than 0.1 ha (Δ size). Both are regressed on megaplant presence (or, for France, on megaplants installed from 2020 onwards) with the full set of controls, estimated separately at the 5km and 500m grids. Across all eight specifications — four for Spain and four for France, at both spatial resolutions — the coefficient on megaplant presence is small and statistically indistinguishable from zero. There is no evidence that the installation of a mega PV plant leads to subsequent consolidation of land ownership.

The second step, reported in Tables 14 and 15, uses the historical concentration measure as the explanatory variable to predict current megaplant and wind park presence, replacing the current cadastral data with the historical snapshot. For Spain (Table 14), land concentration as of 2005 predicts megaplant presence with coefficients very close to the baseline estimates, at both 5km and 500m resolution. The wind results are similarly stable. For France (Table 15), concentration as of 2017 predicts both all megaplants (column 1 and 4) and post-2019 megaplants specifically (columns 2 and 5), with the latter arguably the cleanest test since these plants were likely planned after the cadastral snapshot. Wind results are again stable across specifications. Taken together, these results confirm that the baseline findings are not an artefact of reverse causality: historical land concentration predicts current renewable energy deployment, and current plant presence does not predict subsequent changes in land ownership structure.

5.3 Alternative outside options: Irrigation

A related question is whether the effect of land concentration varies with the productivity of agricultural land. Intuitively, owners of highly productive parcels — irrigated land, greenhouses, or other intensive agricultural uses — face a more valuable outside option when considering a solar lease: their land generates higher rents, and it often embodies substantial sunk investments in infrastructure (canals, drainage systems, levelling works, water rights) that would be dismantled or abandoned under a long-term lease, with uncertain prospects of restoration. Higher reservation values make landowners more reluctant to accept a developer’s offer, and this reluctance is plausibly stronger for larger estates, where the productive infrastructure is more extensive and valuable. We should therefore expect the positive effect of land concentration on mega PV deployment to be attenuated in highly productive agricultural areas. For wind, by contrast, no comparable attenuation is expected: hosting a turbine occupies only a small fraction of the parcel and is compatible with continuing the pre-existing agricultural use, so even owners of highly productive land forgo little by

accepting. The expected pattern is thus asymmetric: a negative interaction between land concentration and agricultural productivity for solar, and no interaction for wind.

Table 16 tests this conjecture using the 500m grid for Spain, the only country in our sample with sufficient spatial variation in irrigated area to identify the interaction. The sample is restricted to arable-land cells (those where more than 50% of the cell is covered by irrigated or non-irrigated arable land according to CLC 2012). Columns 1 and 2 use log average parcel size as the concentration measure; columns 3 and 4 use the share of cell area in parcels ≥ 10 ha. For each measure, columns 1 and 3 estimate the PV equation and columns 2 and 4 the wind equation, both including an interaction with the irrigated land share. The results strongly support the expected pattern. For solar, the interaction between land concentration and irrigated land share is negative and significant in both specifications (columns 1 and 3), indicating that the positive effect of concentration on megaplant presence is significantly attenuated in irrigated areas. The coefficient on land concentration remains large and significant, confirming the baseline result for rainfed areas. For wind, by contrast, neither the concentration coefficient nor the interaction is statistically significant (columns 2 and 4). The negative interaction for solar is consistent with the reservation value intuition: the concentration effect is weaker precisely where landowner outside options are more valuable, and irrigated areas are exactly those cells. The absence of any interaction for wind confirms that this attenuation is not a general feature of irrigated landscapes but is specific to solar, consistent with the compatibility of wind turbines with the pre-existing agricultural use of the parcel.

6 Concluding remarks

The global energy transition is reshaping agricultural landscapes at an unprecedented pace. Driven by falling technology costs and ambitious climate targets, total solar PV installed capacity has expanded tenfold over the past decade, driven increasingly by utility-scale facilities that account for the majority of new capacity additions. Yet the deployment of large solar facilities is not random across space: it requires assembling contiguous blocks of land from multiple private owners, a problem whose difficulty depends fundamentally on the structure of land ownership. This paper has examined how that structure shapes the geography of the energy transition across six European countries.

Our central finding is that land ownership concentration is a powerful and robust predictor of mega PV plant location. A one-standard-deviation increase in the share of agricultural area in large cadastral parcels raises the probability of hosting a megaplant by approximately 68% relative to the mean — an effect consistent across all six countries, robust to the transi-

tion from NUTS-region to municipality fixed effects, and confirmed using historical cadastral data predating the solar boom. The mechanism is a land assembly problem typical in the anticommons literature: solar plants require unanimous consent from every landowner within a contiguous footprint, so fragmented ownership raises the probability that at least one owner refuses. Two additional results sharpen this interpretation. First, a horse race between cadastral concentration and farm operational size shows that it is ownership, not farming scale, that drives the result — consistent with the assembly constraint being legal rather than agricultural. Second, the effect is attenuated in irrigated areas, where more profitable and infrastructure-intensive outside options raise landowner reservation values, particularly for larger estates.

The wind results provide a natural comparative benchmark. The effect of land concentration on mega wind park location is five times smaller than for solar in the pooled sample, heterogeneous across countries, and unaffected by irrigation. This asymmetry is precisely what our conceptual framework predicts: wind turbines require neither a contiguous footprint nor unanimous consent, and their small parcel footprint means that accepting a turbine lease leaves the agricultural use of the remaining land essentially intact — reducing the effective reservation value and weakening the link between ownership structure and deployment.

These patterns point to a policy tension at the heart of the energy transition. Concentrated land ownership facilitates large-scale solar deployment — a one-standard-deviation increase in land concentration raises total solar area within a cell by 62.4%, an effect mostly driven by the mega-plant margin — but it also concentrates the economic benefits among a few large landowners, many of whom are absentee, while the costs fall on the affected municipalities. The distributional concerns raised by local communities are therefore grounded in a real economic asymmetry.

Policymakers seeking to accelerate deployment while broadening its benefits might consider mechanisms that lower assembly costs in fragmented landscapes — such as land pooling schemes, cooperative leasing arrangements, or developer obligations to engage with small landowner groups. Agrivoltaics deserves particular attention in this respect: by allowing agricultural production to continue beneath or between the panels, it reduces the share of agricultural use that landowners must forfeit — in terms of our conceptual framework, it moves solar toward the low- δ configuration that makes wind deployment insensitive to land fragmentation — and could thereby unlock large-scale solar development in fragmented, smallholder landscapes that the current technology systematically bypasses. Understanding which communities host large renewable facilities, and who captures the rents they generate, is not a secondary distributional question: it is central to the political economy of the energy

transition itself.

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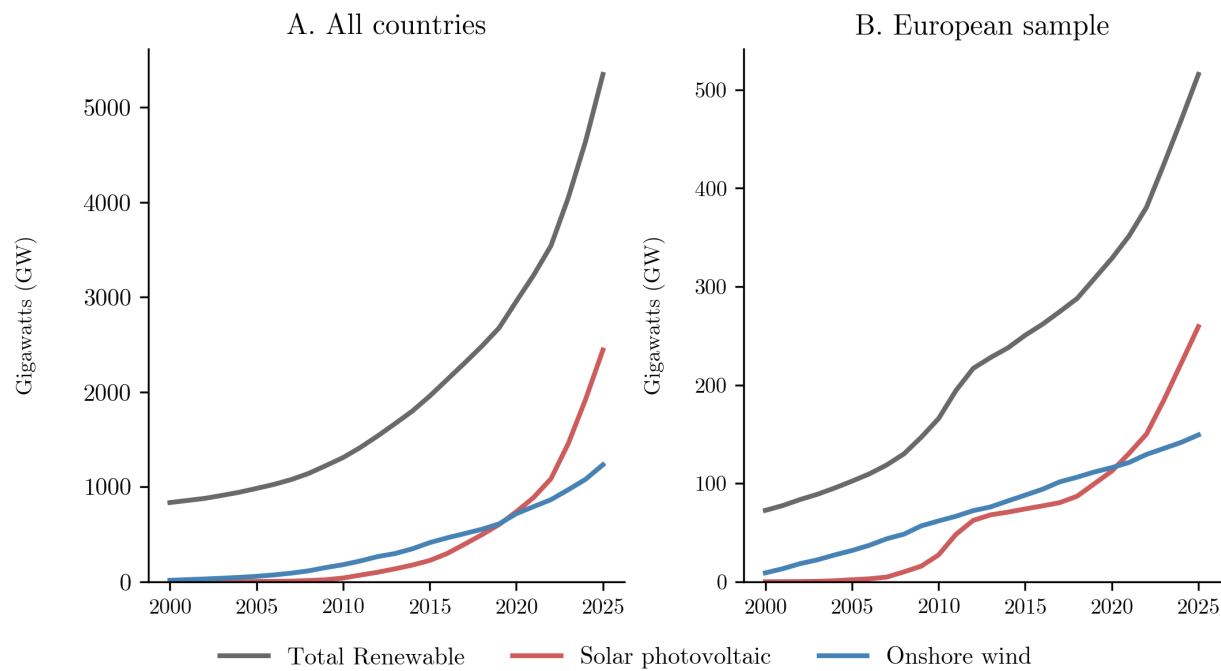
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FIGURES AND TABLES

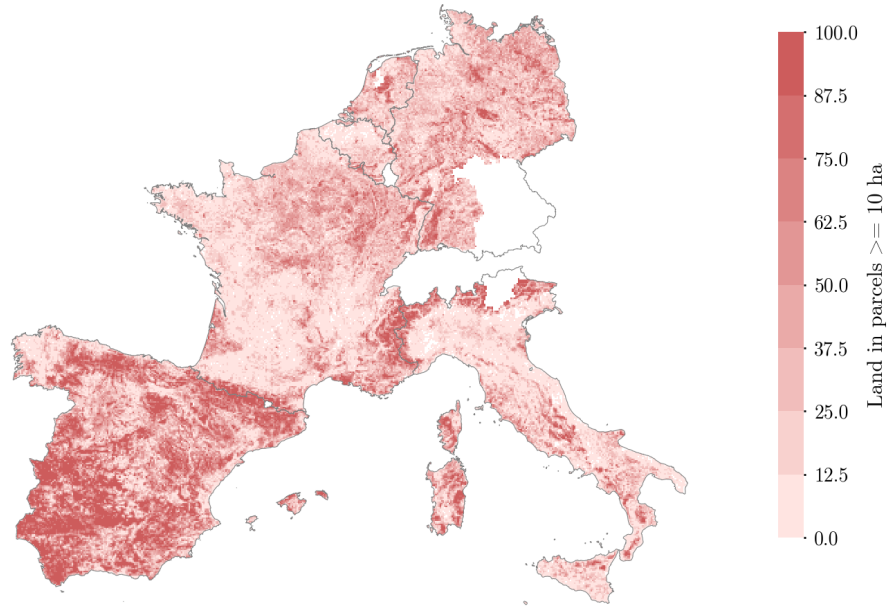
Figure 1. Total Renewable and Photovoltaic Solar Energy
Electricity Installed Capacity 2000 - 2025



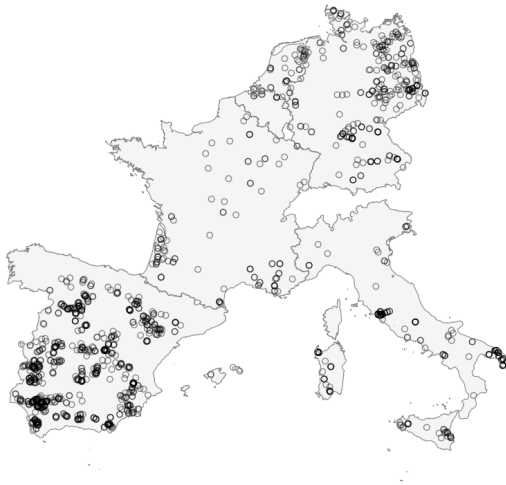
Source: IRENA – International Renewable Energy Agency.
Panel B includes Belgium, France, Germany, Italy, Netherlands, and Spain.

Figure 1: Evolution of renewable energy installed capacity

A. Cadastral land concentration



B. Large PV plants



C. Large turbine parks

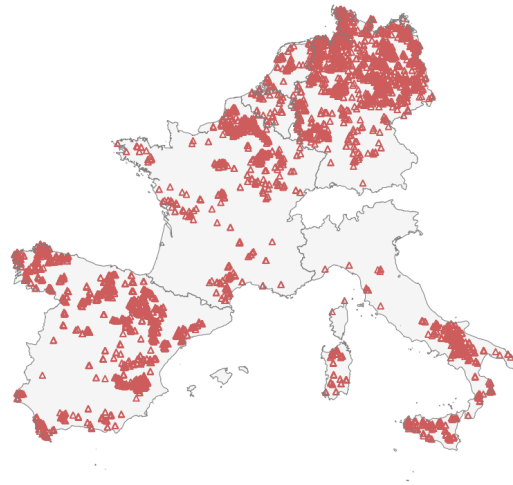
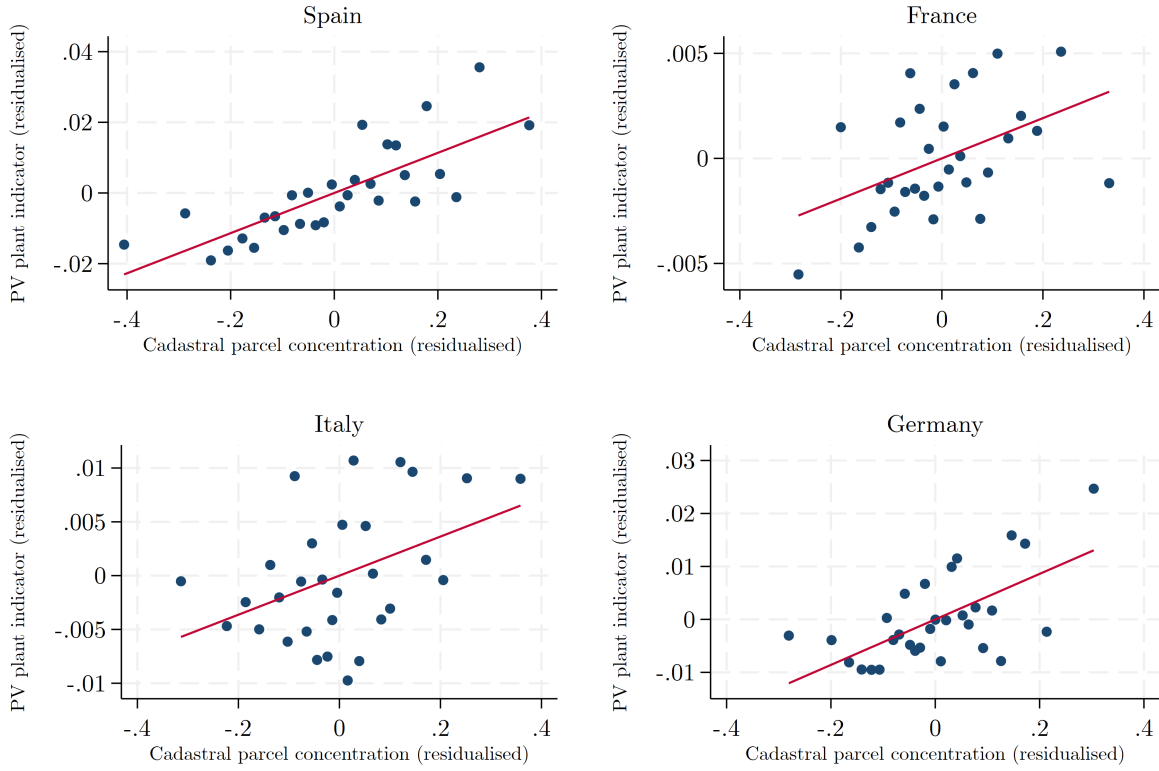


Figure 2: 5 km grid with the main variables

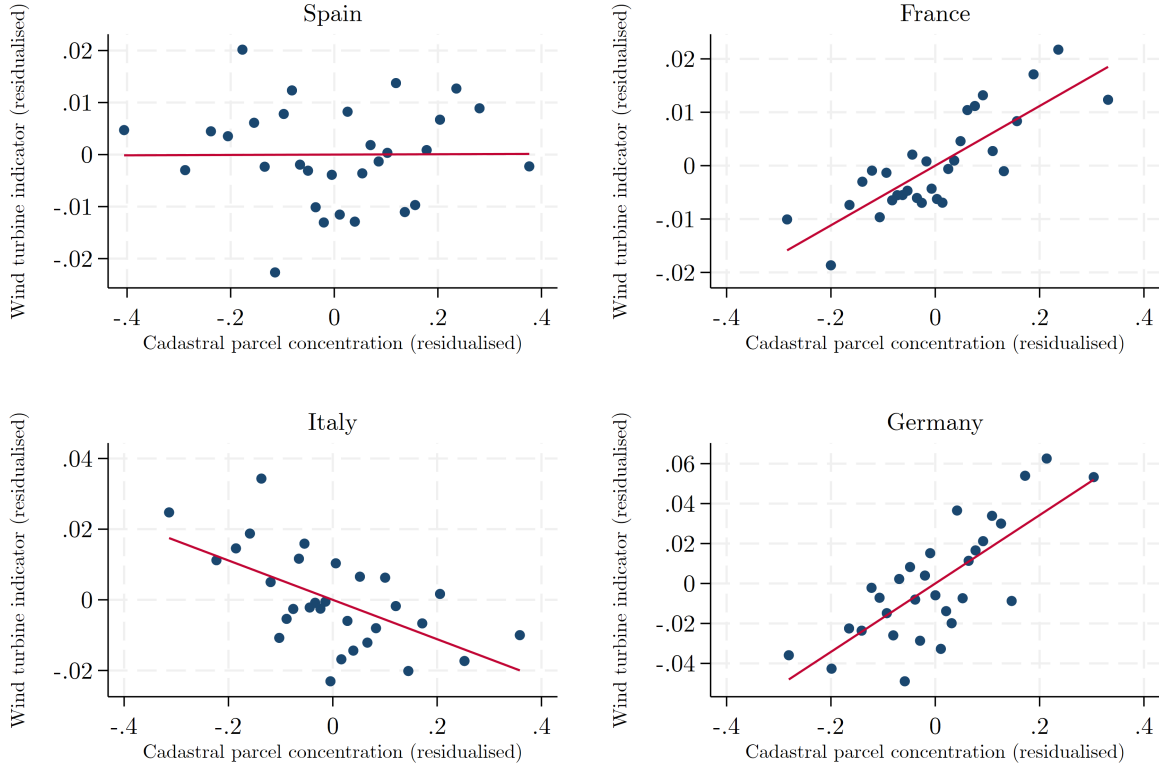
PV Plant Probability and Land Concentration



Land (pct.) in parcels ≥ 10 ha. 30 equal-mass bins. Residuals after NUTS-region FE and controls.

Figure 3: PV Plant Probability and Land Concentration — Four Largest Countries.

Wind Turbine Probability and Land Concentration



Land (pct.) in parcels ≥ 10 ha. 30 equal-mass bins. Residuals after NUTS-region FE and controls.

Figure 4: Wind Turbine Probability and Land Concentration — Four Largest Countries.

Table 1: Baseline results

	Mega PV plant			Mega wind park		
	(1)	(2)	(3)	(4)	(5)	(6)
	Basic	+ Land cover	Full	Basic	+ Land cover	Full
Cell area in	0.017***	0.039***	0.036***	-0.021**	0.000	0.006
parcels ≥ 10 ha	(0.004)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)
Mean elevation	-0.002***	-0.001***	-0.001*	-0.001	-0.002	-0.001
(100 m)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Std. dev.	-0.004*	0.000	0.001	-0.009	-0.003	-0.000
elevation (100 m)	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)	(0.006)
PV output	0.007***	0.003	0.001	0.012	0.008	0.013
potential	(0.002)	(0.002)	(0.002)	(0.010)	(0.009)	(0.009)
Wind power	0.002**	0.000	0.001*	0.029***	0.027***	0.028***
density	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
CLC:		-0.066***	-0.155***		0.177***	0.082***
agricultural land (%)		(0.016)	(0.025)		(0.028)	(0.024)
CLC:		-0.102***	-0.184***		0.133***	0.056**
forest/semi-natural (%)		(0.019)	(0.027)		(0.022)	(0.025)
CLC: wetlands		-0.144***	-0.197***		0.011	-0.016
(%)		(0.029)	(0.036)		(0.048)	(0.056)
CLC: water		-0.107***	-0.172***		-0.159*	-0.168*
bodies (%)		(0.038)	(0.041)		(0.090)	(0.088)
Log dist. to HV			-0.007***			-0.009***
line (km)			(0.001)			(0.002)

Pop. 10-99			0.002			0.008*
			(0.004)			(0.005)
Pop. 100-999			-0.004			-0.002
			(0.004)			(0.005)
Pop. 1k-9.9k			-0.018***			-0.022***
			(0.005)			(0.006)
Pop. $\geq 10k$			-0.054***			-0.044***
			(0.008)			(0.009)
Log dist. to pop. centre (km)			-0.006**			0.007
			(0.003)			(0.004)
Nature: 10%			-0.004**			-0.020***
			(0.002)			(0.004)
Nature: 50%			-0.016***			-0.037***
			(0.002)			(0.006)
Nature: 100%			-0.018***			-0.059***
			(0.003)			(0.009)
Constant	-0.076***	0.048*	-0.184	-0.168	-0.273**	0.954
	(0.026)	(0.028)	(0.520)	(0.128)	(0.128)	(1.605)
N	64,980	64,980	64,980	64,980	64,980	64,980
R ²	0.0349	0.0393	0.0513	0.1014	0.1061	0.1160
Coef.x SD/mean(Y)	32.4	74.0	67.6	-10.9	0.0	3.2

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Standardized semi-elasticity: $\text{coef.} \times \text{SD}(\text{X}) / \text{mean}(\text{Y})$, in %.

Spatial polynomial (lat/lon) included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Mega PV plant

	(1) ALL	(2) BENL	(3) ES	(4) DE	(5) FR	(6) IT
Cell area in parcels ≥ 10 ha	0.0356*** (0.0068)	0.0741* (0.0373)	0.0568*** (0.0133)	0.0430* (0.0214)	0.0096** (0.0048)	0.0182* (0.0097)
N	64,980	2,158	19,581	10,925	21,221	11,095
R ²	0.0513	0.0686	0.0726	0.0335	0.0223	0.0311
Coef.x SD/mean(Y)	67.6	115.7	56.2	55.7	60.2	54.9

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Standardized semi-elasticity: coef. $\times$ SD(X) / mean(Y), in %.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Mega wind plant

	(1) ALL	(2) BENL	(3) ES	(4) DE	(5) FR	(6) IT
Cell area in parcels ≥ 10 ha	0.0061 (0.0114)	0.1816** (0.0826)	0.0003 (0.0163)	0.1712*** (0.0336)	0.0559*** (0.0172)	-0.0557** (0.0240)
N	64,980	2,158	19,581	10,925	21,221	11,095
R ²	0.1160	0.1985	0.1121	0.1427	0.0965	0.1037
Coef.x SD/mean(Y)	3.2	79.6	0.2	27.6	48.8	-37.5

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Standardized semi-elasticity: coef. $\times$ SD(X) / mean(Y), in %.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Solar (PV)

	(1) Small (≥ 10 ha)	(2) Medium (10-50ha)	(3) Mega (≥ 50 ha)
Cell area in parcels ≥ 10 ha	0.0410*** (0.0146)	0.0271*** (0.0080)	0.0356*** (0.0068)
N	64,980	64,980	64,980
R ²	0.1931	0.0725	0.0513
Coef. $\times$ SD / mean(Y) (%)	9.0	15.6	67.6

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Standardized semi-elasticity: coef. $\times$ SD(X) / mean(Y), in %.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Wind

	(1) Small (1 turb.)	(2) Medium (2-10)	(3) Mega (≥ 10)
Cell area in parcels ≥ 10 ha	-0.0102** (0.0048)	0.0269** (0.0115)	0.0061 (0.0114)
N	64,980	64,980	64,980
R ²	0.0965	0.1471	0.1160
Coef. $\times$ SD / mean(Y) (%)	-10.9	9.2	3.2

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Standardized semi-elasticity: coef. $\times$ SD(X) / mean(Y), in %.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Solar (PV)

	(1)	(2)	(3)	(4)	(5)
	(1) Total	(2) Non-mega	(3) Mega	(4) Total effect	(5) + Mediator
Cell area in parcels ≥ 10 ha	1.6911*** (0.2150)	0.2793* (0.1464)	2.3446*** (0.2775)	1.6911*** (0.2150)	0.7535*** (0.1527)
Megaplant present (0/1)					3.5675*** (0.1335)
N	42,932	42,932	42,932	42,932	42,932
$(e^{\hat{\beta} \cdot \text{SD}} - 1) \times 100$	62.4	8.3	95.9	62.4	24.1
Indirect effect (%)					55.4

Standard errors in parentheses

PPML with NUTS-region FE (ppmlhdfe). SE clustered by NUTS region.

Sample: NUTS regions with at least one megaplant.

$(e^{\hat{\beta} \cdot \text{SD}} - 1) \times 100$: % change in expected outcome for a 1-SD increase in land concentr.

Indirect effect (%): share of col. (4) total effect operating through megaplant presence.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Wind

	(1)	(2)	(3)	(4)	(5)
	(1) Total	(2) Non-mega	(3) Mega	(4) Total effect	(5) + Mediator
Cell area in parcels ≥ 10 ha	0.5787*** (0.2126)	0.7379*** (0.1779)	0.5198* (0.2658)	0.5787*** (0.2126)	0.2495** (0.1008)
Mega park present (0/1)					2.9814*** (0.1221)
N	49,704	47,851	49,704	49,704	49,704
$(e^{\hat{\beta} \cdot \text{SD}} - 1) \times 100$	17.4	22.7	15.5	17.4	7.2
Indirect effect (%)					56.9

Standard errors in parentheses

PPML with NUTS-region FE (ppmlhdfe). SE clustered by NUTS region.

Sample: NUTS regions with at least one mega wind park.

$(e^{\hat{\beta} \cdot \text{SD}} - 1) \times 100$: % change in expected outcome for a 1-SD increase in land concentr.

Indirect effect (%): share of col. (4) total effect operating through mega-park presence.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Solar (PV)

	(1)	(2)	(3)	(4)	(5)
Cell area in parcels ≥ 10 ha	0.0356*** (0.0068)			0.0342*** (0.0087)	
Log average parcel size (ha)		0.0057*** (0.0011)		0.0004 (0.0012)	0.0055*** (0.0011)
Log avg. UAA per holding (+0.1) (ha)			0.0037*** (0.0013)		0.0019 (0.0012)
N	64,980	64,980	62,572	64,980	62,572
R ²	0.0513	0.0506	0.0502	0.0513	0.0513
Coef. $\times$ SD/mean: concentration	67.6			64.9	
Coef. $\times$ SD/mean: parcel size		54.7		3.3	51.1
Coef. $\times$ SD/mean: farm size			27.4		13.6

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Cols. (1)-(3): standalone regressions. Cols. (4)-(5): joint horse races.

Coef. $\times$ SD/mean: $(\hat{\beta} \times \text{SD}(X) / \text{mean}(Y)) \times 100$.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Wind

	(1)	(2)	(3)	(4)	(5)
Cell area in parcels ≥ 10 ha	0.0061 (0.0114)			-0.0245 (0.0183)	
Log average parcel size (ha)		0.0036* (0.0021)		0.0075** (0.0034)	0.0020 (0.0022)
Log avg. UAA per holding (+0.1) (ha)			0.0118*** (0.0031)		0.0111*** (0.0031)
N	64,980	64,980	62,572	64,980	62,572
R ²	0.1160	0.1161	0.1194	0.1162	0.1194
Coef. $\times$ SD/mean: concentration	3.2			-12.7	
Coef. $\times$ SD/mean: parcel size		9.5		19.5	5.1
Coef. $\times$ SD/mean: farm size			23.9		22.6

Standard errors in parentheses

LPM with NUTS-region FE (reghdfe). SE clustered by NUTS region.

Cols. (1)-(3): standalone regressions. Cols. (4)-(5): joint horse races.

Coef. $\times$ SD/mean: $(\hat{\beta} \times \text{SD}(X) / \text{mean}(Y)) \times 100$.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effect of land concentration on PV megaplants

	(1) ALL	(2) ES	(3) DE	(4) IT	(5) FR	(6) BENL
Share of cell area in parcels 10 ha	0.0403*** (0.0031)	0.0441*** (0.0042)	0.0296*** (0.0060)	0.0407*** (0.0084)	0.0224* (0.0114)	-0.0024 (0.0061)
N	395,756	266,929	55,046	41,185	14,162	18,434
R ²	0.0909	0.0921	0.1315	0.0685	0.1323	0.0230
Coef. $\times$ SD / mean(Y) (%)	58.9	58.7	40.9	57.1	20.0	-6.0

Standard errors in parentheses

LPM with municipality FE (reghdfe). SE clustered by municipality.

Sample: municipalities with ≥ 1 megaplant.

Coef. $\times$ SD / mean(Y): standardized semi-elasticity in %.

Spatial polynomial (lat/lon) included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effect of land concentration on mega wind parks

	(1) ALL	(2) ES	(3) DE	(4) IT	(5) FR	(6) BENL
Share of cell area in parcels 10 ha	0.0140*** (0.0025)	0.0187*** (0.0042)	0.0161*** (0.0037)	-0.0018 (0.0061)	0.0278** (0.0125)	-0.0038 (0.0134)
N	552,328	228,331	201,659	81,615	17,099	23,624
R ²	0.0963	0.1006	0.0923	0.1248	0.1310	0.0832
Coef. $\times$ SD / mean(Y) (%)	12.1	20.3	11.0	-1.4	9.6	-3.3

Standard errors in parentheses

LPM with municipality FE (reghdfe). SE clustered by municipality.

Sample: municipalities with ≥ 1 mega wind park.

Coef. $\times$ SD / mean(Y): standardized semi-elasticity in %.

Spatial polynomial (lat/lon) included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Specificity — mega vs. small-scale presence

	(1) Megaplant	(2) Small plant	(3) Mega wind park	(4) Small park
Share of cell area in parcels 10 ha	0.0403*** (0.0031)	-0.0016** (0.0006)	0.0140*** (0.0025)	-0.0008* (0.0004)
N	395,756	438,954	552,328	282,382
R ²	0.0909	0.0315	0.0963	0.0282
Coef. × SD / mean(Y) (%)	58.9	-9.7	12.1	-22.8

Standard errors in parentheses

LPM with municipality FE (reghdfe). SE clustered by municipality.

Cols. (1),(3): municipalities with megaplant and mega wind park $i=1$, respectively.

Cols. (2),(4): restricted to municipalities selected for the other technology only, where the listed outcome faces no sample-selection pressure. Full set of controls included but not shown.

Coef. × SD / mean(Y): standardized semi-elasticity in %.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Reverse causality: Does megaplants increase parcel size?

	5km grid				500m grid			
	(1) Δ concentr Spain	(2) Δ size Spain	(3) Δ concentr France	(4) Δ size France	(5) Δ concentr Spain	(6) Δ size Spain	(7) Δ concentr France	(8) Δ size France
PV megaplant (0/1)	-0.0007 (0.0172)	-0.0142 (0.0157)			-0.0235*** (0.0058)	0.0052 (0.0091)		
PV megaplant (0/1) installed ≥ 2020			-0.0211 (0.0440)	-0.0159 (0.0525)			0.0358 (0.0303)	-0.0036 (0.0148)
N	16,357	16,357	4,325	4,325	261,763	261,763	4,260	4,260
R ²	0.0784	0.0524	0.1205	0.1490	0.0663	0.0630	0.1958	0.2315

Δ concentr and Δ size are dummies capturing an increase in land concentration in parcels ≥ 10 ha and in the average parcel size, respectively. These variables refer to the period 2005-2025 for Spain and the period 2017-2025 for FRANCE. LPM with municipality FE (reghdfe). SE clustered by NUTS region (cols. 1-4) and municipality (cols. 5-8) are in parenthesis. Sample restricted to NUTS (cols. 1-4) and municipalities (cols. 5-8) with at least 1 mega PV plant. Full set of controls included. * p $\leq$ 0.10, ** p $\leq$ 0.05, *** p $\leq$ 0.01.

Table 14: Robustness with Historical Cadastral data: Spain

	5km grid (1) Mega PV plant	(2) Wind park	500m grid (3) Mega PV plant	(4) Wind park
Land concentr in parcels ≥ 10 ha	0.0595*** (0.0150)	0.0010 (0.0172)	0.0424*** (0.0042)	0.0227*** (0.0044)
N	16,357	17,508	261,763	216,511
R ²	0.0754	0.1109	0.0938	0.1003

Cadastral data (land concentration) refer to 2005.

LPM with municipality FE (reghdfe). SE clustered by NUTS region (cols. 1-2) and municipality (cols. 3-4) are in parenthesis. Sample restricted to NUTS (c. 1-2) and municipalities (c. 3-4) with at least 1 mega PV plant (c. 1, 3) or 1 turbine park (c. 2, 4).

Full set of controls included. * p_i0.10, ** p_i0.05, *** p_i0.01.

Table 15: Robustness with Historical Cadastral data: France

	5km grid			500m grid		
	(1)	(2)	(3)	(4)	(5)	(6)
	Mega PV plant	Mega PV _i = 2020	Wind park	Mega PV plant	Mega PV _i = 2020	Wind park
Land concentr in parcels $\geq$ 10 ha	0.0239*** (0.0082)	0.0096** (0.0044)	0.0651*** (0.0195)	0.0361*** (0.0112)	0.0620*** (0.0162)	0.0324** (0.0140)
N	7,599	4,325	11,706	13,863	4,260	15,288
R ²	0.0290	0.0261	0.0905	0.1266	0.1621	0.1319

Cadastral data (land concentration) refer to 2017.

LPM with municipality FE (reghdfe). SE clustered by NUTS region (cols. 1-3) and municipality (cols. 4-6) are in parenthesis.

Sample restricted to NUTS (c. 1-3) and municipalities (c. 4-6) with at least a mega PV plant ever installed (c. 1, 4), a mega plant installed after 2019 (c. 2, 5) or a turbine park ever installed (c. 3, 6).

Full set of controls included. * p_i0.10, ** p_i0.05, *** p_i0.01.

Table 16: Irrigation heterogeneity — Spain

	(1) PV	(2) Wind	(3) PV	(4) Wind
Log average parcel size (ha)	0.0222*** (0.0028)	0.0023 (0.0021)		
Log parcel × irrigated land share	-0.0001** (0.0000)	0.0000 (0.0000)		
Share of cell area in parcels 10 ha ≥10 ha			0.0787*** (0.0086)	0.0091 (0.0068)
× irrigated land share			-0.0003*** (0.0001)	0.0000 (0.0001)
clc_212_irrig	0.0000 (0.0001)	-0.0000 (0.0001)	-0.0000 (0.0001)	-0.0000 (0.0001)
N	98,951	64,993	98,951	64,993
R ²	0.1393	0.1263	0.1385	0.1263
Coef. × SD / mean(Y) (%)	70.3	9.4	66.3	9.6

Standard errors in parentheses

Arable-land cells only (≥50% irrigated or non-irrigated arable).

LPM with municipality FE (reghdfe). SE clustered by municipality.

Coef. × SD / mean(Y): standardized semi-elasticity in %, for the uninteracted concentration measure.

Full set of controls included but not shown.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendices

A Descriptive statistics

Table A1: Descriptive Statistics — Pooled Sample (5km grid)

	Mean	SD	Median	Min	Max	N
PV megaplant ≥ 50 ha (0/1)	0.015	0.120	0.000	0.000	1.000	64984
Mega wind park ≥ 10 turbines (0/1)	0.054	0.226	0.000	0.000	1.000	64984
Small PV plant < 10 ha (0/1)	0.127	0.332	0.000	0.000	1.000	64984
Medium PV plant 10–50 ha (0/1)	0.049	0.215	0.000	0.000	1.000	64984
Single turbine (0/1)	0.026	0.160	0.000	0.000	1.000	64984
Medium wind park 2–10 turbines (0/1)	0.082	0.274	0.000	0.000	1.000	64984
Cell area in parcels ≥ 10 ha	0.357	0.279	0.288	0.000	1.000	64984
Log avg. parcel size (ha)	2.643	1.406	2.433	-1.923	6.215	64984
Mean elevation (100 m)	4.491	4.398	3.100	-0.051	34.409	64983
Std. dev. elevation (100 m)	0.626	0.766	0.338	0.000	6.913	64983
PV output potential (100s kWh/kWp)	13.434	2.244	13.196	9.512	18.168	64983
Wind power density (100s W/m ²)	2.798	1.413	2.571	0.146	18.145	64984
Log dist. to HV line (km)	1.805	1.344	2.040	-10.913	5.146	64984
Dist. to pop. centre (km)	40.105	22.604	36.478	0.186	178.943	64984
Natura 2000 share	0.210	0.330	0.019	0.000	1.000	64984
CLC: agricultural land (%)	0.560	0.314	0.618	0.000	1.000	64984
CLC: forest/semi-natural (%)	0.387	0.328	0.308	0.000	1.000	64984
CLC: wetlands (%)	0.003	0.027	0.000	0.000	1.000	64984
CLC: water bodies (%)	0.006	0.023	0.000	0.000	0.250	64984

Unit of observation: 5×5 km grid cell. Sample restricted to cells with cadastral data, water body share $\leq 25\%$, and urban fabric share $\leq 25\%$.

CLC shares expressed as percentage of cell area (CORINE Land Cover 2012).

Table A2: Descriptive Statistics by Country — Main Variables (5km grid)

	All Mean	N	Spain Mean	N	France Mean	N	Germany Mean	N	Italy Mean	N	Belg-Neth Mean	N
PV megaplant ≥50 ha (0/1)	0.015	64984	0.030	19581	0.004	21223	0.016	10925	0.008	11097	0.014	2158
Mega wind park ≥10 turbines (0/1)	0.054	64984	0.052	19581	0.026	21223	0.128	10925	0.038	11097	0.050	2158
Cell area in parcels ≥10 ha	0.357	64984	0.543	19581	0.264	21223	0.332	10925	0.251	11097	0.259	2158

Unit of observation: 5×5 km grid cell.

Belgium and the Netherlands are pooled (BENL).

Table A3: Descriptive Statistics — Pooled Sample (500m grid)

	Mean	SD	Median	Min	Max	N
PV megaplant ≥ 50 ha (0/1)	0.028	0.164	0.000	0.000	1.000	395756
Mega wind park ≥ 10 turbines (0/1)	0.045	0.208	0.000	0.000	1.000	552328
Small PV plant < 50 ha (0/1)	0.008	0.091	0.000	0.000	1.000	836711
Small wind park < 10 turbines (0/1)	0.005	0.073	0.000	0.000	1.000	836711
Cell area in parcels ≥ 10 ha	0.458	0.404	0.406	0.000	1.000	836711
Log avg. parcel size (ha)	2.578	1.706	2.357	-2.816	6.215	836711
Mean elevation (100 m)	3.877	3.582	2.919	-2.589	29.794	836711
Std. dev. elevation (100 m)	0.105	0.124	0.057	0.000	1.839	836711
PV output potential (100s kWh/kWp)	1413.109	268.816	1521.632	919.334	1826.980	836711
Wind power density (100s W/m ²)	313.837	152.737	294.529	15.449	5563.750	836711
Log dist. to HV line (km)	1.627	1.360	1.853	-10.869	5.117	836711
Dist. to pop. centre (km)	7.594	6.327	5.876	0.000	113.433	836711
Natura 2000 share	0.168	0.359	0.000	0.000	1.000	836711
CLC: agricultural land (%)	63.643	42.304	92.000	0.000	100.000	836711
CLC: forest/semi-natural (%)	34.013	41.940	0.000	0.000	100.000	836711
CLC: wetlands (%)	0.392	5.467	0.000	0.000	100.000	836711
CLC: water bodies (%)	0.042	0.615	0.000	0.000	12.000	836711

Unit of observation: 500×500 m grid cell. Sample restricted to municipalities with at least one megaplant (for PV outcomes) or one mega wind park (for wind outcomes). Megaplant and turbine park dummies are missing outside their respective samples. CLC shares expressed as percentage of cell area (CORINE Land Cover 2012).

Table A4: Descriptive Statistics by Country — Main Variables (500m grid)

	All		Spain		France		Germany		Italy		Belg-Neth	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
PV megaplant												
≥50 ha (0/1)	0.028	395756	0.029	266929	0.041	14162	0.027	55046	0.023	41185	0.014	18434
Mega wind park												
≥10 turbines (0/1)	0.045	552328	0.037	228331	0.104	17099	0.050	201659	0.042	81615	0.043	23624
Cell area in												
parcels ≥10 ha	0.458	836711	0.593	438595	0.423	31315	0.317	224796	0.235	109173	0.400	32832

Unit of observation: 500×500 m grid cell.

N for megaplant and turbine park reflects their respective estimation samples.

Belgium and the Netherlands are pooled (BENL).