Farm Size, Spatial Externalities, and Wind Energy Development

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Abstract

The global push for renewable energy must overcome the local challenge of convincing neighboring landowners to lease their properties for wind power. Is this challenge more or less pronounced in rural landscapes with small landholdings? Our theoretical model combines ideas from literatures on the commons, anticommons, and spatial externalities to explain conditions when small landholdings could promote or inhibit voluntary leasing for wind energy. Empirically, we estimate the effects of landholding size and landscape fragmentation on wind farm uptake across rural areas of the United States over the past 20 years. Evidence from three spatial levels of analysis (counties, square-mile sections, and individual parcels) indicates that areas with more landowners have less installed wind capacity after controlling for windiness, access to transmission lines, and other relevant factors that vary across and within counties. The findings imply that fragmented ownership - which is an overlooked factor in studies of the feasibility of decarbonization through onshore wind development - will grow as an impediment to future wind expansion on private land as remaining areas without wind development become disproportionately fragmented.

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> Over the past few years Dewey Engle... who lives on the outskirts of Tahoka, a small farming town in west Texas, has acquired a new view from his back porch. Dozens of wind turbines hum 300ft over the cotton fields behind his bungalow. Some people might be disturbed by the sudden arrival of such monstrous machines practically in their garden. Mr. Engle says that his only problem with them is that they are not on his modest patch of farmland, so he does not get any royalties. "I would love to have that money coming in," he says. "I'd like to have ten of them." (*The Economist*, March 12, 2020).

Many pathways to aggressive energy decarbonization in the United States and abroad would require significant increases in onshore wind energy development. Consider the Princeton "Net-Zero America" Report, which offers five scenarios for achieving net-zero emissions in the U.S. electricity sector by 2050 (Larson et al. 2021). The required increases in onshore wind by 2050 range from 4 to 17 times the 2020 level of installed capacity.[1]

Projections such as these raise questions about feasibility that studies are only beginning to address. Is there enough land with abundant wind and conducive topography to support such large-scale expansions? And how much of the suitable land is in jurisdictions enjoying political support for wind energy? Whereas Larson et al. (2021) try to account for physical constraints by disallowing wind turbines on certain land types such as urban and wetlands, other scholars highlight local regulatory constraints and numerous permitting obstacles to onshore wind development (see, e.g., Lopez et al. 2021; Mai et al. 2021; Lerner 2022; Winikoff 2022).

This paper focuses on another land-use feasibility constraint that, to our knowledge, has

[1]The report notes that "By 2050 installed wind capacity is 6 to 28 times larger [than 2020]" but this includes onshore and offshore wind (Larson et al. 2021, p. 101). We exclude offshore wind from this calculation by dividing the low (375 GW) and high (2210 GW) forecasts for 2050 onshore wind production by 2020 onshore wind capacity (130 GW) from page 102.

not been considered in the literature on net-zero pathways. Even in rural jurisdictions with good wind endowments, suitable topography, political support, and streamlined permitting, wind developers still must overcome the challenge of convincing neighboring private landowners to voluntarily lease their properties for wind power. We evaluate, theoretically and empirically, whether that challenge is greater or lesser in areas with relatively small landholdings. In doing so, we demonstrate how rural land ownership configurations constrain where wind development can most readily occur in the United States.

Our theoretical analysis focuses on the offsetting effects of two local externalities.[2] First, wind turbines may cause "disamenity externalities" by creating visual and audio disturbances that extend to neighboring tracts of land. This implies that subsidies for wind can cause too many turbines from the perspective of local communities. Moreover, standard externality theory suggests the likelihood of wind energy development will increase with N, the number of prospective rural landowners in a wind farm. This assumes each landowner bears only $1/N$ of the disamenity costs from adding a turbine but receives the full payment for hosting it.[3] The implication is that, left unregulated, turbines are more likely where landholdings are small, leading to more local disamenities[4] but more success from the perspective of national policymakers seeking to advance wind energy.

Our theory embeds a second local externality problem, less often considered, that is an offsetting force towards less wind development in rural areas with small landholdings. It

[2]We do not focus on how wind energy may reduce global externality problems associated with greenhouse gas emissions (Cullen 2013; Novan 2015; Fell and Kaffine 2018; Fell and Johnson 2021).

[3]In 2019, wind energy developers paid private landowners an estimated $706 million for leases to host wind turbines (AWEA 2020).

[4]For example, Jensen, Panduro and Lundhede (2014), Gibbons (2015), and Jarvis (2022) find negative property value effects in close proximity to wind turbines. Krekel and Zerrahn (2017) demonstrates those who live near wind farms in Germany self-report lower well-being.

arises because wind farms exhibit "economies of density" and can be profitably employed only at scales much larger than most individual landholdings.[5] Even a relatively small utility-scale wind project (50 megawatts (MW)) requires 4500 acres, far greater than the 2012 average size of agricultural landholdings in the United States, which is 434 acres (Denholm et al. 2009; USDA NASS 2014). Moreover, approximately 57 percent of U.S. agricultural holdings are smaller than 100 acres, implying that, in many cases, wind developers would have to contract with over 40 landowners to lease an area large enough for a profitable wind farm.[6]

Fragmented ownership creates an "exclusion externality" problem that increases with N, the number of landowners in a prospective wind farm. This is because each landowner sets a price (e.g., an annual lease payment) that a developer must pay before erecting turbines and individual landowners do not consider how their prices affect the expected payments available for other landowners. Whereas a sole owner bears the full cost of charging a higher price in terms of lowering the probability of wind farm development, smaller landowners who can exclude an entire project bear only a fraction of this cost. This causes the aggregate price of development to rise with N, leading to reductions in the probability a wind farm will be built and less success from the perspective of national policymakers seeking to advance wind energy.

To understand how ownership fragmentation (i.e., progressively smaller landholdings in a landscape) influences leasing likelihood, we develop a theoretical model of each

[5]Wind farms exhibits economies of density because production involves high fixed costs of setting up in a location and also network infrastructure (e.g., transmission lines) such that average infrastructure cost is minimized when wind farming spans large contiguous areas (Holmes and Seo 2012).

[6]Globally, 84 percent of farms are smaller than five acres (Lowder, Skoet and Raney 2016; Foster and Rosenzweig 2017).

landowner's decision to enter into a lease agreement with a wind developer. The model shows that increases in ownership fragmentation could lead to local overinvestment (i.e., landowners enter into lease contracts more frequently) or underinvestment (fewer lease contracts) relative to the case of sole ownership. Whether over- or underinvestment occurs depends on the magnitude of disamenities associated with turbines. When disamenities are large, the failure of landowners to fully internalize the costs of the turbines dominates, leading to overinvestment. This is similar to other contexts in which common property resources spanning multiple landholdings are overused relative to use under sole ownership.[7]

When disamenities are small, the failure of landowners to fully internalize the exclusion externality dominates, leading to underinvestment. This theoretical outcome resembles a "tragedy of the anticommons" because the wind resource is underused due to the failure of multiple property owners to coordinate on a leasing price that would increase rents to all owners (Heller 1998; Buchanan and Yoon 2000). Put differently, the technological necessity that wind farms must be larger than single landholdings denies some landowners the opportunity to financially benefit from their wind endowments, such as Dewey Engle in the epigraph.[8]

[7]A large empirical literature illustrates cases in which sole ownership appears to solve common-property problems of "overuse" in settings ranging from soil erosion (Hansen and Libecap 2004), conventional oil drilling (Libecap and Wiggins 1984), commercial fisheries (Kaffine and Costello 2011; Deacon, Parker and Costello 2013), and groundwater extraction (Pfeiffer and Lin 2012). Similarly, research also finds that effective common pool resource use is confounded by large numbers of users (Agrawal and Goyal 2001; Smith 2016).

[8]Buchanan and Yoon (2000) call this a "pecuniary" externality but we prefer "exclusion" because the anticommons problem causes a true misallocation of resources. The anticommons model is often applied to cases in which multiple regulatory agencies have the authority to prevent or tax economic activity ranging from cell phone use (Mitchell and Stratmann 2015) to water irrigation in the western United States (Bretsen and Hill 2009). Leonard and Parker (2021), apply the theory to the problem of horizontal drilling for oil (fracking) through multiple private landholdings. And many examples of "anticommons" in Heller (1998,

We test for the effects of ownership fragmentation on U.S. wind energy development by conducting empirical analyses at three different spatial scales. First, we run a national analysis at the county level and find that counties with larger average and median agricultural holdings – which is our best nationally available measure of rural land ownership concentration - have accumulated more installed wind energy capacity when controlling for other determinants of wind farming emphasized in previous literature (Yin and Powers 2010; Hitaj 2013; Menz and Vachon 2016; Aldy, Gerarden and Sweeney 2018; Johnston 2019; Zhou and Solomon 2020; Mullen and Dong 2022; Feldman and Levinson 2023). For example, a doubling of the average farm size is associated with a 72 percent increase in MW of wind capacity. These relationships occur conditional of other determinants of wind energy, including wind speed, transmission access, land characteristics, and state fixed effects that account for key differences in policy and local climactic conditions.

To further ensure that we are isolating the effects of land ownership, we run parallel analyses at a more micro scale, using parcel-level data from 185 windy counties and analyzing wind turbine placement within Public Land Survey System (PLSS) square-mile sections and individual parcels. The evidence indicates that sections are much more likely to host turbines as land ownership becomes more concentrated, even when controlling for wind speeds, transmission access, local land use, and infrastructure. Similarly, larger parcels with fewer unique neighboring landowners are more likely to host wind turbines. The findings, which are robust to multiple definitions of fragmentation, randomization inference, and spatial econometric techniques, indicate that land ownership fragmentation is, on net, a hindrance to wind energy development. We provide evidence that our findings

2008) involve private parties rather than government agencies including, for example, the "gridlock" problem of combining patents owned by multiple entrepreneurs to create significant innovations.

are not solely driven by local zoning and setback regulations that favor large landholdings and instead are driven, at least in part, by fundamental differences in the incentives that small versus large owners have when contracting with wind developers as our theory emphasizes. We also explain how the findings might be affected by related theoretical mechanisms such as holdups, coordination costs, and tax incentives.

The study contributes to ongoing discussions about renewable energy policy. First, it indicates that any realistic assessment of the costs and feasibility of decarbonizing economies must account for the challenges of promoting wind farming across landscapes with fragmented ownership. We show that areas with larger landholdings have been the first to adopt wind farms, implying that future contracting challenges will be more formidable than those already undertaken. The findings also suggest that fragmented ownership has pushed wind development from areas with smaller farms in the U.S. Midwest toward areas with larger farms in the Great Plains, in spite of the Great Plains requiring more new transmission line development.

Second, the findings highlight how state and local regulations, such as strict setbacks from property lines, amplify contracting hurdles to wind developments in areas where small landholdings dominate. Whereas our empirical findings suggest an "exclusion" externality is limiting wind energy development on fragmented landscapes, local zoning regulations focus on a wind turbine's disamenity externalities and, in this sense, increase one externality problem while addressing another. Furthermore, zoning regulations on wind energy may increase rural inequality by further pushing subsidized wind development to larger farms owned by wealthier individuals.

The analysis and findings also contribute to the literature assessing how ownership fragmentation affects the use of spatially expansive natural resources. It has typically focused on common property resources such fishery patches (Kaffine and Costello 2011), oil drilling (Libecap and Wiggins 1984, 1985), and groundwater extraction (Pfeiffer and Lin 2012; Edwards 2016). We contribute by explaining how fragmentation can cause underutilization in addition to the overuse problem more often emphasized in the large literature on the tragedy of the commons (see Frischmann, Marciano and Battista 2019; Stavins 2011).

Wind Energy in the United States

Due to a combination of policy incentives and technological advancements, the wind energy industry has rapidly expanded over the previous two decades. In 2000, the United States had about 4,000 megawatts (MW) of installed wind energy capacity. This increased to approximately 136,000 MW by early 2022.[9] This wind power is primarily located in rural areas in the Great Plains and Midwest, as well as parts of the Northeast and Northwest (see Figure 1). Forecasts (which ignore the role of fragmented ownership under study here) predict wind energy installations to spread to other parts of the country and to continue rapidly increasing as technological costs decline and federal and state policy incentives expand.[10]

Economists have sought to understand the primary determinants of prior wind energy development at county, state, and regional levels. Hitaj (2013) conducts a county-level empirical analysis and finds that transmission infrastructure and state and federal policies,

[9] *Wind Power Facts:* https://cleanpower.org/facts/wind-power/.

[10] See, for example, (Larson et al. 2021).

particularly tax credits and production incentives, encourage wind energy growth. Other studies have also estimated the response of wind uptake to federal and state policies, such as production tax credits (Metcalf 2009), Renewable Portfolio Standards (Yin and Powers 2010; Menz and Vachon 2016; Feldman and Levinson 2023), the 2009 American Reinvestment and Recovery Act (Mullen and Dong 2022), investment and production subsidies (Aldy, Gerarden and Sweeney 2018), and cost-based grants (Johnston 2019). In general, these findings confirm that policies creating economic incentives have been important catalysts for onshore wind development on private lands.

The potential negative externalities associated with turbines complicate the landowner's decision to enter into a lease agreement. Several studies examine the effects of local disamenities from wind farms, such as shadow flicker (the phenomenon in which the rotating blades of the turbine periodically create shadows) and noise, on property values and well-being. Some (Jensen, Panduro and Lundhede 2014; Gibbons 2015; Krekel and Zerrahn 2017; Jarvis 2022) find negative effects from proximity to wind farms, although Hoen et al. (2011) and Vyn and McCullough (2014) find no such effect. [11]

The role of landownership patterns in determining wind energy uptake has been mostly overlooked. This may be an important oversight because, in order to construct wind farms on privately owned land, wind energy developers must obtain the consent of landowners to build turbines, access roads, and transmission lines and getting consent will likely depend on the number of landowners who must be part of a wind farm project. In return for their consent, landowners are compensated through lease and royalty payments.[12]

[11] There can also be positive local externalities. Kaffine (2019) finds that U.S. counties with more installed wind energy capacity saw small increases in crop yields as a result of microclimate impacts from wind turbines.

[12] The types of compensation packages can vary, from lump-sum payments to per-turbine or per-MW

To be sure, a small literature asks if fragmented ownership could cause a spatially inefficient pattern of wind power installations. Kaffine and Worley (2010) show that under shared ownership, upwind producers ignore turbine wake externalities and overcapitalize on upwind sites (and downwind producers undercapitalize) when compared with the sole ownership situation, leading to lower economic rents. Taking this theory to data, Lundquist et al. (2019) find substantial "wake effects" on a downwind farm in Texas. [13] Instead of studying how wind energy developers may dissipate rents by competing with one another, our analysis focuses on how the number of local landowners in an area affects wind farm siting (i.e. where/if a wind farm is built) and sizing decisions (i.e. how many turbines).

There are numerous obstacles to siting wind farms that may be exacerbated by having to contract with multiple landowners, suggesting disadvantages (from the prospective of wind energy developers and the set of landowners who desire wind leases) of fragmented ownership. Some landowners can slow or prevent development by demanding greater compensation for leasing their land or by taking legal action.[14] Opposition from landowners can lead to the reduction in size or the cancellation of wind farms altogether.[15] In other

payments to royalties, which are a share of the revenues generated from electricity production (Shoemaker 2007). Developers may also acquire easements from neighboring landowners so that they agree to refrain from building structures that obstruct wind flow. The amount of compensation for wind energy leases can vary as well, with recent estimates ranging from $3,000 to $6,000 per MW annually (AWEA 2018). The average size of a turbine constructed in 2017 was 2.32 MW, suggesting an approximate per-turbine payment range between $7,000 and $14,000 (AWEA 2018). Hitaj, Weber and Erickson (2018) find that per-farm payments for wind energy were $8,287 in 2014.

[13] These findings suggest a potential role for a "cathedral rule" laws in which downwind landowners compensate upwind owners to not overcapitalize (Rule 2009).

[14] For example, a lawsuit occurred in Oklahoma, where landowners sued to maintain protections from property value losses. Source: "Oklahoma Landowners Sue over Wind Farm Plan: https://www.washingtontimes.com/news/2014/aug/28/oklahoma-landowners-sue-over-wind-farm-plan/. "

[15] The Macalester College project, "Wind Energy Landscapes" provides several anecdotes of the wind farm development process. The project highlights cases in which wind farms were scaled back due to landowner opposition, and one in which it was cancelled altogether. See https://www.macalester.edu/windenergy/casestudies/casehome.html.

situations, some landowners may hold out in hopes of acquiring more favorable lease agreements. This has led some developers to adopt an "all or nothing" approach, requiring the consent of all landowners for a wind farm project to move forward (Wetsel and DeWolf 2014).

Anecdotes from wind developers and landowners point to the potential importance of ownership concentration. Wind energy developers note their preference towards negotiating with owners of large parcels of contiguous tracts of land (Taylor and Parsons 2008; Mills 2015). Other observers assert that just a few disinterested landowners "can and have made or broken many projects" (Walker 2008). Small farms have been cited as a reason why Wisconsin, for example, has lagged behind other Midwestern states in wind development (Pyrek 2017).

Additional anecdotes indicate that landowners do not always consider the effects of wind turbines on their neighbors when deciding to lease their properties to developers. One report notes that landowners "felt so betrayed their friend who lived right next to them had never told them they leased to the company" (Le Coz and Sherman 2017). Elsewhere, landowners complain that those who enter into lease agreements with developers do not live on their land and consequently do not have to deal with the turbine disamenities on a daily basis (Swanson 2017; Eller and Hardy 2017).

To summarize, there is qualitative evidence that, in the presence of fragmented land ownership, wind energy development is affected by the two conflicting externalities discussed above. The "disamenity" externality involves neighboring landowners not fully considering the potential disamenities of turbines on neighboring properties. The "exclusion" externality involves a small number of landowners preventing wind farm development even if many neighbors want to lease their land. In the next section, we develop a theoretical model demonstrating when each of these externalities may dominate. The model provides a framework for predicting how wind investments adjust to different levels of land ownership fragmentation.

Theory

This model builds on the previous literature examining the commons and anticommons, particularly Buchanan and Yoon (2000), who models the problem of using a resource when each of N owners has to consent, and Leonard and Parker (2021) and Vissing (2017), who model the problem of developing shale oil via horizontal fracking when individual owners of parcels within a large area of land for drilling must consent. Our framework expands upon these models in two ways. Whereas in the traditional anticommons setting one excluder can prevent any resource use, some resource use can occur without full consent in our model. That is, a wind farm can still be built if not all adjacent landowners participate, although it will be smaller. Second, and more fundamentally, we model a context in which an individual's participation creates a disamenity externality for neighboring owners.[16]

Consider a land area of L undeveloped and homogenous acres of farmland. Within this area, land is divided evenly among $N = L/S$ identical landowners, where S is the size of each individual's landholdings. An increase in S therefore corresponds with an increase in land ownership concentration with fewer individuals owning land. A developer considers contracting with these landowners for a wind farm by paying royalties in exchange for

[16]The theoretical frameworks in Leonard and Parker (2021) and Vissing (2017) do not account for the possible pollution and noise externalities caused by horizontal drilling.

erecting turbines on their land.[17] The payment is made on a per-acre basis. That is, for a payment of r the landowner receives $r * S$.

The negotiation happens in two stages. First, each landowner i independently chooses a royalty rate, the share of per-acre revenue from wind development on her land, denoted as $r_i \epsilon (0, 1)$. Second, in response to the royalty rates demanded by all L/S individuals, the profit-maximizing firm decides whether to build the wind farm altogether, as well as whether to erect turbines on each individual $i's$ land.[18] From landowner i's perspective, there are three potential outcomes: (1) the wind farm does not get built, (2) the wind farm gets built, but no turbines are sited on parcel i, or (3) the wind farm gets built, and turbines are erected on parcel i.

To the landowner, there are two unknowns about the profit-maximizing developer's decisions. First, she is unaware of the maximum royalty rate the developer will accept. If she selects a royalty rate too high, the developer will not agree to operate a turbine on her land. She does not know, however, what rate is "too high," and she assumes the maximum royalty rate she can choose and still host turbines is uniformly distributed between 0 and 1. The probability her land is used in the project, given a requested royalty rate r_i, is $1 - r_i$. The expected number of acres of her parcel leased for wind turbine development is $S * (1 - r_i)$.

The second unknown to the landowner is how large the project must be to cover fixed

[17]Although payments for wind leasing come in various forms, our model focuses on royalties because they are the most common form of compensation. The general logic of the model extends to other forms of compensation, including the "whatever price the landowner chooses" framing used in Buchanan and Yoon (2000).

[18]As explained in more detail below, we do not explicitly model the second stage of the profit-maximizing firm. Instead, it is embedded in the first stage through the *expected* number of acres leased.

costs.[19] The landowner knows there is a threshold amount of land that the developer needs to have under lease for the wind farm to profitably cover fixed costs. The share of land needed, denoted $\bar{S}$, is unknown to the landowner. She assumes it is uniformly distributed between 0 and L. From the landowner's perspective, the wind farm is only built if the expected number of acres under lease is greater than $\bar{S}$. The probability the wind farm is built is therefore equivalent to

$$\begin{aligned} Prob(WindFarmBuilt) &= Prob(ExpectedAcresLeased > \bar{S}) \\ &= Prob(\bar{S} < \sum_{i=1}^{L/S} S(1-r_i)) = F_{\bar{S}}(\sum_{i=1}^{L/S} S(1-r_i)) \\ &= \frac{\sum_{i=1}^{L/S} S(1-r_i)}{L}, \end{aligned} \tag{1}$$

where $F_{\bar{S}}$ is the uniform CDF of $\bar{S}$.

Assume that royalty payments are fully capitalized into land values and the landowner's objective is to maximize her expected land value. Her property value increases with the amount of revenue she receives from wind turbines, given they are built. The expected added value, given the wind farm is built, is therefore $S(1-r_i) * r_i$.

Wind turbines also create disamenities that capitalize into property values if wind farming takes place on the undeveloped landscape.[20] We assume a per-acre disamenity,

[19]The fixed costs imply increasing returns to scale or density of the wind farm. The costs may encompass transmission costs, legal fees, and the costs of assessing the viability of a site for development. It can also represent the requirement from a utility or power purchaser for the wind farm to supply a minimum level of power. Given that turbines are clustered together in projects developed at the same time, the assumption of returns to scale and density is appropriate. It is appropriate because, as is generally true of production exhibiting economies of density (see Holmes and Lee 2012), spatial proximity and connectivity of turbines makes wind farms more profitable.

[20]The model does not consider any disamenity affects on neighboring land that is already in residential development. Those issues are addressed in an empirical literature focused on measuring the effects of nearby

denoted $e\epsilon(0,1)$. Because all landholders in the area can hear and see the turbines, each individual only bears $1/N$, or S/L of the cost from each turbine. The expected loss of land value for individual i from her own turbines is $S/L\big(S * e(1-r_i)\big)$. The expected loss in land value from turbines on the others' land is $S/L\big(\sum_{j\neq i} S * e(1-r_j)\big)$.

The landowner chooses a royalty rate to maximize her expected land value, where the value changes only if the wind farm is constructed. Her maximization problem is therefore:

(2)

$$\max_{r_i} Prob(WindFarmBuilt) * (value \mid WindFarmBuilt)$$
$$= \frac{S(1-r_i) + \sum_{j\neq i} S(1-r_j)}{L} * (Sr_i(1-r_i) - S/L * e(S(1-r_i) + \sum_{j\neq i} S(1-r_j))).$$

Because all landowners are identical, the landowner's maximization problem can be solved as a symmetric Cournot equilibrium. The privately optimal royalty rate is

(3)
$$r^* = \frac{1 + 2e\frac{S}{L}}{2 + \frac{S}{L}}.$$

It follows that the expected number of leased acres, $L(1-r^*)$, is

(4)
$$ExpectedAcres = L * (1 - \frac{1 + 2e\frac{S}{L}}{2 + \frac{S}{L}}).$$

Two comparative static results come from this model. First, as the disamenity value associated with wind turbines, e, increases, the privately optimal royalty rate increases (and thus the expected number of wind turbines decreases). When turbines become more costly

turbines on home values, rather than the question of where turbines get developed under focus in our study. Furthermore, our model does not account for positive global externalities from reduced carbon emissions.

to landowners, individuals demand more compensation to put up with the disamenities.

The second result, and the primary focus of this paper, is the response to an increase in S, the share of total acreage owned by an individual. As S increases, holding L constant, land ownership is more concentrated among fewer individuals. The derivative of the optimal royalty rate with respect to S,

$$\frac{\partial r^*}{\partial S} = \frac{\frac{2e}{L}(2+\frac{S}{L}) - \frac{1}{L}(1+2e\frac{S}{L})}{(2+\frac{S}{L})^2},$$

is positive only if e is sufficiently large.[21] At high levels of turbine disamenities, land ownership concentration increases royalty rates, therefore decreasing the expected number of turbines. At low levels of turbine disamenities, land ownership concentration yields lower royalty rates, thereby increasing the expected number of turbines. Figure 2 shows a visual depiction of this relationship with $L = 1,000$ for the fragmented case ($N = 10$) and concentrated case ($N = 2$) at varying levels of the disamenity.

What is the intuition of this result? Consider first the case of high turbine disamenities. If land ownership is concentrated, fewer individuals internalize more of the turbine costs and therefore demand higher compensation for leasing their land. When land is fragmented, however, landowners can pass on most of the disamenity costs of turbines to their neighbors, and therefore do not require as much compensation to host wind turbines. In this scenario, the disamenity externalities are the dominant effect, and fragmentation yields overinvestment in wind energy relative to sole ownership leading to a local "tragedy of the commons."

[21]The cutoff is $e > \frac{1}{4}$, which is arbitrary and a reflection of the quadratic nature of the maximization problem.

When turbine disamenities are small, the ability of landowners to pass on external costs to their neighbors is less important and instead the primary driving factor in choosing royalty rates is the desire to earn maximum expected compensation. The landowner must trade off between asking for higher payments on one hand and a lower probability of a wind farm being built because the developer cannot cover fixed costs on the other. The former effect should cause the landowner to increase her royalty rate, and the latter should cause her to decrease it. However, when land ownership is fragmented, any particular landowner does not bear the full cost of the reduced wind farm probability because her private maximization calculus does not consider potential royalty payments to her neighbors. Therefore, relative to the case of concentrated land ownership, an exclusion externality dominates (when disamenities are low) and the landowners collectively underinvest in wind energy leading to a "tragedy of the anticommons."

Either over or underinvestment relative to the sole-owner case indicates a deviation from the level of wind development that a social planner would pick from this model in which landowners ignore the external effects of their behavior on neighboring landowners. Whether there is an actual, empirical effect of land fragmentation additionally depends on the magnitude of coordination costs among landowners, which we do not explicitly model here. In fact, both the "overinvestment" and "underinvestment" problems we model implicitly assume that coordination costs are non-zero and grow with fragmentation and this prevents landowners from coordinating to erect the socially optimal number of turbines except under sole ownership.[22] The anecdotes from landowners, discussed in the

[22]This is consistent with common property and anticommons models that implicitly assume that resource owners cannot coordinate to fix disamenity or overpricing externalities. That is, the "tragedies" occur because coordination does not happen when coordination would have caused socially preferable outcomes (see, e.g., Dietz, Ostrom and Stern 2003; Frischmann, Marciano and Battista 2019; Buchanan and Yoon 2000; Coase

background section, suggests there is imperfect coordination among landowners and hence unaddressed externality problems of the nature described in our theoretical model. [23]

We emphasize the theory does not explicitly model strategic hold-ups that could occur if wind farm projects requiring more landholdings are subjected to a higher likelihood that some landowner will try to capture the full project surplus by demanding high payment. Whereas the anticommons is due to a failure to coordinate, hold-up models emphasize the ability of "pivotal" resource owners to extract rents by refusing to participate in a land-assembly project (Menezes and Pitchford 2004; Brooks and Lutz 2016). Whether one landowner holds a "pivotal" site will depend on context. As Isaac, Kitchens and Portillo (2016) demonstrate, the ability of hold-ups to block projects falls dramatically when unanimity is relaxed because the number of feasible leasing arrangements increases combinatorially. Because unanimity is not required for wind leasing, we think it is more appropriate to model the more general problems of exclusion and disamenity externalities rather than strategic hold up although we acknowledge that holdup and anticommons problems are closely related.

Data and Empirical Strategy

Our goal is to estimate the average causal effect of rural ownership fragmentation on the likelihood and amount of installed wind energy capacity across geographical locations.

1960).

[23]There are related transaction costs that grow with the number of landowners that we do not model here. On the developer's side, gaining permission to launch the project entails transaction costs of finding owners and negotiating and writing leases. On the landowner's side, transaction costs may entail hiring lawyers, researching liability laws, and monitoring the developer. These transaction costs would act as a tax on the value of the project and reduce the probability of it occurring by decreasing its expected surplus with increases in the number of landowners.

The theoretical model describes why wind development can either decrease or increase with increases in ownership fragmentation in the presence of local externalities. If there were no land externalities – or if the coordination costs of solving externalities were zero – then fragmentation would have no effect on the observed level of development (i.e., $\frac{\partial r^*}{\partial S} = 0$). Empirically this would result in $\beta = 0$ in the models described below. [24]

To aid in identifying causal effects in the absence of natural experiments, we conduct analyses of the effect of land ownership on wind development at three geographic scales. First, we run a national, county-level analysis using publicly available data. Second, we examine wind development at a more micro scale, utilizing proprietary parcel-level data from a subset of windy counties to analyze wind turbine placement within Public Land Survey System (PLSS) square-mile sections. [25] Third, we analyze the placement of turbines on individual parcels using the same subsample of parcel-level data.

Data

We construct dependent variables from the United States Wind Turbine Database (USWTDB) (Hoen et al. 2018). The publicly available database includes Geographic Information System (GIS) shapefiles of all U.S. turbines with location verified within 10 meters of the actual placement and contains characteristics including capacity, height, and year built. The data are up to date through 2021 and cover 70,808 turbines.

[24]Note that even if local externalities were zero or local coordination costs were zero, it is still the case that the presence of positive global externalities from the reduction of greenhouse gas emissions, which are not included in the theoretical model, would cause global underinvestment in wind, implying that even a case where $\beta = 0$ would fall below the global social planner's optimal level of wind development.

[25]Most of the counties within our sample were surveyed using the PLSS, which divided land based on 36 square-mile townships and one square-mile sections. This was not used in Texas or Beaver County, OK, however, so we manually create our own grids.

The primary explanatory variable for the county-level regressions is the county's average agricultural farm size. This variable, along with county-level covariates, comes from the United States Department of Agriculture (USDA) 2012 Census of Agriculture (USDA NASS 2014). [26] The census is a comprehensive survey, conducted every five years, of all U.S. farms and ranches. We use the 2012 data because this represents the midpoint of the wind energy boom (post-2000).

We use GIS tools to connect wind turbine placement with parcel ownership and PLSS location within counties. The parcel-level data come from the spatial data company Real Estate Portal USA (ReportAll), and our sample draws from 185 counties in 13 states: Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, North Dakota, Oklahoma, Oregon, South Dakota, Texas, Washington, and Wyoming. These states are leaders in wind energy capacity and represent different cultures, landscapes, and primary means of agricultural production. [27] Figure 1 shows the sample of counties, overlayed with turbine locations. Average wind speed is considerably higher in the sample counties: 7.73 meters per second (m/s) compared to 7.13 m/s in the remaining counties, a difference of eight percent.

The data contain parcel-level GIS polygon shapefiles and indicate the size, boundaries, and owner's name for each parcel. This allows us to measure land ownership concentration examining how much land within a PLSS 1x1 mile section is owned by the same person or company. [28] Importantly, some individuals and companies own multiple parcels; our

[26] In the census, the USDA defines farms as those that typically produced or sold more than $1,000 worth of agricultural products in a given year.

[27] Due to limits to our research budget, and hence the amount of data we could purchase from ReportAll, we study data for a subset of counties within the 13 states having the greatest wind capacity and potential. More specifically, we chose available counties from the union of those counties with the highest installed wind capacity at the time of data collection and the highest wind speeds. This allowed the inclusion of counties with existing wind farms and those that were likely to host wind farms in the future.

[28] Although we use the term "concentration", we do not mean to suggest it relates to market power in

approach of matching parcels with ownership (by full name) accounts for this. For a subset of counties, we also have the mailing address of the parcel owner, which we utilize to measure absentee ownership as discussed below.

To better identify the causal effect of land ownership patterns, we employ several control variables to account for spatially-based factors that may affect wind turbine siting decisions. We control for wind speed using a national map of the mean speed in 2012 at 100m (in meters/second) from NREL. We calculate the mean wind speed at every unit of analysis in the dataset (e.g., county-level averages, 1x1 mile section-level averages, and parcel averages). We utilize spatial data from the National Land Cover Database (NLCD) from 2011 (USGS 2014) to determine land-use proportions within 1x1 mile sections. We use data from the United States Geological Survey (USGS) to calculate elevation, land slope, ruggedness, and irrigation.[29] We measure distances to infrastructure such as transmission lines from the Homeland Infrastructure Foundation (HIF 2021), railroads, roads, and metropolitan areas from the U.S. Census (USCB 2021), and airports from the Federal Aviation Administration (FAA 2021). We use the Protected Area Database (PAD-US) to determine how much land is publicly owned (USGS 2016) by federal, state, and local governments, and Native American Tribes because obstacles are in place that explicitly or implicitly prevent wind development in these areas (Zimmerman and Reames 2021; Daniels 2021).

agriculture.

[29] The "Terrain Ruggedness Index" is defined by Wilson et al. (2007). Similar measures are used in Nunn and Puga (2012) and Leonard, Parker and Anderson (2020).

Empirical Strategy

By analyzing wind turbine placement at multiple scales, we can examine both the extensive (whether to build a wind farm) and intensive (where to place turbines) margin in ways that help isolate the causal effect of ownership patterns. County-level regressions focus on the extensive margin because wind farms are generally contained within the boundaries of one specific county. Section-level and parcel-level analyses allow us to look within the boundaries of a specific wind farm and analyze with spatial precision individual turbine siting outcomes. The multiple scales additionally provide robustness for one another, as consistent results across specifications suggest the findings are less likely driven by omitted variables.

County and Section-Level Models and Estimating Samples

The first two levels of analysis, the county and PLSS section models, evaluate the effects of land ownership on wind turbine placement using geography-level measures of ownership concentration (which is the inverse of fragmentation). We implement a cross-sectional analysis in which installed 2021 wind energy capacity is determined by ownership concentration and other relatively time-invariant covariates. Our regression equation is

$$WindCapacity_i = \alpha + \beta LandOwnershipConcentration_i + \delta X_i + \epsilon_i, \tag{5}$$

where i is the county or section-level observation. $WindCapacity_i$ measures the cumulative wind energy installations within the relevant geography, $LandOwnershipConcentration_i$ is the primary variable of interest, and X_i represents a vector of controls that may influence wind development. County measures of wind capacity include an indicator for whether a county has a wind farm, the MW (or inverse hyperbolic sine, IHS) of installed wind energy, and MW per 1,000 acres of land.[30,31] For the section-level regressions, we measure wind capacity with an indicator for whether a section hosts a turbine and by the number of turbines or installed MW within a section. When the dependent variable is the natural logarithm, the sample is limited to geographies with positive installed capacity.

The model also includes spatial fixed effects to account for factors unaccounted for by covariates. The county-level regressions include state fixed effects, which control for policies such as production tax credits, renewable portfolio standards, as well as other institutional factors that may influence wind energy such as regulated electricity prices. The section-level regressions include township-level (a 36 square-mile grid) fixed effects to account for state and county level policies (because townships do not cross county borders), as well as other spatial factors that covariates may not capture such as local cultural attitudes about wind development.

County-level analysis allows us to build from previous studies using this scale (Hitaj 2013). We define land ownership concentration as the natural log of the mean farm size within a county. A larger mean indicates higher land ownership concentration, and a smaller mean indicates greater fragmentation. A positive coefficient β implies that increased fragmentation yields less wind energy development. A negative coefficient implies the opposite.

Table 1 shows summary statistics for the county-level sample, with all variables in

[30]We define a wind farm as a cluster of more than ten turbines within a county built in the same year with the same project name. We do this to eliminate smaller, community-level wind projects.

[31]The inverse hyperbolic sine allows us to use a log specification without dropping those observations with zero wind turbines.

Table A.1. After data cleaning, we have a sample of 2,494 counties representing about 80 percent of the national total.[32] About 16 percent of the counties had installed wind farms by the end of 2021. The average county had 26 wind turbines and the average installed capacity was 47 MW. The distribution is highly skewed; some counties had over 3,000 MW. The mean farm size across our sample of counties is 637 acres, more than three times the median farm size. [33]

The section-level analysis allows for a more micro-level analysis of wind turbine siting. We develop the sample as follows. First, we eliminate all counties lacking wind turbines because those counties do not have useful variation. Next, we eliminate all sections for which more than one percent of the acreage does not have an identified parcel owner. We next identify the percent of land in each section that can be classified as developed and undeveloped land and calculate how much land within each section is privately owned (i.e., not local, state, federal, or tribal land). We then limit the sample to those sections for which 95 percent of the section is privately owned and undeveloped. This lets us assess land most fit for wind energy (non-developed, rural land which is the focus of our theoretical model) because it is least encumbered with infrastructure obstacles.

To measure land ownership concentration for section-level estimates, we distinguish between landowners of undeveloped and developed land because developed parcels with buildings and built infrastructure are unlikely to host a wind turbine for legal or technical reasons. We designate parcels as developed or undeveloped based on the most frequent

[32]We make one sample modification by limiting our analysis to those counties in the continental United States covered by more than ten percent agricultural land in 2012. This eliminates most urban counties that are not suitable for wind power.

[33]We employ the mean as the primary measure of ownership concentration because the median is influenced by urban counties, which are more likely to have small-scale hobby farms not suitable for wind development. We present robustness to using the median in the appendix.

land cover category classified by the NLCD.[34] This strategy ensures the findings reflect the effects of agricultural landowner concentration, rather than homeowner concentration, who may have different motivations for affecting wind development beyond those highlighted in our theoretical model. Concentration is measured by the unique number of undeveloped landowners within each section.

Although the number of undeveloped landowners in a section provides a simple, intuitive measure of land ownership concentration, this measure ignores heterogeneity in land ownership size. To better accommodate land ownership heterogeneity, we also use the inverse of the Herfindahl-Hirschmann Index (HHI). The HHI is calculated as $HHI = \sum_i s_i^2$, where s_i denotes each individual i's share of the total land. Adelman (1969) and Libecap and Wiggins (1984) show that the inverse of the HHI can be interpreted as the equal-share landowner equivalent. In other words, a measure of four means that the landownership is concentrated as if four landowners each owned $1/4$ of the section. This measure more closely aligns with the theory, which assumes equally divided parcels.

Table 2 shows summary statistics for the main section-level variables, with all variables in Appendix Table A.2. The cleaned sample has nearly 98,000 observations of one square-mile sections. About 7 percent of sections held a turbine as of 2021 with a mean of 0.43 MW capacity per section. On average, there are 5.8 undeveloped landowners per section with an equal-share equivalent of about 3.1 landowners. Because both measures are skewed right, we transform the variables with the natural log in our regressions to minimize the influence of outliers.

[34] Because the footprint of turbines is small relative to the large size of agricultural parcels, we do not expect the classifications of turbines as developed or undeveloped to bias the findings in an empirically significant way.

It is important to emphasize how the section-level land ownership and county-level farm size variables differ as empirical measures of concentration. Many farms are operated by tenants who lack authority to lease land for on-farm wind turbines. Furthermore, one landowner may lease to multiple farmers and therefore the average farm size may underestimate landownership concentration. To address this in the county-level regressions, we include a control for the amount of farm acres that are actually owned by the farm operator. This ensures that any relationship between wind development and farm size is not due to correlation between wind potential and the amount of owned vs. rented farm acres. Beyond this, we note that although not perfect substitutes, farm size and land ownership are closely correlated as shown in Figure 3 for the counties from which we have land ownership data. This strong correlation, which is -0.74, suggests that farm size is a good measure for the number of undeveloped landowners at the county level.

Parcel-Level Model and Estimating Sample

While the county and section-level models measure land ownership concentration within a geography, our parcel models measure concentration relative to an individual parcel's surroundings, as in studies of other natural resources (Leonard and Parker 2021). This allows us to hold constant heterogeneity in parcel's own size while assessing fragmentation in neighboring lands. Specifically, we employ the following cross-sectional regression:

$$WindTurbine_i = \alpha + \beta IHS(SurroundingOwners)_i + \delta Size_i + \gamma X_i + \epsilon_i, \tag{6}$$

where the dependent variable equals one if a given parcel i hosts a wind turbine. Our primary measure of ownership concentration is the inverse hyperbolic sine of the number of unique surrounding landowners (not parcels because multiple parcels are sometimes owned by a single landowner) within a given radius. We present results with three radii- a quarter mile, a half mile, and a mile. We emphasize that $Size_i$, the acreage of a given parcel, may also capture land-ownership concentration, although larger parcels will be more likely to fit a turbine on their property, regardless of any common property effects. X_i represents a series of parcel-level controls, including township-level fixed effects.

We limit the sample of parcels (drawn from the same counties used in the section-level regressions) to those greater than 20 acres and for which the primary land use is cropland, pasture, grassland, or shrubland. These parcels will be large enough to fit a wind turbine and these land uses capture most turbines within the sample. We additionally limit the sample to those counties for which the mailing address of the parcel owner is provided to measure absentee ownership.

Table 3 posts summary statistics from the sample with a quarter mile radius (with all variables in Table A.3) and we note that the statistics are similar when the larger radii are used. About 2.3 percent of parcels host turbines. The average number of landowners within a quarter mile of each parcel's boundaries is 10.2, and the average parcel is 141 acres.

Identification Concerns and Strategies

Regression estimates could be biased if (i) land ownership concentration has systematically sorted to reflect wind energy potential, and (ii) the covariates and fixed effects at the three different scales of analysis fail to account for any systematic correlations between the inherent economic profitability of wind leasing and land ownership concentration. We think the first part of this threat (i) is minimized because land ownership concentration and farm sizes have remained relatively steady since the 1970's (Baltensperger 1987), well before wind energy was a viable economic option. This suggests that cross-sectional variation in farm size is primarily a result of the optimal scale of agricultural production, rather than being intentionally selected to match the scale of secondary land uses such as wind energy. Nevertheless, to help rule out reduce causality, we also include instrumental variable (IV) estimates for the county-level models by instrumenting for modern farm size with historical farm sizes as discussed below. [35]

With respect to (ii), we include several covariates to mitigate omitted variable bias, such as wind speeds (the primary predictor of productive wind turbines) and elevation, slope, land cover, infrastructure, and accessibility to transmission lines (the primary predictors of costs and feasibility from the perspective of wind developers). We also control for factors measuring the inherent productivity of agriculture, which are empirically correlated with farm size and landowner concentration in the estimating samples (see Tables A.4 – A.6). A concern here is that the opportunity cost of hosting wind turbines may be significantly higher for small farms because each acre in small farms tends to be more productive and wind turbines reduce acreage for agricultural productivity. [36] We include several

[35]Anecdotal evidence also suggests that farms have not concentrated in recent years to capitalize on wind energy potential. A large majority of U.S. farms are family owned and are passed down over generations (Lobley, Baker and Whitehead 2010). Selling a farm appears to be a last resort for most family-run farms. Only about 20 percent of farmers plan on selling their farmland upon retirement and farmers under financial stress are more likely to rent farmland or find off-farm labor than to sell their land (Mishra, Johnson and Morehart 2003).

[36]This concern is valid but perhaps minimal because the land lost for wind development is quite small. Using direct land requirement data from Denholm et al. (2009), a 2 MW turbine would permanently require

covariates to control for the correlation between agricultural productivity and landowner concentration. At the county level, we include covariates for the value of each county's agricultural production, as well as the land value per acre, and the relative distribution of crop and pasture land (which occurs on larger farms with worse soil quality, particularly in the Great Plains region), which should all capitalize land profitability (Plantinga and Miller 2001).[37] In the section and parcel-level models, we do not observe farm profitability, but we control for soil quality, irrigation, and the land cover of each parcel, which should be correlated with farm productivity.

A final identification concern is that small farms may be less inclined to develop wind if those living on-farm are more exposed to externalities from turbines that are necessarily closer to homes than on larger farms. To address this, we control for the share of farmers in a county who actually live on their farm, county population density, and distance to metropolitan areas. In the section and parcel regressions, we control explicitly for owners of developed land to separate this effect and make sure the effect of farm size is conditional on an equal number of off-farm homes.

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about 1.5 acres. The lost production would likely be exceeded by energy payments. Furthermore, smaller farms, which generally grow crops (as opposed to raising livestock), may benefit from increased crop yields in the presence of wind turbines that may make up for lost crop revenue (Kaffine 2019).

[37]Many small, hobby farms lose money, per the official USDA classification of a farm, and may not grow crops in a given year.

Results and Implications

County-Level Regressions

Table 4 shows regression results from our county-level specification, with controls shown in Table A.7. In Column (1) the dependent variable is an indicator for whether a county has a wind farm. In Columns (2) and (3) the dependent variables are the number of installed megawatts (MW) of capacity and the inverse hyperbolic sine of MW, respectively. In column (4), the dependent variable is installed capacity (in MW) per 1,000 acres of land. Column (5) limits the sample to only counties with positive wind capacity, and the dependent variable is natural logarithm of installed capacity.

Across specifications, we find that counties with larger farms have more installed wind energy capacity. The column (2) coefficient implies doubling a county's average farm size leads to a 32 MW increase in installed wind capacity, nearly 70 percent relative to the mean of 46. The column (5) coefficient implies that in counties with some wind power, doubling farm sizes yields a 72 percent increase in installed capacity. These county-level findings provide evidence that more concentrated (fragmented) land ownership has promoted (hindered) installed wind energy. This finding is consistent with the "exclusion externality" dominating the "disamenity externality."

The control variables (seen in the appendix Table A.7) correlate with wind investments in intuitive ways. There is more wind capacity in windier counties with greater access to transmission lines. Counties with more dense populations, which may have less space for wind farms and a population more exposed to turbine disamenties, install less wind energy, consistent with Hitaj (2013). Counties with more irrigated land, for which drains and irrigation equipment may interfere with wind development, have less installed wind power. [38,39]

Section-Level Regressions

Table 5 shows the section-level results in which landowner concentration is measured as the natural log of the number of private landowners of undeveloped land, with control variables in Table A.8. Table 6 shows the analogous results for the log of equal-share landowners (inverse HHI). In column (1), the dependent variable is the probability that a section hosts a wind turbine. In columns (2) and (3), the dependent variable is the number of MW and the inverse hyperbolic sine (IHS) of MW installed. In column (4) the dependent variable is the natural log of installed capacity, with the sample limited to those with some installed wind energy.

Our primary variable of interest, the log of private landowners of undeveloped land within a section, appears in the top row and is negatively associated with wind capacity. Sections with more landowners host fewer MW of wind energy, conditional on the model's covariates. The coefficient in column (2) suggests doubling the landowners within a section reduces installed capacity by 0.056 MW, 13 percent relative to the mean. Column (4) suggests doubling the number of landowners within a section reduces capacity by 14 percent in sections with some MW installed. Results are qualitatively and quantitatively similar using the equal-share landowner measurement, although slightly less precise.

[38] See Cooley and Smith (2022) for a full discussion of the tradeoffs between irrigation and wind power.

[39] We also find that counties in which more of the farm operators live off farm have more installed wind capacity. Landowners who live off their land will be less exposed to wind turbine disamenities, particularly those that are most impactful at night while trying to sleep. Hence, this finding is consistent with anecdotes that landowners who do not have to "put up" with turbines are more likely to agree to leases with developers (Swanson 2017; Eller and Hardy 2017).

Appendix Table A.8 shows regression coefficients on key control variables. Wind speed is positively correlated with wind energy capacity, as is access to transmission lines, consistent with our county-level findings. Sections nearer to roads and airports, which may face regulatory or technical and safety obstacles, are less likely to host turbines. Parcels with increased slopes are less likely to host wind turbines, although more rugged terrains are more likely to have installed capacity. Conditional on land-use fixed effects, soil quality does not affect wind power development. Consistent with the county-level analysis, these findings from section-level analysis also imply that fragmented landscapes are a barrier to wind energy development. [40]

Parcel-Level Regressions

Table 7 shows parcel-level regressions in which the dependent variable is an indicator for whether a turbine is located within parcel boundaries, with control variables in Table A.9. The columns increase the radius by which the number of landowners surrounding a parcel are measured, from a quarter-mile in column (1), a half-mile in column (2), to a mile in column (3).[41]

The findings indicate that the primary variable of interest, the Inverse Hyperbolic Sine (IHS) of the number of private landowners within the given radius of each parcel, negatively affects the probability that a parcel hosts a wind turbine. Focusing on column (1), doubling the number of landowners within a quarter mile decreases the probability of hosting a

[40]Differing from the county-level analysis, we do not find section-level evidence that irrigation hinders wind development, although this null finding may be driven by the fact that most of the sample is from Midwest counties in states with relatively little irrigation (e.g., Illinois, Indiana, Iowa, Minnesota).

[41]The sample size decreases from column to column because parcels that are within the radius of each county border are dropped.

wind turbine by 0.002, about 10 percent relative to the mean of 0.023. Furthermore, larger parcels (in acreage) are more likely to host a turbine. While this effect is in part mechanical (larger parcels have more room for turbines), it also reflects increased land ownership concentration. Both findings suggest that land ownership concentration has increased the likelihood of hosting wind turbines.

We highlight additional results from the regressions in Appendix Table A.9. As in previous models, wind speed and transmission access are positively associated with wind power, while proximity to other built infrastructure is negatively correlated. More public land surrounding a parcel dramatically reduces the likelihood of hosting a turbine. Finally, the distance from the parcel to the landowner's mailing address is negatively associated with wind development. This suggests non-absentee landowners are more likely to host turbines. Although this result somewhat contradicts the county-level result that a higher share of off-farm operators increases the likelihood of wind development, it may suggest additional benefits to living near a prospective wind farm, such as reduced coordination costs in negotiation or better information about wind farming.

Robustness Checks

We incorporate robustness checks at all levels of analysis. First, as emphasized above, U.S. agricultural land ownership infrequently moves out of families, even upon the retirement or death of the farm-operator (Lobley, Baker and Whitehead 2010; Mishra, Johnson and Morehart 2003). Nonetheless, if land ownership patterns dynamically respond systematically to wind development prospects, our estimates could embed reverse causality. The direction of the bias is unclear. On one hand, wind farm royalties could allow smaller farms to stay profitable, increasing the number of small farms and preventing land ownership consolidation. On the other hand, wind royalties could also give larger farms more revenue and enable them to buy out smaller operators, thereby increasing land ownership concentration.

We address this potential bias in the county regression by instrumenting average farm size in 2012 with average farm size in 1997. Because farm ownership patterns are relatively stable, the 1997 instrument is highly correlated with 2012 farm sizes. Moreover, the instrument should satisfy the exclusion restriction because there was almost no wind energy development prior to 1997. Table A.10 shows results from the IV regressions. Across specifications, the coefficients on the instrumented average farm size are positive and significant, eliminating concerns of upward bias. [42,43] Next, we show that the county-level regressions are robust to using median (rather than average) farm sizes in Table A.11: using the median does not qualitatively change our findings.

Another concern is that the coefficient estimates on farm size and owner concentration are highly sensitive to the inclusion or exclusion of specific key control variables, which could be indicative of omitted variable bias. To diagnose this possibility, we rerun the primary models from a simple bivariate regression and subsequently add controls. The county regressions in Table A.12 show stability, regardless of the excluded covariates. In Table A.13, the effect of the number of landowners is positive (rather than negative) in the simple bivariate model. After the inclusion of land cover controls, however, the effect is negative and significant and remains so as further controls and fixed effects are added.

[42]The first stage F statistics of at least 700 suggest a strong instrument.

[43]We cannot run a similar IV regression for the section and parcel regressions because we do not have older versions of the land ownership data.

This does not raise concerns that omitted variables confound our main finding, however; rather, the sign flips because large parcels concentrated in unfarmable (for both agriculture and wind) land uses such as water, wetlands, and barren land are not distinguished from those concentrated in crop or pastureland in the bivariate model. Similarly, the coefficient on the number of neighbors in the parcel regressions in Table A.14 is positive until land cover controls are added but the coefficient is otherwise relatively stable to the inclusion of township fixed effects, which account for local policies and other geographic factors. Overall, the relative stability across specifications provides confidence that the results are not driven by specification choice or by omitted variables.

We also control for possible non-linear correlations by estimating the effects of farm size/ownership concentration conditional on non-parametric controls for wind speed and transmission access. Tables A.15 - A.17 show the results when wind speed and transmission access effects are binned by quartiles, where the first column represents the initial regression. The findings across models are similar, suggesting the linear model specification is not driving results.

To further account for possible omitted variable bias, we use a modified spatial first differences regression (Drukenmiller and Hsiang 2018) for both the county (Table A.18) and section (Table A.19) regressions. We discuss model details in the appendix, and note that results are qualitatively similar to the main findings. The standard errors are less precise, however, because the model necessitates a significantly smaller sample size.

For the parcel regressions, where spatial first difference models are less feasible, we show robustness using randomization techniques discussed in Fisher (1935). Figure A.1 shows the results from randomly re-assigning the treatment variable to a parcel within the same township and re-running the regression 500 times. The actual regression result from Table A.9, column (1) appears in the middle in red and is larger in magnitude, suggesting the results are not spurious. The results from these robustness checks, coupled with the similar findings across three different spatial scales, provide strong evidence that fragmentation has slowed wind energy development.

Alternative Mechanisms: Setback Regulations and Tax Incentives

As explained in Winikoff (2022), U.S. counties regulate wind farming through the use of zoning and turbine "setback" requirements. Setbacks dictate a minimum distance between a landholding's property line and the placement of a turbine. The rationale is to protect neighboring landowners from negative disamenities resulting from proximity to a turbine. Small landholders may be denied opportunities to benefit financially from wind energy leasing because a turbine setback reduces the amount of land available for wind development.

To assess the extent to which our findings are driven by setbacks, we would ideally compare the effects of fragmentation within counties with and without setback requirements. We exploit the fact that Texas and Oklahoma have limited setback regulations. [44] Tables A.20 and A.21 show results limiting the sample to Texas and Oklahoma observations for the section and parcel regressions, respectively.[45] Results suggest smaller effects in these states, although still generally significant and consistent with those from the full sample. The findings suggest that although setbacks may play a role in explaining some of the

[44]Texas forbids county regulations, and therefore none of our sample counties in Texas have setback laws (Linowes 2018). Oklahoma has limited state-wide setback regulations, and those establish only minimum distances from turbines to airports, schools, and hospitals (Heibel and Durkay 2015).

[45]Due to the small sample size, we do not show the analogous regression for the county sample.

observed effects of fragmentation, these regulations are unlikely to account for the full effect.[46]

Another possible explanation relates to tax incentives. Larger MW wind farms require larger investments and therefore benefit to a greater extent from tax credits for wind power development (Bolinger and Wiser 2009; Schwabe et al. 2017). Tax incentives may therefore proportionally strengthen the incentive for larger landholders to lease for wind farming depending on how much of the tax benefit passes through. If tax incentives are a strong, underlying mechanism explaining why landowner concentration leads to more wind farming, we would expect small, community-run wind developments that are not eligible for investment tax benefits (e.g., one or two turbines to power local schools, etc.) to be built primarily in areas with smaller landholdings. To diagnose if this is driving our findings, we re-run the county analysis described in Table A.7 after limiting the sample to counties with more than 20 MW of wind power (thereby purging the sample of small, community wind farms). We find no difference in the findings, meaning the results hold when we eliminate counties that have exclusively smaller, community projects (see Table A.22). This is an indication that tax incentives are unlikely to be driving our results.

Discussion

The findings from all three levels of analysis indicate that fragmented landownership (i.e., small, rural landholdings) have deterred wind development. What are the broad-stroke implications of this result? To shed light, we design a simple counterfactual analysis. Using the county-level regressions from Table A.7, Column 2, we compute the difference between

[46]Notably, when limiting the sample to just Texas and Oklahoma, irrigated land is negatively associated with wind development, consistent with findings from Cooley and Smith (2022).

predicted wind development under existing farm sizes and the counterfactual in which all counties have an average farm size equal to the 2012 average of 434 acres. We aggregate the predicted differences by state, and Figure 4 plots the differences among the 20 states with the most observed wind production as of 2021. This exercise indicates that if average farm sizes were equal in all states, and all other factors were the same, then less wind production to date would be occurring in the Great Plains, where farms are larger, and more wind production would have developed in the Midwest, where average farm sizes are smaller.

The findings have two additional big-picture implications. First, contracting challenges due to small farms and ownership fragmentation are causing wind farming to be developed further from pre-existing transmission lines. Counties above the median in average farm size ($>$279 acres) have 19 percent fewer kilometers of transmission lines when compared to counties below the median (224 km vs. 269 km). This is important because the physical and regulatory costs of extending transmission lines to utility-scale wind farms grows with distance. A second implication is that windy geographies with lower contracting challenges (i.e., more landowner concentration) have already developed wind power suggesting the low-hanging fruit of an energy transition to renewables has already been picked. Figure 5 plots the density of average farm sizes across counties, organized by those with and without 100 MW of wind power already installed. The figure demonstrates that large-farm counties have already been disproportionately developed. The remaining onshore areas tend to have more fragmented ownership and therefore will face more obstacles for future wind development unless landowner coordination costs decrease over time.

Conclusion

Our study emphasizes the important role that private rural land ownership patterns will play in influencing where and if future expansions of wind farming will occur. At the county, square-mile, and parcel levels, we find that installed wind energy capacity decreases sharply with increases in ownership fragmentation in the area. This finding is consistent with the dominance of an “anticommons” in which private leases become less likely as the number of relevant landowners increases.

What are the ramifications of this finding? First, it indicates that landowners of large rural tracts have disproportionately participated in the growth of wind energy. Because the wind industry is subsidized at both the state and federal level, our finding imply that these landowners have received a larger share of government subsidies when compared to owners of small rural tracts. If these landowners of larger parcels are also wealthier, then subsidies may have disproportionately flowed to wealthier landowners.

Second, the results suggest that global efforts to address climate change through on-shore wind energy will be more challenging than models ignoring rural land ownership patterns predict. Although agricultural farm consolidation has occurred in the United States (MacDonald and Hoppe 2017) and other developed countries, farm sizes are getting smaller in much of the developing world. Furthermore, within the United States, geographies with concentrated land ownership have already been disproportionately developed for wind power, meaning wind developers will eventually have to focus on areas with smaller landholdings. Net-zero and decarbonization forecasts, which do not account for the contracting obstacles studied here, overstate the potential effectiveness of renewable energy expansion because they do not account for land ownership patterns. Large-scale expansion of wind energy may be more feasible in oceans offshore or on publicly owned lands where private landowner contracting is averted.

Third, our research suggests that the growing number of local zoning and setback policies restricting wind energy utilization may amplify the effects of fragmented ownership modeled in this paper. These regulations intend to protect landowners from disamenities associated with wind energy such as shadow flicker, noise, and ice throw, but they also disqualify owners of smaller landholdings from hosting wind turbines. This further limits the amount of land available for wind energy development.

Tables and Figures

Table 1: Summary Statistics for Sample of Counties

	Mean	SD	Min	Max
=1 if Wind Farm	0.162	0.369	0	1
Turbine Count	26	108	0	3,499
Turbine Capacity (MW)	47	167	0	3,221
MW/1000 Acres	0.080	0.282	0	3.920
Avg. Farm Size (Acres)	637	1,208	39	32,728
Avg. 1997 Farm Size (Acres)	714	1,329	47	18,581
Median Farm Size (Acres)	192	345	2	6,000

Note: N = 2,494. Counties in the continental United States with greater than 10 percent of land occupied by farms are included. All variables appear in Appendix Table A.1.

Table 2: Summary Statistics for Section-Level Sample

	Mean	SD	Min	Max
=1 if Turbine	0.069	0.253	0	1
Turbine Count	0.227	1.026	0	36
Turbine Capacity (MW)	0.428	1.902	0	34.400
Undeveloped, Private Landowners	5.798	7.083	1	377
Equal Share Undeveloped Landowners (Inverse HHI)	3.119	2.181	1	100.081

Note: N = 97,981. Sample is limited to PLSS sections with greater than 95 percent of land privately owned and undeveloped in counties with wind development. All variables appear in Appendix Table A.2.

Table 3: Summary Statistics for Parcel-Level Sample

	Mean	SD	Min	Max
=1 if Turbine	0.023	0.150	0	1
Landowners within Radius	10.213	19.434	0	$1,672$
Parcel Size (Acres)	141	303	20	$21,242$

Note: N = 334,392 Sample is limited to parcels greater than 20 acres located on crop, pasture, shrub, or grassland in counties with wind development. Radius is one quarter mile from parcel borders. All variables appear in Appendix Table A.3.

Table 4: County-Level Regression Estimates

	Dependent variable:				
	Wind Farm	MW	IHS(MW)	MW/1000 Acres	Log(MW) $\|MW > 0$
	(1)	(2)	(3)	(4)	(5)
Log(Avg. Farm Size)	0.043	32.139***	0.285*	0.056***	0.715*
	(0.026)	(10.043)	(0.154)	(0.017)	(0.355)
Observations	2,494	2,494	2,494	2,494	522
R^2	0.315	0.212	0.346	0.196	0.432

Note: Standard errors (clustered by state) in parentheses. The dependent variable measures accumulated wind capacity as of 2021. All models include state FEs and controls from Appendix Table A.7. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Section-Level Estimates with Number of Landowners Measure

	Dependent variable:			
	= 1 if Turbine	MW	IHS(MW)	Log (MW | MW >0)
	(1)	(2)	(3)	(4)
Log(Undeveloped Landowners)	−0.002	-0.056^{***}	-0.011^{***}	-0.136^{***}
	(0.002)	(0.014)	(0.004)	(0.021)
Observations	97,981	97,981	97,981	6,751
R^2	0.448	0.382	0.437	0.578

Note: All specifications also include township FEs and covariates for land use shares and controls from Appendix Table A.8. All standard errors are clustered at the township level. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Section-Level Estimates with Equal-Share Landowner Measure

	Dependent variable:			
	= 1 if Turbine	MW	IHS(MW)	Log (MW | MW >0)
	(1)	(2)	(3)	(4)
Log(Equal-Share Undeveloped Landowners)	0.001	-0.052^{***}	−0.007	-0.139^{***}
	(0.002)	(0.015)	(0.005)	(0.022)
Observations	97,981	97,981	97,981	6,751
R^2	0.448	0.381	0.437	0.578

Note: Standard errors (clustered by state) in parentheses. All models include township FEs and controls from Table A.8. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Parcel Level Regression Estimates

	Dependent Variable =1 if Turbine		
	(1)	(2)	(3)
IHS(Landowners Within Radius)	-0.0020^{***}	-0.0021^{***}	-0.0031^{***}
	(0.0007)	(0.0007)	(0.0008)
Log(Acres)	0.0164^{***}	0.0172^{***}	0.0176^{***}
	(0.0015)	(0.0015)	(0.0016)
Radius (Miles)	0.25	0.5	1
Observations	334,392	322,402	295,739
R^2	0.1802	0.1806	0.1868

Note: All specifications also include township and land use fixed effects, and control variables from Appendix Table A.9. All standard errors are clustered at the township level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

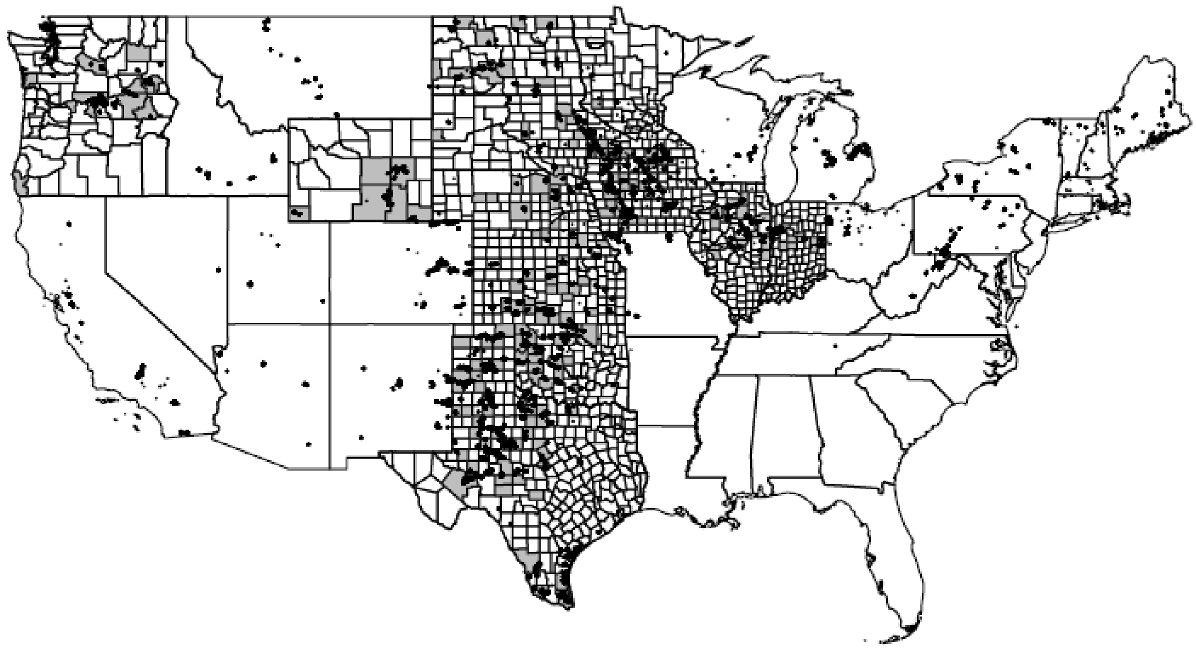

Figure 1: Wind turbine installations in the United States through 2021 (Hoen et al. 2018). The section and parcel-level data samples come from highlighted counties, with data from ReportAll USA.

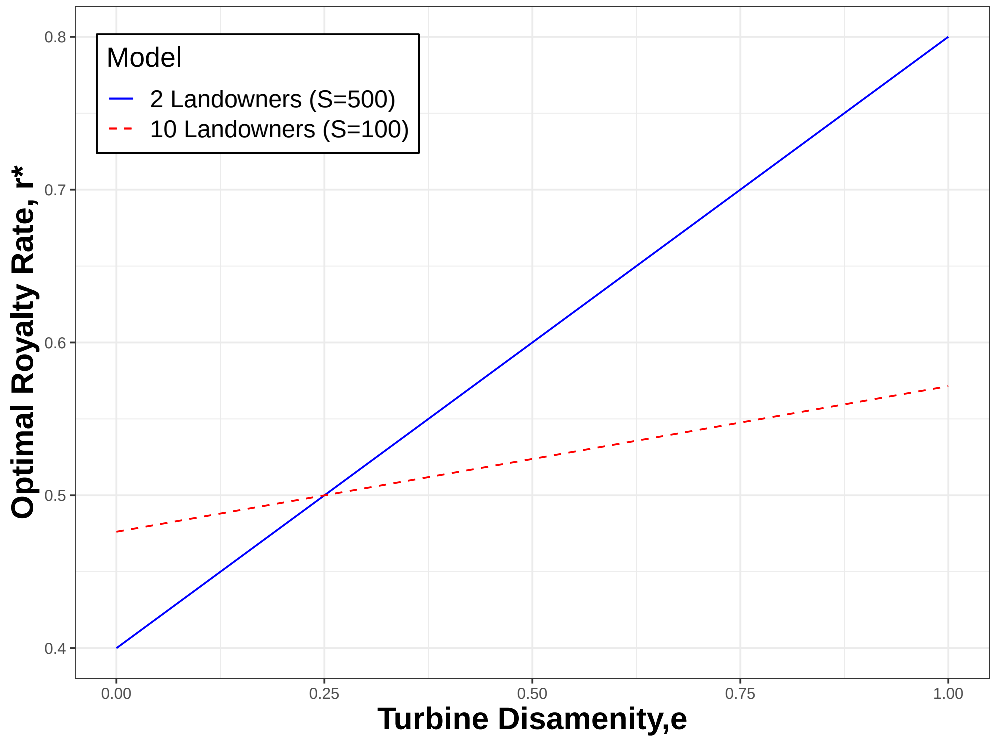

Figure 2: Example of privately optimal royalty rate from Equation (3) in fragmented (dashed red) and concentrated (solid blue) cases. A higher royalty rate reduces the probability of wind farm construction.

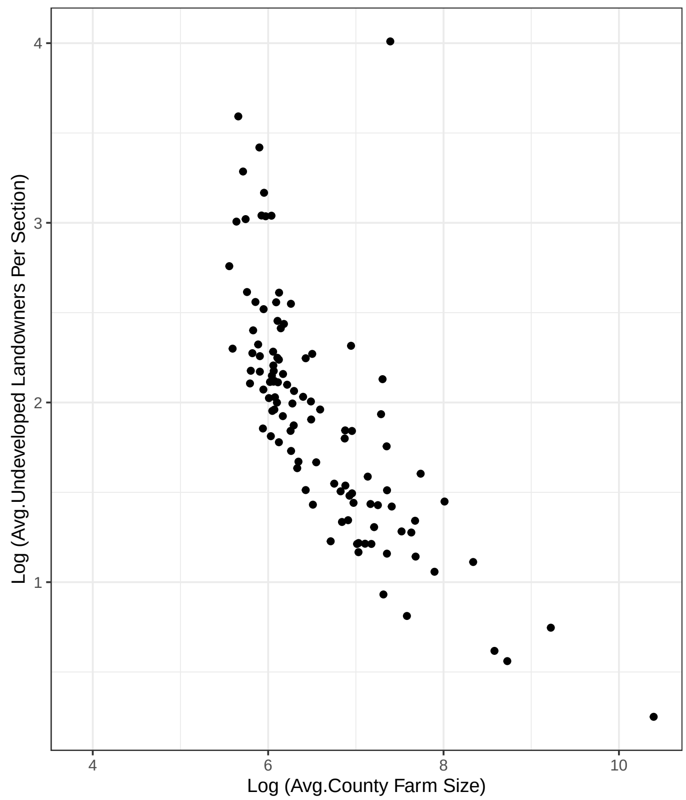

Figure 3: Scatter plot of between county farm size and the county average number of undeveloped landowners per section for the shaded counties in Figure 1.

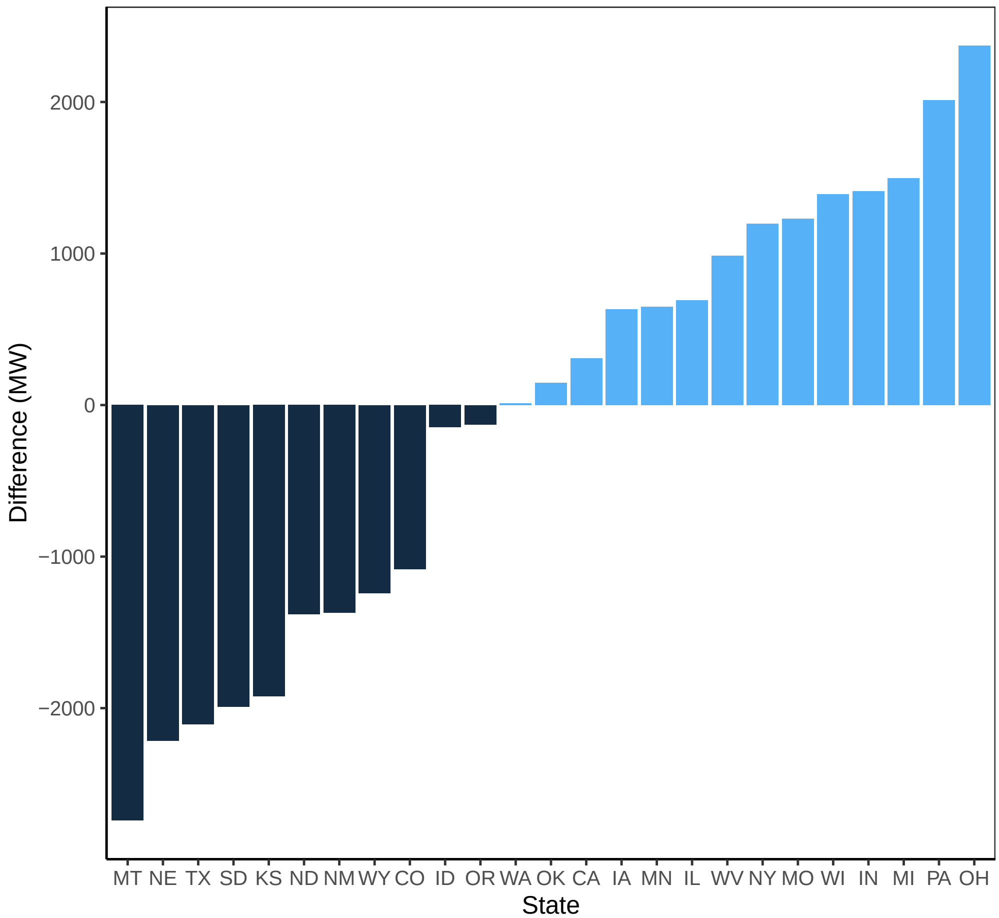

Figure 4: Difference between predicted counterfactual in which all farms were equal to 434 acres, the average size in 2012, and predicted capacity from the regression in Table 4, Column 2. Results shown for top 20 states in wind production as of 2021.

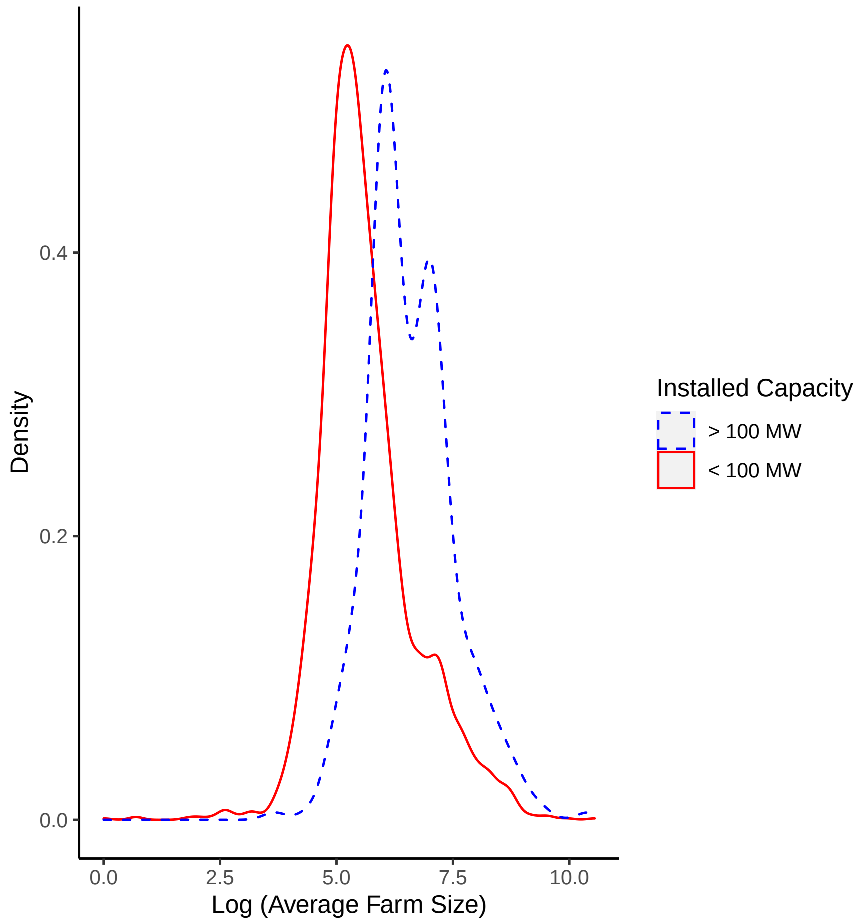

Figure 5: Density of county farm sizes organized by installed wind capacity as of 2021. The dotted blue line represents the density of farm sizes for counties with more than 100 MW installed. It is greater than the density shown by the solid red line for counties with less than 100 MW already installed.

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Spatial First Differences Robustness Checks

There may be concerns that the conditional independence assumption (CIA) required for causal identification is violated given the simple cross-sectional specification. The CIA states that for a given observation i, treatment x_i, and outcome y_i, $E[y_i|x_j] = E[y_j|x_i]$ for any $j \neq i$. In other words, if two observations are exposed to the same treatment (conditional on other controls), we should expect the same outcome for each. This assumption is unlikely satisfied in many real-world settings where unobservables likely influence outcomes. While panel and regression discontinuity methods, among others, allow for more plausibly causally identified estimates when omitted variable bias is possible, those approaches are often not suitable for spatial settings such as our study.

Drukenmiller and Hsiang (2018) propose a solution by offering a much weaker assumption of conditional independence. Instead of assuming independence between all observations, we can assume it only between one observation i, and its immediate neighbor $i-1$. The authors demonstrate that under this assumption, we can eliminate omitted variable bias between neighbors by regressing the first differences between these adjacent observations. We implement this "Spatial First Differences" (SFD) approach using code from Drukenmiller and Hsiang (2018). We slice the continental United States into 50 different sampling rows of approximately 30 miles each, running from west to east. Each of these rows represents "panel-like units" of counties. Starting in the northern-most row, we subtract the relevant covariates from its neighbor immediately to the west. We then do this for each subsequent row to the south, omitting counties that have already been included in a sample to the north. We then run the same empirical specification on the differences between adjacent counties:

(7)

$$\Delta WindCapacity_i = \alpha_2 + \beta_{SFD}\Delta LandOwnershipConcentration_i + \delta_{SDF}\Delta X_i + \Delta\epsilon_i.$$

Table A.18 shows the county spatial-difference regression results. Note that our primary sample here (1,720 counties) is substantially smaller than in our cross-sectional approach. There are two reasons for this. First, because we regress the differences across rows, the western-most county for each slice cannot be included because there is no county with which to difference the covariates. We also drop the western-most counties in each state because it is unlikely that even the relaxed conditional independence assumption holds in this context, given omitted factors that vary from state to state, such as renewable portfolio standards. Furthermore, we omit column (5) from the Table A.7 because there are few counties with positive wind capacity, and many are not adjacent to one another, thereby weakening the relaxed independence assumption.

Nonetheless, Table A.18 delivers similar qualitative results to our primary specification in Table A.7. In Column (2) for example, doubling farm size increases the MW installed by 36.6 MW, nearly 78 percent relative to the primary sample mean. Although standard errors are larger relative to the OLS regressions, in part due to the smaller sample, the findings suggest the county regressions are generally consistent with the SFD specification.

We additionally modify the code from Drukenmiller and Hsiang (2018) to implement a spatial first differences regression and apply it to the section-level regressions. Table A.19 shows the results. They support our main findings and suggest the primary finding is not driven by the conditional independence assumption and that increased fragmentation does in fact reduce wind development. In fact, coefficients nearly identical to those from the OLS models, and in several cases larger (in magnitude) than those from the main model.[47]

Additional Tables and Figures

[47]Because of the sample restrictions in the parcel-level model, not all adjacent parcels appear in the regressions. We therefore do not run such a model for the parcel regressions.

Table A.1: Summary Statistics for Sample of Counties

	Mean	SD	Min	Max
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Turbine Count	26	108	0	3,499
Turbine Capacity (MW)	47	167	0	3,221
MW/1000 Acres	0.080	0.282	0	3.920
Avg. Farm Size (Acres)	637	1,208	39	32,728
Avg. 1997 Farm Size (Acres)	714	1,329	47	18,581
Median Farm Size (Acres)	192	345	2	6,000
Wind Speed (m/s)	6.681	0.835	3.077	9.248
km Transmission Lines	247	233	0	3,164
Pop. Density (per Acre)	0.192	0.388	0.0004	5.965
Share Publicly Owned	0.114	0.160	0	1.003
Dist. to Metro Area (km)	28	40	0	303
Acres Irrigated	21,313	55,899	0	968,727
Ag. Products Sold (1,000s)	146,339	253,706	973	4,973,041
Land Value/Acre	3,469	2,346	202	22,248
Share Live Off-Farm	0.250	0.120	0.041	0.792
Fully Owned Acres	116,504	169,424	1,697	3,841,819
Share Cropland	0.494	0.268	0.002	0.981
Elevation (ft)	429	477	0	3,043
Acres Land Area	588,173	701,044	55,130	10,988,685

Note: N = 2,494. Counties in the continental United States with greater than 10 percent of land occupied by farms are included.

Table A.2: Summary Statistics for Section-Level Sample

	Mean	SD	Min	Max
=1 if Turbine	0.069	0.253	0	1
Turbine Count	0.227	1.026	0	36
Turbine Capacity (MW)	0.428	1.902	0	34.400
Undeveloped, Private Landowners	5.798	7.083	1	377
Equal Share Undeveloped Landowners (Inverse HHI)	3.119	2.181	1	100.081
Wind Speed (m/s)	7.822	0.707	3.477	12.351
Elevation (100s ft)	6.541	4.806	0.013	31.671
Slope	1.606	1.901	0.002	26.792
Terrain Ruggedness Index	1.908	2.217	0.002	34.904
Soil Quality	12.245	3.349	1	18
Share Irrigated	0.045	0.144	0	1
Transmission $<$ 5km	0.492	0.500	0	1
Airport $<$ 5km	0.093	0.291	0	1
Distance to Rail (km)	0.064	0.341	0	10.986
Distance to Road (km)	3.728	2.427	0	24.722
Share Undeveloped	0.999	0.004	0.950	1
Share Non-Federal	1.000	0.003	0.950	1
Share Non-State/Local	1.000	0.002	0.951	1
Developed Landowners	0.311	2.443	0	124

Note: N = 97,981. Sample is limited to PLSS sections with greater than 95 percent of land privately owned and undeveloped in counties with wind development.

Table A.3: Summary Statistics for Parcel-Level Sample

	Mean	SD	Min	Max
=1 if Turbine	0.023	0.150	0	1
Landowners within Radius	10.213	19.434	0	1,672
Parcel Size (Acres)	141	303	20	21,242
Distance to Mailing Address (km)	151	421	0	9,287
Wind Speed (m/s)	7.753	0.638	3.477	11.651
Parcel Perimeter (ft.)	9,714	7,936	3,656	405,549
Trans. Within Radius	0.060	0.237	0	1
Road Within Radius	0.704	0.456	0	1
Airport Within Radius	0.001	0.034	0	1
Rail Within Radius	0.031	0.173	0	1
Soil Quality	12.972	3.028	0	18
Share Irrigated	0.042	0.163	0	1
Share Surrounding Public	0.026	0.107	0	1
Share Surrounding Developed	0.006	0.034	0	0.979

Note: N = 334,392 Sample is limited to parcels greater than 20 acres located on crop, pasture, shrub, or grassland in counties with wind development. Radius is one quarter mile from parcel borders.

Table A.4: Correlation Coefficients: Key County Variables

	Farm Size	Wind Speed	Transmission	Pop. Density	Value/Acre	Owned Acres	Share Crop
Farm Size	1						
Wind Speed	0.266	1					
Transmission	-0.018	-0.189	1				
Pop. Density	-0.175	-0.196	0.437	1			
Value/Acre	-0.352	-0.187	0.084	0.530	1		
Owned Acres	0.480	0.112	0.224	-0.165	-0.334	1	
Share Crop	-0.228	0.360	-0.120	0.059	0.366	-0.340	1

N = 2,494.

Table A.5: Correlation Coefficients: Key Section Variables

	Undeveloped Landowners	Wind Speed	Soil Quality	Elevation	Transmission	Developed Landowners
Undeveloped Landowners	1					
Wind Speed	-0.133	1				
Soil Quality	0.144	-0.062	1			
Elevation	-0.214	0.411	-0.331	1		
Transmission	0.087	-0.028	0.105	-0.068	1	
Developed Landowners	0.337	-0.038	0.042	-0.057	0.028	1

N = 97,981.

Table A.6: Correlation Coefficients: Key Parcel Variables

	Surrounding Landowners	Acres	Wind Speed	Transmission	Soil Quality	Share Surrounding Developed
Surrounding Landowners	1					
Acres	-0.032	1				
Wind Speed	-0.079	0.078	1			
Transmission	0.053	-0.020	-0.032	1		
Soil Quality	0.010	-0.192	0.020	0.002	1	
Share Surrounding Developed	0.580	-0.036	-0.062	0.062	0.007	1

N = 334,392.

Table A.7: County-Level Regression Estimates

	Dependent variable:				
	Wind Farm	MW	IHS(MW)	MW/1000 Acres	Log(MW) $\mid MW > 0$
	(1)	(2)	(3)	(4)	(5)
Log(Avg. Farm Size)	0.043	32.139***	0.285*	0.056***	0.715*
	(0.026)	(10.043)	(0.154)	(0.017)	(0.355)
Wind Speed	0.225***	76.347***	1.367***	0.125***	1.193***
	(0.033)	(16.134)	(0.198)	(0.029)	(0.280)
IHS(Transmission)	0.046***	24.966***	0.316***	0.041***	0.220**
	(0.008)	(4.997)	(0.043)	(0.009)	(0.084)
Log(Pop. Density)	−0.113**	−43.200***	−0.691***	−0.089***	−1.950**
	(0.045)	(9.113)	(0.254)	(0.029)	(0.731)
Share Public	−0.120	−60.656	−0.819	−0.052	−2.228*
	(0.098)	(48.135)	(0.627)	(0.069)	(1.216)
IHS(Dist. Metro Area)	−0.001	−1.462	−0.013	0.004	0.066
	(0.005)	(2.303)	(0.036)	(0.004)	(0.062)
IHS(Acres Irrigated)	−0.018***	−6.604***	−0.108***	−0.013***	−0.092*
	(0.004)	(2.177)	(0.023)	(0.003)	(0.048)
Log(Ag. Products Sold)	0.046***	10.726**	0.281***	0.016***	0.061
	(0.009)	(4.542)	(0.063)	(0.005)	(0.132)
Value/Acre	0.008	4.626	0.067	0.025	0.911*
	(0.047)	(15.172)	(0.291)	(0.038)	(0.450)
Perc. Live Off-Farm	0.452***	159.645***	2.969***	0.170***	1.389
	(0.102)	(48.089)	(0.585)	(0.056)	(1.428)
Log(Fully Owned Acres)	−0.067***	−14.090*	−0.379***	−0.036**	−0.576*
	(0.023)	(7.411)	(0.133)	(0.018)	(0.287)
Share Cropland	−0.150**	−26.638	−0.786**	0.020	−0.403
	(0.057)	(29.646)	(0.349)	(0.054)	(0.834)
IHS (Elevation)	0.055***	16.673*	0.367***	0.030*	−0.123
	(0.016)	(9.681)	(0.094)	(0.016)	(0.350)
Log (Land Area)	0.054*	9.557	0.279	−0.030	0.997**
	(0.029)	(16.616)	(0.185)	(0.024)	(0.430)
Observations	2,494	2,494	2,494	2,494	522
R^2	0.315	0.212	0.346	0.196	0.432

Note: Standard errors (clustered by state) in parentheses. The dependent variable measures accumulated wind capacity as of 2021. All models include state FEs. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Section-Level Estimates with Number of Landowners Measure

	Dependent variable:			
	= 1 if Turbine	MW	IHS(MW)	Log (MW | MW >0)
	(1)	(2)	(3)	(4)
Log(Undeveloped Landowners)	−0.002	−0.056***	−0.011***	−0.136***
	(0.002)	(0.014)	(0.004)	(0.021)
Wind Speed (m/s)	0.091***	0.548***	0.205***	0.370***
	(0.008)	(0.064)	(0.020)	(0.102)
Elevation (100s ft)	0.028***	0.319***	0.087***	0.423***
	(0.005)	(0.054)	(0.014)	(0.111)
Land Slope	−0.002	−0.106*	−0.025	−0.190*
	(0.007)	(0.058)	(0.017)	(0.101)
Terrain Ruggedness Index	0.003	0.071	0.019	0.158*
	(0.006)	(0.049)	(0.014)	(0.086)
Soil Quality	−0.001	−0.002	−0.001	0.012
	(0.001)	(0.005)	(0.002)	(0.009)
Share Irrigated	0.010	−0.073	−0.007	−0.333***
	(0.012)	(0.081)	(0.028)	(0.090)
Airport < 5km	−0.016***	−0.116***	−0.040***	0.001
	(0.005)	(0.033)	(0.011)	(0.050)
Transmission < 5km	0.017***	0.161***	0.049***	0.080***
	(0.004)	(0.029)	(0.010)	(0.029)
Distance to Rail (km)	−0.003	−0.009	−0.005	−0.044
	(0.002)	(0.016)	(0.005)	(0.035)
Distance to Road (km)	−0.003***	−0.025***	−0.007***	−0.018***
	(0.001)	(0.004)	(0.001)	(0.005)
Share Undeveloped	0.785***	6.194***	1.966***	0.918
	(0.217)	(1.783)	(0.536)	(2.687)
Share Non-Federal	1.177***	8.713***	2.879***	−5.915
	(0.252)	(2.120)	(0.655)	(10.470)
Share Non-State/Local	0.599**	2.485	1.184	−1.093
	(0.300)	(2.899)	(0.805)	(3.283)
Log (Developed Landowners)	−0.002	−0.006	−0.004	−0.037
	(0.002)	(0.017)	(0.006)	(0.025)
Observations	97,981	97,981	97,981	6,751
R^2	0.448	0.382	0.437	0.578

Note: All specifications also include township FEs and covariates for land use shares. All standard errors are clustered at the township level. *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Parcel Level Regression Estimates

	Dependent Variable =1 if Turbine		
	(1)	(2)	(3)
IHS(Landowners Within Radius)	-0.0020^{***}	-0.0021^{***}	-0.0031^{***}
	(0.0007)	(0.0007)	(0.0008)
Log(Acres)	0.0164^{***}	0.0172^{***}	0.0176^{***}
	(0.0015)	(0.0015)	(0.0016)
IHS(Dist. to Mailing Address)	-0.0005^{**}	-0.0005^{**}	-0.0004^{*}
	(0.0002)	(0.0002)	(0.0002)
Wind Speed	0.0525^{***}	0.0516^{***}	0.0507^{***}
	(0.0044)	(0.0044)	(0.0046)
Log(Perim.)	−0.0034	-0.0043^{*}	-0.0041^{*}
	(0.0022)	(0.0022)	(0.0023)
Slope	−0.0015	−0.0013	−0.0013
	(0.0014)	(0.0014)	(0.0015)
Ruggedness	0.0017	0.0016	0.0015
	(0.0012)	(0.0013)	(0.0014)
Trans. Within Radius	0.0044^{**}	0.0030^{*}	0.0055^{***}
	(0.0019)	(0.0017)	(0.0017)
Road Within Radius	-0.0056^{***}	−0.0008	0.0054
	(0.0008)	(0.0018)	(0.0034)
Airport Within Radius	−0.0025	−0.0034	−0.0017
	(0.0043)	(0.0021)	(0.0020)
Rail Within Radius	-0.0029^{**}	-0.0035^{***}	-0.0023^{*}
	(0.0013)	(0.0013)	(0.0013)
Soil Quality	−0.00002	−0.0001	−0.0001
	(0.0003)	(0.0003)	(0.0003)
Share Irrigated	−0.0045	−0.0043	−0.0032
	(0.0032)	(0.0032)	(0.0033)
Share Surrounding Public	-0.0158^{***}	-0.0169^{***}	-0.0208^{**}
	(0.0047)	(0.0059)	(0.0082)
Share Surrounding Developed	0.0120^{**}	0.0118	0.0254^{**}
	(0.0058)	(0.0077)	(0.0106)
Total Surrounding Land	−0.0002	−0.0010	−0.0020
	(0.0012)	(0.0019)	(0.0029)
Radius (Miles)	0.25	0.5	1
Observations	334,392	322,402	295,739
R^2	0.1802	0.1806	0.1868

Note: All specifications also include township and land use fixed effects. All standard errors are clustered at the township level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.10: County-Level Regression Estimates with IV Specification

	Dependent variable:				
	Wind Farm	MW	IHS(MW)	MW/1000 Acres	Log(MW) $\|MW > 0$
	(1)	(2)	(3)	(4)	(5)
Log (Avg. Farm Size)	0.051^{*}	32.861^{***}	0.332^{*}	0.060^{***}	0.856^{**}
	(0.028)	(12.153)	(0.172)	(0.019)	(0.396)
First Stage F Stat.	3096.3	3096.3	3096.3	3096.3	696.4
Observations	2,494	2,494	2,494	2,494	522
R^2	0.315	0.212	0.346	0.196	0.432

Note: Standard errors (clustered by state) in parentheses. All models include state FEs and controls from Table A.7. 2012 mean farm size is instrumented with 1997 mean farm size. *p<0.1; **p<0.05; ***p<0.01.

Table A.11: County Regressions with Median Farm Size

	Dependent variable:				
	Wind Farm	MW	IHS(MW)	MW/1000 Acres	Log(MW) $\|MW > 0$
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Log (Median Farm Size)	0.026	32.138^{**}	0.142	0.034	0.245
	(0.026)	(12.655)	(0.150)	(0.021)	(0.189)
Observations	2,494	2,494	2,494	2,494	522
R^2	0.314	0.214	0.345	0.193	0.425
Panel B: IV					
Log (Median Farm Size)	0.062^{**}	39.293^{***}	0.308^{*}	0.053^{**}	0.464
	(0.028)	(13.719)	(0.161)	(0.024)	(0.302)
First Stage F Stat.	1440	1440	1440	1440	361.2
Observations	2,494	2,494	2,494	2,494	522
R^2	0.312	0.213	0.344	0.193	0.423

Note: Standard errors (clustered by state) in parentheses. All models include state FEs and controls from Table A.7. 2012 median farm size is instrumented with 1997 median farm size. *p<0.1; **p<0.05; ***p<0.01.

Table A.12: County-Level Regression Estimates: Control Tests

	Dependent Variable: MW Installed wind Capacity				
	(1)	(2)	(3)	(4)	(5)
Log (Average Farm Size)	42.748***	49.396***	38.051***	34.836***	32.139***
	(11.097)	(11.171)	(9.993)	(10.236)	(10.043)
Wind/Trans. Controls	N	Y	Y	Y	Y
State FEs	N	N	Y	Y	Y
Demographic/Topography Controls	N	N	N	Y	Y
Farm Controls	N	N	N	N	Y
Observations	2,732	2,732	2,731	2,731	2,494
R^2	0.066	0.130	0.192	0.200	0.212

Note: Standard errors (clustered by state) in parentheses. Demographic and Topography controls include population density, public land, distance to metropolitan areas, elevation, and land area. Farm controls include irrigation, ag. products sold, farm values, those living off-farm, cropland, and fully owned land. *p<0.1; **p<0.05; ***p<0.01.

Table A.13: Section-Level Regression Estimates: Control Tests

	Dependent Variable: MW Installed Wind Capacity					
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Undeveloped Landowners)	0.034*	−0.043**	−0.091***	−0.077***	−0.071***	−0.056***
	(0.018)	(0.018)	(0.014)	(0.014)	(0.014)	(0.014)
Land Cover Controls	N	Y	Y	Y	Y	Y
Township FEs	N	N	Y	Y	Y	Y
Wind/Trans. Controls	N	N	N	Y	Y	Y
Topographic Controls	N	N	N	N	Y	Y
Infrastructure Controls	N	N	N	N	N	Y
Observations	98,078	98,078	98,078	97,981	97,981	97,981
R^2	0.0002	0.007	0.372	0.379	0.381	0.382

Note: Standard errors (clustered by township) in parentheses. Land cover controls include the land area and percentage of land in each land cover category. Topographic controls include perimeter, elevation, slope, ruggedness, soil quality, and irrigation. Infrastructure controls distance to airports railroads, and roads, publicly owned land, and number of developed landowners. *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Parcel-Level Regression Estimates: Control Tests

	Dependent Variable = 1 if Wind Turbine					
	(1)	(2)	(3)	(4)	(5)	(6)
IHS (Landowners Within Radius)	0.0002	−0.0009	−0.0034***	−0.0025***	−0.0023***	−0.0020***
	(0.0009)	(0.0009)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Log (Acres)	0.0109***	0.0124***	0.0161***	0.0153***	0.0173***	0.0164***
	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0015)	(0.0015)
Land Cover Controls	N	Y	Y	Y	Y	Y
Township FEs	N	N	Y	Y	Y	Y
Wind/Trans. Controls	N	N	N	Y	Y	Y
Topographic Controls	N	N	N	N	Y	Y
Infrastructure Controls	N	N	N	N	N	Y
Observations	334,392	334,392	334,392	334,392	334,392	334,392
R^2	0.0040	0.0055	0.1762	0.1798	0.1798	0.1802

Note: The radius is measured as a quarter mile from parcel borders. Standard errors (clustered by township) in parentheses. Land cover controls include the predominant land cover category. Topographic controls include perimeter, elevation, slope, ruggedness, soil quality, and irrigation. Infrastructure controls distance to airports railroads, and roads, publicly owned land, and developed land surrounding, and distance to mailing address. *p<0.1; **p<0.05; ***p<0.01.

Table A.15: County-Level Regression: Non-Parametric Controls

	Dependent Variable: MW Installed wind Capacity			
	(1)	(2)	(3)	(4)
Log (Average Farm Size)	32.139***	35.828***	29.770***	33.519***
	(10.043)	(9.550)	(9.938)	(9.491)
Wind Quartiles	N	Y	N	Y
Trans. Quartiles	N	N	Y	Y
Observations	2,494	2,494	2,494	2,494
R^2	0.212	0.205	0.209	0.202

Note: Standard errors (clustered by state) in parentheses. Columns indicate binning of wind and transmission controls by quartiles. All other controls from Table A.7 included. *p<0.1; **p<0.05; ***p<0.01.

Table A.16: Section-Level Regression: Non-Parametric Controls

	Dependent Variable: MW Installed wind Capacity			
	(1)	(2)	(3)	(4)
Log (Undeveloped Landowners)	-0.056^{***}	-0.058^{***}	-0.057^{***}	-0.059^{***}
	(0.014)	(0.014)	(0.014)	(0.014)
Wind Quartiles	N	Y	N	Y
Trans. Quartiles	N	N	Y	Y
Observations	97,981	97,981	97,981	97,981
R^2	0.382	0.383	0.382	0.383

Note: Standard errors (clustered by township) in parentheses. Columns indicate binning of wind and transmission controls by quartiles. All other controls from Table A.8 included. *p<0.1; **p<0.05; ***p<0.01.

Table A.17: Parcel-Level Regression: Non-Parametric Controls

	Dependent Variable = 1 if Wind Turbine			
	(1)	(2)	(3)	(4)
IHS (Landowners Within Radius)	-0.002^{***}	-0.003^{***}	-0.002^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Acres)	0.016^{***}	0.017^{***}	0.016^{***}	0.017^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Wind Quartiles	N	Y	N	Y
Trans. Quartiles	N	N	Y	Y
Observations	334,392	334,392	334,392	334,392
R^2	0.180	0.179	0.180	0.179

Note: The radius is measured as a quarter mile from county borders. Standard errors (clustered by township) in parentheses. Columns indicate binning of wind and transmission controls by quartiles. All other controls from Table A.9 included. *p<0.1; **p<0.05; ***p<0.01.

Table A.18: County-Level Spatial-First Differences Regressions

	Dependent variable:			
	Wind Farm	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)
Log (Avg. Farm Size)	0.015	39.488**	0.124	0.045*
	(0.030)	(19.729)	(0.206)	(0.025)
Observations	1,720	1,720	1,720	1,720
R^2	0.090	0.065	0.097	0.066

Note: Standard errors (clustered by state) in parentheses. All models include controls from Table A.7. Regressions are run on Spatial First Differences by regressing differences between covariates of adjacent counties as described in Drukenmiller and Hsiang (2018). *p<0.1; **p<0.05; ***p<0.01.

Table A.19: Section-Level Spatial First Differences Regressions

	Dependent variable:			
	=1 if Turbine	MW	IHS(MW)	Log(MW) | MW>0
	(1)	(2)	(3)	(4)
Panel A:				
Log (Undeveloped Landowners)	−0.001	−0.069***	−0.011***	−0.153***
	(0.002)	(0.015)	(0.004)	(0.029)
Observations	85,714	85,714	85,714	3,860
R^2	0.045	0.047	0.050	0.194
Panel B:				
Log(Equal-Share Undeveloped Landowners)	0.002	−0.052***	−0.005	−0.138***
	(0.002)	(0.016)	(0.005)	(0.030)
Observations	85,714	85,714	85,714	3,860
R^2	0.045	0.047	0.050	0.191

Note: Standard errors (clustered by township) in parentheses. All models include controls from Table A.8. Regressions are run on Spatial First Differences by regressing differences between covariates of adjacent sections as described in Drukenmiller and Hsiang (2018). *p<0.1; **p<0.05; ***p<0.01.

Table A.20: Section Regressions: Texas and Oklahoma Only

	Dependent variable:			
	= 1 if Turbine	MW	IHS(MW)	Log (MW | MW >0)
	(1)	(2)	(3)	(4)
Panel A:				
Log(Undeveloped Landowners)	−0.002	−0.064**	−0.012	−0.098***
	(0.003)	(0.025)	(0.008)	(0.032)
Panel B:				
Log (Equal Share Undeveloped Landowners)	−0.001	−0.062**	−0.009	−0.112***
	(0.004)	(0.028)	(0.009)	(0.037)
Observations	30,100	30,100	30,100	2,457
R^2	0.465	0.400	0.457	0.549

Note: All variables from cross-sectional regression in Table A.8 included.*p<0.1; **p<0.05; ***p<0.01.

Table A.21: Parcel Level Regression Estimates: Texas and Oklahoma

	Dependent Variable =1 if Turbine		
	(1)	(2)	(3)
IHS(Landowners Within Radius)	−0.0030**	−0.0019	−0.0025*
	(0.0013)	(0.0012)	(0.0015)
Radius (Miles)	0.25	0.5	1
Observations	89,886	85,799	79,632
R^2	0.2159	0.2184	0.2268

Note: Model includes the same controls as Table A.9. All standard errors are clustered at the township level.*p<0.1; **p<0.05; ***p<0.01.

Table A.22: County-Level Regression Estimates: >20 MW Wind

	Dependent variable:		
	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)
Log (Avg. Farm Size)	140.099***	0.488***	0.169**
	(44.359)	(0.103)	(0.068)
Observations	380	380	380
R^2	0.319	0.340	0.365

Note: Standard errors (clustered by state) in parentheses. All models include state FEs and controls from Table A.7. *p<0.1; **p<0.05; ***p<0.01.

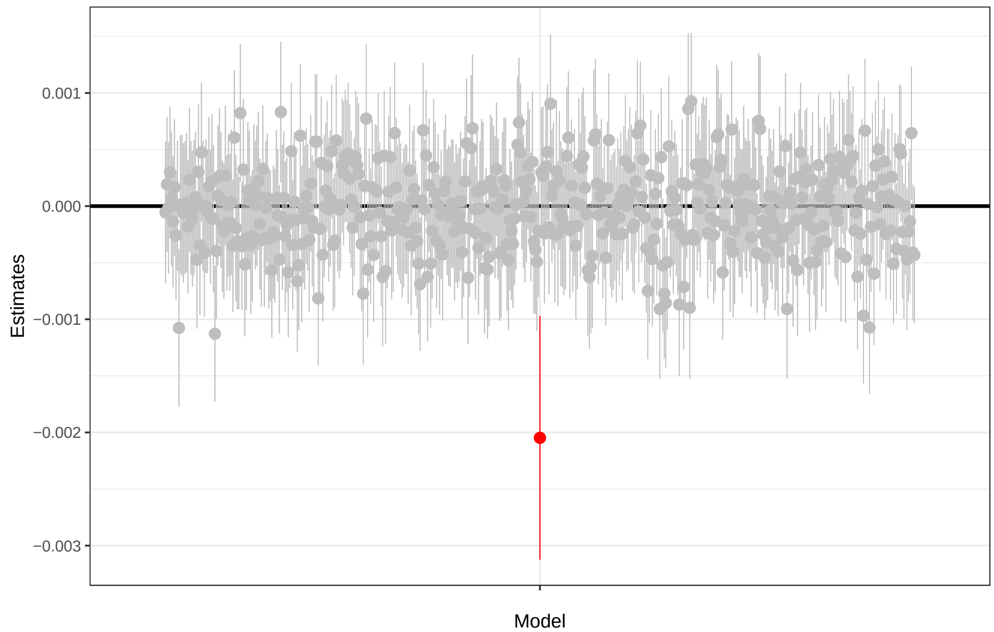

Figure A.1: Randomization Inference: Parcel Regressions

Note: Regression coefficients from 500 regressions in which the "treatment," the inverse hyperbolic sine of unique landowners within a quarter mile of a parcel, is randomized within each township. The dependent variable is an indicator equal to one if a parcel hosts a wind turbine in Table A.9, column (1). The "true" regression coefficient appears in red in the middle.