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 enticing neighboring private landowners to lease their properties for wind farming. Will this challenge be more or less severe in landscapes of 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. Empirically, we estimate the effects of landholding size and landscape fragmentation on wind farming uptake across the United States over the past 20 years. Evidence from county-level aggregates and from parcel-level analyses within counties indicates that small holdings and fragmentation have stunted wind farming: doubling of the average land holding size across counties is associated with a 29 to 78 percent increase in installed wind energy capacity. The findings suggest that fragmented ownership is likely to limit future wind expansion on private land absent policies that encourage landowner coordination in leasing.

Keywords: Wind Energy, Property Rights, Anticommons, Land Use
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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).

1 Introduction

Wind energy poses a dilemma for policymakers. On one hand, promoting it can counteract some of the global externality problems associated with greenhouse gas emissions (Cullen, 2013; Novan, 2015; Fell and Kaffine, 2018). On the other hand, wind farming can cause local externality problems by creating visual and audio disamenities that extend to neighbors beyond wind farm borders. This implies that aggressive promotion of wind might improve global welfare at the expense of local welfare, by causing "overuse" in turbines from the perspective of some local communities.

Moreover, standard externality theory suggests that local overuse will increase with N, the number of landowners in a landscape. This assumes each landowner bears only $1/N$ of the disamenity costs from adding a turbine to the landscape but receives the full payment for hosting it.[1] The implication is that, left unregulated, more turbines will be erected where landholdings are small, leading to more extreme disamenity problems and property value losses.[2]

Is this the full story? Are policymakers, in their desire to address climate change, inevitably choosing to incentivize overuse of turbines at the local level when subsidizing wind production? In this paper, we argue that a fuller understanding of the wind-energy policy dilemma requires a more comprehensive and balanced assessment of spatial externalities.

The fundamental issue is that wind farm projects are larger than most individual landholdings. Even a relatively small commercially viable wind project (50 megawatts (MW)) requires 4500 acres, far greater than the average size of agricultural landholdings in the

[1] In 2017, wind energy developers paid private landowners an estimated $267 million to lease farmland to build wind farms (AWEA, 2018).

[2] For example, citejensen and Gibbons (2015) 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.

United States, which is 441 acres (Denholm et al., 2009; USDA, 2019). 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.[3]

To understand how ownership fragmentation (e.g., progressively smaller landholdings in a landscape) influences leasing likelihood, we develop a stylized theoretical model of each individual landowner's decision to enter into a lease agreement with a wind developer. The model shows that, under certain circumstances, increases in land 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 that span multiple landholdings are overused relative to use under sole ownership.[4]

Our model embeds another externality problem, less often considered, that is relevant to natural resources such as wind that exhibit "economies of density" and can be profitably used only at spatial scales exceeding the size of individual landholdings.[5] When negotiating with the wind developer, each landowner sets a price (e.g., an annual lease payment) for turbine placement. The developer must pay the asking prices of each landowner in a prospective wind farm before erecting turbines. An exclusion externality problem arises because 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 wind developer a higher price in terms of lowering the probability of wind farm development, smaller landowners bear only a fraction of this cost. This causes the aggregate price of development to rise with N, relative to what a sole owner would charge, leading to

[3] The challenge would be more daunting in other parts of the world because, globally, 84 percent of farms are smaller than five acres (Lowder et al., 2016; Foster and Rosenzweig, 2017).

[4] 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, 2004a), conventional oil drilling, (Libecap and Wiggins, 1984), commercial fisheries (Kaffine and Costello, 2011; Deacon et al., 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).

[5] Wind farming exhibits economies of density because its 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).

reductions in the probability a wind farm will be built.

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 creates what we refer to as an "exclusion" externality.[6] Its effect is to deny some landowners the opportunity to financially benefit from their wind endowments, such as Dewey Engle in the epigraph.

We test for the effects of ownership fragmentation on American wind energy development by conducting two separate empirical analyses. First, we run a national analysis at the county level and find evidence that counties with larger average and median agricultural holdings have accumulated more installed wind energy capacity when controlling for other determinants of wind farming emphasized in previous literature (e.g. Menz and Vachon, 2016; Yin and Powers, 2010; Hitaj, 2013; Aldy et al., 2018; Johnston, 2019) . For example, a doubling of the average land holding size across counties is associated with a 29 to 78 percent increase in installed MW of wind energy capacity. Second, we run a (first of its kind) analysis at a more micro scale, using parcel-level data from over 180 windy counties in the U.S and analyzing wind turbine placement within Public Land Survey Survey (PLSS) square-mile sections. The evidence indicates that sections are much more likely to host turbines as land ownership in the section becomes more concentrated even when controlling for local infrastructure and several characteristics of land at the parcel and section levels. 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 are not solely driven by local regulations that favor large landholdings and instead are driven, at least in part, by fundamental differences in the ease of contracting with large rather than small landowners as our theory emphasizes.

[6] Buchanan and Yoon (2000) call it a "pecuniary" externality but we prefer "exclusion" because, unlike a classic pecuniary externality, 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 (2020), however, apply the theory to the problem of horizontal drilling for oil (fracking) through multiple private landholdings. And many examples of "anticommons" in Heller (1998, 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.

The analysis and findings contribute to ongoing policy discussions about local wind regulation. They suggest that regulatory bans on wind farming are superfluous in areas where small landholdings dominate because the market coordination costs of developing in these areas are already high enough to discourage wind farming.[7] In fact, landowners in areas with small landholdings might be better served by polices that help landowners coordinate in their bargaining with wind developers. Although our empirical findings suggest an "exclusion" externality is limiting wind energy development on fragmented landscapes, local zoning regulations focus primarily on a wind turbine's disamenity externalities. These policies may be steering communities further away from levels of wind investment that would maximize rents to local communities while also frustrating climate change mitigation. Furthermore, higher costs to siting turbines on smaller farms (amplified by zoning regulations) may increase rural inequality by pushing development to larger farms owned by wealthier individuals thereby making wind farming infeasible in poorer regions of the United States.

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 et al., 2019; Stavins, 2011).

2 Wind Energy in the United States

Due to a combination of technological advancements and policy incentives, 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 about 2,500 percent to about 105,000 MW by 2019.[8] This wind power is primarily located in rural areas in the Midwest (see Figure 1). However, wind energy installations are

[7] Recent examples of commercial wind farm bans include Pulaski County, IN (see "Pulaski County Plan Commission Votes to Ban Wind Turbines:" https://wkvi.com/2018/07/pulaski-county-plan-commission-votes-to-ban-wind-turbines/) and Hardin County, IA (see "Hardin County places indefinite moratorium on wind turbine permits:" https://www.kcci.com/article/hardin-county-places-indefinite-moratorium-on-wind-turbine-permits/30203308).

[8] *Wind Energy Facts at a Glance:* https://www.awea.org/wind-energy-facts-at-a-glance.

forecasted to spread to other parts of the country and to continue rapidly increasing as costs declines and federal and state policy incentives expand.[9]

Economists have sought to understand the primary determinants and barriers to wind energy development at local and regional levels. Hitaj (2013) conducts a comprehensive county-year-level empirical analysis accounting for changes in electricity prices, policy incentives, and electricity market structure. She finds that a variety of state and federal policies, particularly tax credits and production incentives, encourage wind energy growth, while renewable portfolio standards (RPS) are less effective. She also finds that access to electricity grids under the regulation of Regional Transmission Organizations (RTOs) promotes wind power development.

Most of the economics literature on wind energy focuses on the influence of federal and state incentives. Metcalf (2009) demonstrates that wind farm investment is very responsive to changes in federal tax policy, and in particular the production tax credit. Yin and Powers (2010) look at the role of renewable portfolio standards in promoting renewable energy generation and their findings suggest significant positive effects, contrasting Hitaj (2013). Similarly, Menz and Vachon (2016) finds evidence that RPS promote wind development, along with requiring power producers to supply "green power options." Aldy et al. (2018) examine the role of federal investment and production subsidies and find that the output subsidy-claiming wind farms vastly outproduced those claiming the investment subsidy. Johnston (2019) studies the implications of developers selecting between non-refundable production tax credits and cost-based grants for wind energy development, finding developers value cost-based grants to a greater extent.

The role of landownership patterns, however, has been mostly overlooked. In order to construct wind turbines on privately owned land, wind energy developers must obtain the consent of landowners to build turbines, access roads, and transmission lines. Furthermore, developers may also need to acquire easements from surrounding property owners so that

[9] In 2019, wind power made up 2.7 percent of all U.S. electricity generation (EIA, 2020c) , and 2020 was a record-setting year for new wind energy installations, with about 23 gigawatts (GW) expected to come online, nearly double the previous record of 13.2 GW added in 2012 (EIA, 2020a). According to U.S. Energy Information Administration (EIA) projections, wind will likely account for more than 12 percent of U.S. generation by 2050 (EIA, 2020b). Joe Biden has advocated for aggressive climate policy with the goal of net-zero carbon emissions by 2050 (White House, 2020). His climate plan as a presidential candidate advocated for 100 percent renewable electricity generation, substantial federal investments, and it highlighted the potential job gains from wind energy installations (Biden for President, 2020). If any of these policy proposals come into fruition, wind power could experience a boom far greater than current projections.

they agree to refrain from building structures that would obstruct wind flow. The types of compensation packages can vary, from lump-sum payments to per-turbine or per-MW payments to royalties, which are a share of the revenues generated from electricity production (Shoemaker, 2007). The amount of compensation for wind energy leases can vary as well, with modern estimates ranging from \$3,000 to \$6,000 per MW annually (AWEA, 2018).[10]

The complexity of wind energy leases and the potential negative externalities associated with wind 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. For example, Jensen et al. (2014) and Gibbons (2015) find a negative relationship between adjacency to wind turbines and property values, although Hoen et al. (2011) and Vyn and McCullough (2014) find no such effect. Krekel and Zerrahn (2017) use well-being data in Germany to demonstrate that proximity to wind farms is associated with lower scores of well-being. Not all local effects of wind energy may be negative, however. 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.

A small literature asks if fragmented property rights could cause a spatially inefficient pattern of wind power installations. Kaffine and Worley (2010), for example, compare sole versus shared ownership of wind farms in a theoretical framework. Under shared ownership, upwind producers ignore turbine wake externalities (the impact an upwind turbine has on wind speed downwind) and overcapitalize on upwind sites (and downwind producers undercapitalize) when compared with the sole ownership situation. Numerical simulations demonstrate that total rents decrease under shared ownership, while total power production increases. Taking this theory to data, Lundquist et al. (2019) find substantial "wake effects" on a downwind farm in Texas. These findings suggest a potential role for a "cathedral rule" laws in which downwind landowners compensate upwind owners to not overcapitalize (Rule, 2009).

Our analysis is at a different scale than that of Kaffine and Worley (2010) and Lundquist et al. (2019). Instead of looking *between* wind farms, where different wind energy developers may compete for the ideal wind farm sites, we look *within* a wind farm, where the number of local landowners may affect wind farm siting (i.e. where/if a wind farm is built) and

[10]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).

sizing decisions (i.e. how many turbines) of a single wind energy developer.

Within a wind farm, 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) to fragmented land. Some landowners can slow or prevent wind farm development by demanding greater compensation for leasing their land or by taking legal action.[11] Opposition from landowners can lead to the reduction in size or the cancellation of wind farms altogether.[12] In other 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).

Wind energy experts also point to benefits of land ownership concentration, noting that leasing contiguous land gives additional flexibility in the turbine siting process and that developers prefer to negotiate with owners of large parcels of contiguous land ownership (Taylor and Parsons, 2008; Mills, 2015). Other observers assert that landowners "can and have made or broken many projects" (Walker, 2008). Small farm sizes have been cited as a reason why Wisconsin, for example, has lagged behind other midwestern states in wind energy development (Pyrek, 2017).

Additional anecdotal evidence suggests that landowners do not 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 developer is frustrated by the two conflicting externalities discussed above. The "disamenity" externality involves neighboring landowners not fully considering

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

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

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 have agreed 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 plausible framework for predicting how wind energy investments might adjust to different levels of land ownership fragmentation.

3 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 (2020), 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 importantly, we model a context in which an individual's participation creates a disamenity externality for neighboring owners.[13]

Consider a land area of L homogenous acres. 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 erecting turbines on their land.[14] 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,

[13] The theoretical frameworks in Leonard and Parker (2020) and Vissing (2017) do not account for the possible pollution and noise externalities caused by horizontal drilling.

[14] 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).

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.[15] 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 and still erect a turbine on her land. If she selects a royalty rate too high, the developer will not agree to build 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 costs.[16] The landowner knows there is a threshold amount of land that the wind 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

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

[15] 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.

[16] The fixed costs represent some 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.

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. We assume a per-acre disamenity, denoted $e\epsilon(0, 1)$. Because all landholders in the area can hear and see the turbines, each individual only bears one Nth, 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:

$$\max_{r_i} Prob(WindFarmBuilt) * (value \mid WindFarmBuilt)$$
$$= \frac{S(1 - r_i) + \sum_{j \neq i} S(1 - r_j)}{S} * (Sr_i(1 - r_i) - S/L * e(S(1 - r_i) + \sum_{j \neq i} S(1 - r_j))). \tag{2}$$

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

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

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

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

Two comparative static results come from this model. First, as the disamenity value associated with wind turbines, e, increases, the optimal royalty rate increases (and thus the expected number of wind turbines decreases). When turbines become more costly 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.[17] 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 **??** shows a visual depiction of this relationship with $L = 1000$ 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."

When turbine disamenities are small, however, 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 hand. 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."[18]

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

[18] This problem might be confused with holdup problems but it is actually a price-setting externality that

Whether there is an actual, empirical effect of land fragmentation additionally depends on the existence and magnitude of transaction costs, which we do not model here. In fact, both the "overinvestment" and "underinvestment" problems we model implicitly assume there are high transaction costs that prevent landowners from coordinating to erect the socially optimal number of turbines.[19] For example, if transaction costs are sufficiently low, additional compensation could be given to those who object to the wind farm to encourage them to accept lower royalty rates (or, conversely, compensation for those who overutilize to reduce land under lease). The anecdotes from landowners, discussed in Section 2, suggests there is imperfect coordination among landowners and hence unaddressed externality problems of the nature described in our theoretical model.

4 Data and Empirical Strategy

4.1 Data

We conduct analyses of the effect of land ownership patterns on wind energy development at three spatial scales. First, we run a national county-level analysis using publicly available data. Second, we examine wind development at a more micro scale, utilizing parcel-level data from a subset of windy counties to analyze wind turbine placement within Public Land Survey System (PLSS) sections. [20] In an appendix, we also analyze the placement of turbines on individual parcels.

We construct dependent variables from wind turbine data compiled by 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 the size (in MW), height, year of installation, and associated wind farm (the "project" in which all turbines were built together by the same developer) of each turbine. The data are up to date through 2018 and cover 58,449 turbines. Figure 1 shows turbine locations.

is akin to the resource-use externality in common property. Rent dissipation under anticommons is due to a failure to coordinate, rather than a strategic attempt to extract surplus by exploiting bargaining power.

[19]In our view, a common property or anticommons model could be nested within a transaction cost framework because each assumes that resource owners cannot coordinate to fix disamenity or overpricing externalities. That is, the "tragedies" occur because coordination does not happen but coordination would happen if transaction costs were low (see, e.g., Dietz et al., 2003; Frischmann et al., 2019).

[20]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 of interest 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 (Haines et al., 2018). The census is a comprehensive survey, conducted every five years, of all U.S. farms and ranches and includes information about the land, crops, animals, financials, and owners of each farm. We use the 2012 data because this represents the midpoint of the wind energy boom (post-2000).[21]

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. 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.[22] [23] Figure 3 shows the sample of counties.

The data, which are comprised of parcel-level GIS polygon shapefiles, indicate the size, boundaries, and owner's name for each parcel. This allows us to measure land ownership concentration (or fragmentation) by examining how much land within a PLSS 1x1 mile section is owned by the same person or company. Importantly, some individuals and companies own multiple parcels; our approach of matching parcels with ownership accounts for this.

We incorporate several control variables to account for existing infrastructure and additional 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.[24] We calculate the mean wind speed at every unit of analysis in the dataset

[21] We later discuss the implications of using agricultural census data that pre-dates the wind energy boom.

[22] 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 may have future wind farm projects in development.

[23] As we note in more detail below, some of these counties drop out of the empirical specifications due to sample restrictions.

[24] Wind turbine sizes have steadily grown over the last few decades. Per the EIA, the mean turbine height installed between 2012 and 2017 was about 80 meters, although many are much larger. *Source:"Wind Turbine Heights and Capacities Have Increased in the Past Decade:" https://www.eia.gov/todayinenergy/detail.php?id=33912.*

(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. (Categories include cropland, pastureland, grassland, shrub-land, developed land, forest, barren, water, and ice.) We use elevation data from the United States Geological Survey (USGS), to calculate land slope and land ruggedness.[25] We measure distances to infrastructure such as transmission lines, road and railroad locations, airports, metropolitan areas from a variety of sources. Finally, we use the Protected Area Database (PAD-US) to determine how much land is publicly owned (USGS, 2016). The database indicates which lands are managed by the federal government, Native American tribes, or state and local government.[26]

4.2 Empirical Strategy

Wind energy investments may respond to variation in land ownership composition at both an extensive and intensive margin. Developers may choose to build a wind farm of any size, or, conditional on building a wind farm, developers may decide not to put a turbine on a specific square-mile section or on a specific parcel. Our empirical strategy of analyzing wind turbine placement at multiple scales allows us to analyze both margins. County-level regressions account for 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 individual turbine siting outcomes.

We implement a cross-sectional analysis in which installed wind energy capacity as of 2018 is determined by land 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, depending on the data set employed. $WindCapacity_i$ measures the cumulative wind energy installations within a county or section, $LandOwnershipConcentration_i$ is the primary variable of interest, and X_i represents a vector of controls that may influence wind development. County measures of wind ca-

[25] The "Terrain Ruggedness Index" is defined by Wilson et al. (2007). Similar measures are used in Nunn and Puga (2012).

[26] Wind farms on tribal land are rare (Ravotti, 2017).

pacity include an indicator for whether a county has a wind farm, the number (or inverse hyperbolic sine, IHS) of installed turbines or MW of wind energy, and MW per 1,000 acres of land.[27,28] For the section-level regressions, we measure wind energy capacity with an indicator for whether a section hosts a turbine, and by the number of turbines or installed MW within a section's boundaries.

We also include spatial fixed effects that account for other unobserved factors correlated over space, as well as policies that promote or discourage wind energy. 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) that are omitted, as well as other spatial factors that our covariates may not capture.

County-Level Sample

We first analyze wind energy development using county-level aggregate data. This scale has been used in previous studies (Hitaj, 2013), allowing us to build from previous literature. 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. After data cleaning, we have a sample of 2,536 counties representing about 80 percent of the national total.[29] About 14 percent (345) of the counties had installed wind farms by the end of 2018. The average county had 20 wind turbines and the average installed capacity was 32.4 MW. The distribution is highly skewed; some counties had over 4,500 turbines and close to 3,000 MW.

[27] 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 that are built with different objectives.

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

[29] 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.

The mean agricultural farm size across our sample of counties was, on average, about 665 acres, more than three times the median farm size. We employ the mean as the primary measure of ownership concentration because the median is relatively more influenced by urban counties, which are more likely to have small-scale hobby farms not suitable for wind development.

Section-Level Sample

We develop the section-level sample as follows. First, we eliminate all counties lacking wind turbines because those counties do not have any 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 land) because it is least encumbered with infrastructure obstacles.

To measure land ownership concentration, we distinguish between landowners of undeveloped and developed parcels. We do this because developed parcels with homes, other buildings, and other infrastructure are unlikely to host a wind turbine for either legal or technical reasons. Our measure of concentration counts the unique number of undeveloped landowners. The more landowners within a section, the less concentrated it is.

Although the number of landowners provides a simple, intuitive measure of land ownership concentration, this measure ignores heterogeneity in land ownership size. In reality, effective concentration may depend not only on the number of landowners but also on heterogeneity in the amount of land owned by each of the owners. If heterogeneity is important, then it matters if four owners within a 640 acre 1x1 mile PLSS section own the same or different proportions of the section. To better accommodate land ownership heterogeneity, we create a Herfindahl-Hirschmann Index (HHI) as a complementary measure of ownership concentration. The HHI is calculated s $HHI = \sum_i s_i^2$, 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 25 percent, or 1/4 of the section. This measure also more closely aligns with the theory, which assumes equally divided parcels. We present results using both the number of landowners and inverse HHI, noting that findings are qualitatively similar.

Table 2 shows summary statistics for the section-level sample. The cleaned sample has more than 90,000 observations of 640-acre, or one square-mile, sections. About 5.5 percent of sections held a turbine as of 2018 with a mean of 0.2 turbines per section. On average, there are 5.9 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.

4.3 Identification Assumptions

The coefficient estimates could be biased if (i) land ownership concentration has systematically sorted to reflect wind energy potential and (ii) the covariates and fixed effects fail to account for any systematic differences. We think the first part of this threat (i) is minimized because land ownership concentration was determined, in part, by historical policies unrelated to wind energy. Instead, land parcels were initially allocated to settlers in 40, 80, 160- and 320-acre farms through the 1862 Homestead Act (Hansen and Libecap, 2004b). These initial allocations were independent of factors relevant to wind energy and occurred long before wind energy development was viable.

While land in the Midwest has remained in farms similar in size to the initial homesteads, farms in the Great Plains have grown in average size. Following droughts from 1917-1921, many farms from western Kansas through eastern Montana declared bankruptcy, and land was consolidated into larger farms. This consolidation reflected different optimal scales for agriculture because soil quality and climate conditions required larger farms to stay profitable (Hansen and Libecap, 2004b). Despite growth in farm sizes across the Great Plains for several decades following the droughts, farm sizes have remained relatively steady since the 1970's (Baltensperger, 1987), suggesting farm size reflects the optimal scale of agricultural production, rather than anything associated with secondary land uses such as wind energy.

Nonetheless, our estimates may be biased if some indicators of the optimal scale of agricultural productivity that are correlated with wind energy potential are also omitted. To account for this possibility, we control for the type of agricultural land, soil quality, and the primary land use (crop, pasture, shrub, grassland etc.). Furthermore, spatial fixed accounts account for other climactic factors such as temperature and rainfall.

Another potential concern is that perhaps land parcels of different sizes have been sold over time in patterns correlated with wind energy potential. Anecdotal evidence suggests this has not generally been the case. A large majority of U.S. farms are family owned and are passed down over generations (Lobley et al., 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 struggling farmers are more likely to rent farmland or find off-farm labor than to sell their land (Mishra et al., 2003).

A related concern is that farm size could affect agricultural profitability, and agricultural profitability could affect the decision to enter into wind energy leases. We account for farm profitability with several covariates at each level of analysis. At the county level we include measures of the value of each county's agricultural production, as well as the land value per acre, which should capitalize land profitability(Plantinga and Miller, 2001). In the section-level regressions, we do not observe the agricultural profitability of each farm. However, we control for the soil quality and land cover of each parcel which should be strongly correlated with farm productivity.

Another potential source of bias would be the omission of factors related to physical terrain. Topography may affect modern landholding size . If these sources of topography also affect a landscape's wind energy potential, our estimates will be biased if topography is omitted. We account for topography with several controls: elevation, land slope, and terrain ruggedness. To assuage remaining concerns that the estimates may be biased because of omitted variables, we test the sensitivity of our findings to alternative regression specifications including instrumental variable estimates based on historical farm size and a spatial difference-and-difference model to account for unobserved differences across neighboring landholdings that might affect wind development and correlate with ownership concentration.

5 Results

5.1 County-Level Regressions

Table 3 shows regression results from our primary county-level specification. In Column (1) the dependent variable is an indicator for whether or not a county has a wind farm. In Columns (2)-(5) the dependent variables are the number (or inverse hyperbolic sine) of installed turbines and MW of wind energy, respectively. In column (6), the dependent variable is installed capacity (in MW) per 1,000 acres of land.

The top row of Table 3 shows coefficients on the primary variable of interest, which is the natural log of average agricultural farm size. Across specifications, we find that counties with larger average farms have more installed wind energy capacity. In all specifications except the linear probability model, these results are statistically distinguishable from zero. In terms of magnitudes, the Column (5) coefficient means that doubling the average farm size is associated with a 29 percent increase in installed MW of wind energy capacity. The estimates in Column (6) mean that doubling the average farm size is associated with .042 more MW per 1,000 acres. This is a 78 percent increase relative to the mean of 0.054.

These county-level findings provide evidence that more concentrated land ownership has promoted installed wind energy. Conversely, counties with more fragmented land ownership have less wind power. This finding is consistent with the "exclusion externality" dominating the "disamenity externality" and suggests that, on fragmented landscapes, there may be underutilization of wind energy.

The control variables correlate with wind turbine investments in intuitive ways. There is more wind energy 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.[30] Counties with higher mean elevation levels have greater levels of installed wind energy capacity. This effect may be capturing some of the effect of wind speed because the elevation data are of a higher resolution than the wind speed data. We find no evidence that the amount of public land within a county, land values, or proximity to a metro area affects wind power development.

Notably, we also find that counties in which more of the farm operators live off farm have more installed wind capacity when controlling for the other covariates. Landowners who live off of 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).

[30]To our knowledge, this is the first paper to demonstrate how agricultural infrastructure may hinder wind energy development.

Robustness Checks

Table 4 indicates that the coefficients estimates are robust to using median agricultural farm size, rather than average farm size, to measure ownership concentration in a county. The coefficients on median farm size are qualitatively similar to the estimates on average farm size, albeit slightly less precisely estimated.

As emphasized above, U.S. agricultural land ownership infrequently moves out of families, even upon the retirement or death of the farm-operator (Lobley et al., 2010; Mishra et al., 2003). Nonetheless, if land ownership patterns respond systematically to wind energy development, our estimates would be biased because our measures of land ownership are static. 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 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 5 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. In fact, the coefficients are larger (and more statistically significant) than in Table 3, implying the OLS estimates may be slightly biased downward. Although we cannot run a similar instrumental variables regression on the section-level sample, these results should mitigate concerns about positive bias, and the larger IV estimates suggest are main coefficients estimates are, if anything, underestimates of the effect of ownership fragmentation.

There may still 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:

$$\Delta WindCapacity_i = \alpha_2 + \beta_{SFD}\Delta LandOwnershipConcentration_i + \delta_{SDF}\Delta X_i + \Delta\epsilon_i. \quad (6)$$

Table 6 shows the spatial-difference regression results. Note that our primary sample here (1,788 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. Nonetheless, panel (a) delivers similar qualitative results to our primary specification in Table 3. In column (6), for example, a ten percent increase in average farm size yields 0.0039 more MW of wind energy per 1,000 acres, which is very similar to the .0042 increase found using OLS methods. Panel (b) shows regression results where the variable of interest is the natural log of mean farm sizes in 1997. These results again are also similar to the OLS and IV estimates described above.

5.2 Section-Level Regressions

Table 7 shows our primary section-level results. We estimate five specifications, each with a different dependent variable to measure wind investment. Column (1) is a linear probability model on the probability that a section hosts at least one turbine. In columns (2) and (3), the dependent variable is the number of turbines and inverse hyperbolic sine (IHS) of turbines. In columns (4) and (5), the dependent variable is the installed capacity (or IHS thereof) in mega-watts (MW). All models include township and land cover fixed effects. Standard errors are clustered at the township level to account for any spatial correlation.

Prior to discussing the primary variable of interest, it is worth noting that regression coefficients on key control variables have intuitive signs. Wind speed is positively correlated with wind energy capacity, as is access to transmission lines. These results are consistent with Hitaj (2013) and our county-level findings. Furthermore, parcels nearer to roads and airports, which may face regulatory or technical and safety obstacles, are less likely to host turbines. Parcels with increased slopes (therefore less flat) are less likely to host wind turbines, although more rugged terrains are more likely to have more installed capacity. Conditional on land-use fixed effects, soil quality does affect wind power development.

Our primary variable of interest, the log of the equal-share landowner equivalent, appears in the top row. Across specifications, sections with additional landowners have less wind energy development when controlling for the other factors. Focusing specifically on column (5), doubling the number of (equivalent) landowners within a section decreases the amount of installed wind capacity by 1.1 percent. In Table 8, we see a similar effect when using the non-transformed number of landowners. Doubling the number of landowners yields a 1.1 percent decrease in installed wind capacity within a section.

Similar to the county-level analysis, these findings from section-level analysis also imply that fragmented landscapes are a barrier to wind energy development. This result is consistent with the presence of an exclusion externality resulting in underuse of wind power on fragmented landscapes as discussed in greater detail below.

Robustness Checks

We test robustness of the section-level results by running a permutation or placebo test (Fisher, 1935). This test allows us to more explicitly assess the extent to which the regression coefficients in Table 7 represent a spurious finding. To do so, we first randomize our "treatment," which is the number of equal-share equivalent landowners in a given section within each township. We then run the regression on the inverse hyperbolic sine of installed capacity in column (5) of Table on 500 randomized samples. We expect that if there is a true negative relationship between wind capacity and additional landowners, our estimate should be among the smallest (most negative) of the 500 randomized samples. If the correlation is spurious and our finding were truly random, it should not appear in the tail of regression estimates.

Figure 4 shows the regression coefficients and confidence intervals for each of these randomized permutations. Each coefficient is shown in grey; the middle observation in red is the truly estimated coefficient from Table 7. The actual regression estimates are smaller than all of the random samples estimated, consistent with a p-value of 0.001. This exercise indicates that our finding is not simply a spurious correlation between wind turbine placement and land ownership concentration.

As an additional robustness check, we modify the code from Drukenmiller and Hsiang (2018) to implement a spatial first differences regression and apply it to the section-level regressions. Table 9 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.[31]

6 Alternative Mechanisms

The finding that fragmented ownership discourages wind farming is consistent with an "exclusion externality" dominating a "disamenity externality" as emphasized in our theoretical model. In the model, increased fragmentation causes landowners to progressively discount the effects that higher royalty requests have on the probability of wind farm development, leading to less development. This is effectively an anticommons mechanism as described by Heller (1998), Buchanan and Yoon (2000), and Leonard and Parker (2020)but stylized to wind farming.

Although the qualitative evidence discussed in Section 2 supports an anticommons-style interpretation of our findings, we cannot precisely test for the functioning of this mechanism and therefore cannot rule out alternative (or complementary) explanations. This section discusses three alternatives: setback regulations, holdups, and transaction costs.

[31] An additional robustness check using parcel-level observations appears in the appendix.

6.1 Setback Regulations

As explained by Winikoff (2020), 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 close proximity to a turbine.

Small landholders may be denied opportunities to benefit financially from wind energy leasing because of setback policies. This is because a turbine setback reduces the amount of land available for wind development. Figure 5 illustrates. The exterior rectangles show an area of land that a developer wishes to use for wind turbine placement. Without a setback rule, any of the grid cells could host the turbine. A setback of one grid cell, however, renders the surrounding rim ineligible to host turbines. The upshot is that setbacks could push development towards larger landholdings as the comparison of panels (a) and (b) demonstrates. If the land area is divided into $N = 4$ landholding instead of $N = 1$, the amount of available land (in white) decreases.[32]

To assess the extent to which our findings are driven by setback laws, we would ideally compare the effects of fragmentation within counties with and without setback requirements. Unfortunately, there is no comprehensive and nationwide inventory of county-level setback laws. However, we can exploit the fact that Texas forbids county regulations, and we therefore know that none of our sample counties in Texas have setback laws (Linowes, 2018).

Table 10 shows the primary county-level regression results when observations from Texas are omitted. The positive relationship between farm size and wind investments remains, although it is smaller in magnitude and less significant. This suggests the Texas counties meaningfully contribute to the positive relationship, despite the lack of setback regulations in the state. Section-level results including only Texas (panel a) and excluding Texas (panel b) appear in Table 11. The coefficient estimates on the fragmentation variables are similar whether or not Texas is included, although they are less precisely estimated when only including Texas. These findings imply that increases in ownership fragmentation lead to less wind development through channels beyond local regulation, such as anticommons contracting mechanisms.

[32] If all farmers choose to participate in the wind farm, they be able to waive setback requirements. However, if one landowner does not participate, the amount of unavailable land can significantly decrease.

6.2 Holdups

Strategic hold-up and bargaining explanations could be plausible mechanisms for our findings 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. For example, landholders are more likely to be pivotal in the case of connecting recreational trails than they are for a wind project. As Isaac et al. (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. For these reasons, we think that strategic hold up - rather than the more general problem of exclusion externalities - is unlikely to be a robust explanation for the findings although we acknowledge that holdup and anticommons problems are closely related.

6.3 Transaction Costs

Transaction costs are a third alternative, and complementary, explanation for our findings. A transaction costs modelling framework would (i) assume that transaction costs increase with more landowners, and that (ii) increases in transaction costs reduce the probability of the project occurring by decreasing its expected surplus. In this sense, transaction costs would act as tax on the value of the project. 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.[33]

Whether anticommons or transaction cost problems are responsible for why fragmentation reduces project likelihood could have important policy implications. If it is transaction costs, policymakers could help by providing small landowners with better information about the benefits and drawbacks of wind farming, and on the reputation and quality of

[33] Arguably, our model could be nested within a transaction cost framework because it assumes that resource owners (small landowners) cannot coordinate to internalize either the exclusion externality or the disamenity externality through side payments (Coase, 1960). Implicit in our model is the assumption that transaction costs prevent coordination across landowners, which is consistent with both our empirical findings and the qualitative evidence in Section 2.

the developer. If it is anticommons, then policymakers could, for example, require developers to offer the same compensation to each participating landowner or implement forced pooling that requires participation when a majority of landowners consent to a wind energy project.

Forced pooling policies, which are commonly applied by states to encourage oil and gas, development resemble eminent domain in that non-participating land owners can be forced into a drilling project if over 50 percent of the additional land needed for a prospective project is under contract. These policies are controversial because of their heavy-handed weakening of individual property rights, but they are effective in encouraging resource development. [34] Forced pooling for wind power would also face significant practical and legal challenges. Because wind is not confined to specific areas, it is not clear which non-participating parcels would be necessary to a wind farm. Implementing forced pooling may depend on how a landowners' wind rights are legally defined. Is wind a mineral like oil and gas with rights severable from the land rights? How would these rights be severed? These legal issues have yet to be resolved.[35]

7 Conclusion

Our study emphasizes the important role that private land ownership patterns will play in influencing where future expansions of wind farming are most likely to 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 "exclusion externality" in which landowners do not account for the potential benefits their neighbors may receive from turbines on their property.

What are the ramifications of this "tragedy of the anticommons" finding, and what can (or should) be done? First, the disproportionate development of wind in areas with more concentrated ownership suggests that wealthier landowners have likely disproportionately benefited from the growth of wind energy. Because the wind industry has and continues

[34] Applying forced pooling to wind would be controversial not only because of the disamenity externalities, but also because some landowners forced into lease agreements may not believe there are true public benefits to wind energy development. Surveys among those live within the boundaries of wind farms suggest landowners — even those whose properties host turbines — do not see mitigation of harm from climate change as one of wind power's primary benefits (Mills et al., 2019).

[35] For a discussion of some of these legal matters in wind energy, see Alexander (2011) and DuVivier (2009).

to be subsidized at both the state and federal level, our finding implies that wealthier landowners have likely received a larger share of government subsidies when compared to smaller farmers. This outcome is inconsistent with federal policy goals that have otherwise emphasized a desire to encourage the survival and prosperity of small farms.

Second, the results suggest that global efforts to mitigate climate change through on-shore wind-farming will be challenging in areas where small and fragmented landholdings dominate. Although farm consolidation is occurring in the United States (MacDonald and Hoppe, 2017) and other developed countries, farm sizes are getting smaller in much of the developing world. [36] If renewable energy policy ignores how fragmentation affects leasing outcomes for wind energy development, then forecasts may overstate the potential effectiveness of policies such as renewable portfolio standards that attempt to address climate change. Moreover, successful expansion may require wind farming in oceans offshore or on publicly owned lands where the private landowner contracting problems are averted.

Third, and most generally, our research suggests that the growing number of local zoning and setback policies restricting wind farm development may be unnecessary and possibly even counterproductive to helping local landowners. These regulations are meant to protect landowners from some of the disamenities associated with wind energy such as shadow flicker, noise, and ice throw, but they also limit the amount of land available for wind energy development. Policymakers should be cognizant that strict regulations can disqualify owners of smaller landholdings from hosting wind turbines and eliminate the potential for their region to receive benefits from wind energy. Ohio, for example, is one state that has enacted strict setback regulations and that is now beginning to reconsider them. One lawmaker noted that communities are "the real losers here" for missing out on potential turbine revenues (Kowalski, 2017).

[36] Globally, 84% of farms are smaller than 5 acres whereas over 90% of farms in the United States exceed 10 acres (Foster and Rosenzweig, 2017; Lowder et al., 2016).

8 Tables and Figures

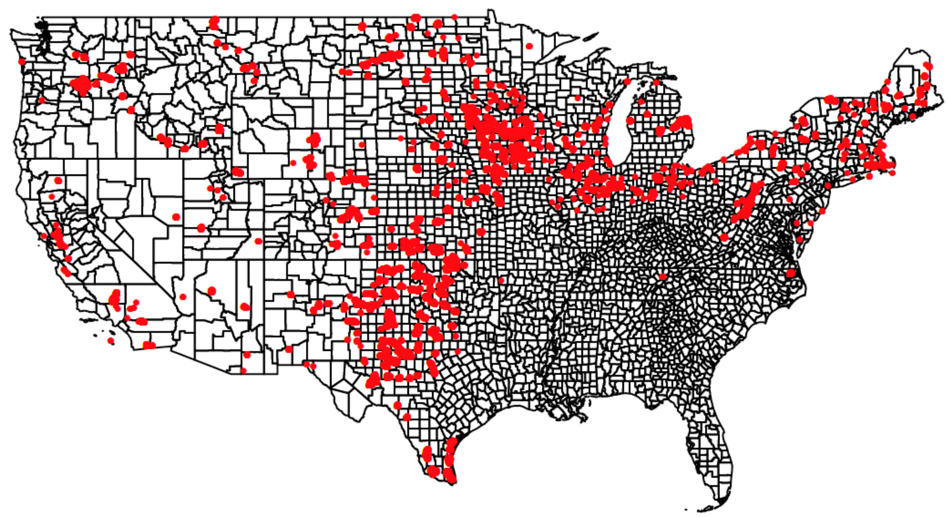


Figure 1: Wind turbine installations in the United States through 2018. *Source:* Hoen et al. (2018)

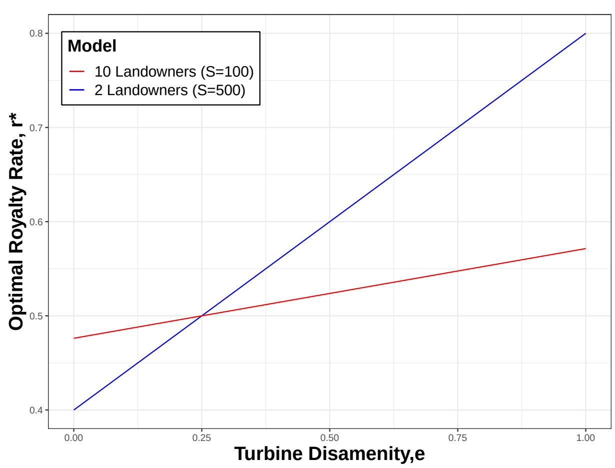


Figure 2: Example of optimal royalty rate from Equation (3) in fragmented (red) and concentrated (blue) cases. A higher optimal royalty rate reduces the probability of wind farm construction.

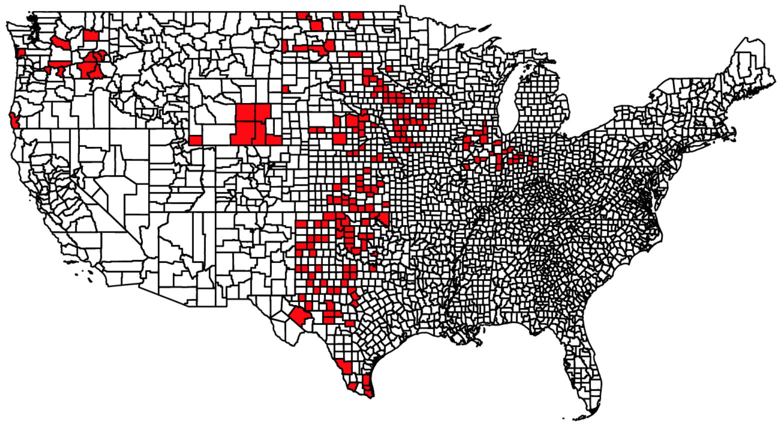


Figure 3: Counties in section-level regression sample. *Note:* Data from ReportAll USA.

Table 1: Summary Statistics for Sample of Counties

	Mean	SD	Min	Max
=1 if Wind Farm	0.136	0.343	0	1
Turbine Count	20	114	0	4,516
Turbine Capacity (MW)	32	133	0	2,925
MW/1000 Acres	0.054	0.212	0	3.614
Avg. Farm Size (Acres)	665	1,474	39	37,952
Median Farm Size (Acres)	207	859	2	39,810
Wind Speed (m/s)	6.676	0.835	3.083	9.246
km Transmission Lines	247	236	0	3,164
Pop. Density (per Acre)	0.191	0.390	0.0002	5.965
Share Publicly Owned	0.127	0.189	0	1.000
Dist. to Metro Area (km)	28	40	0	303
Acres Irrigated	21,122	55,513	0	968,727
Ag. Products Sold (1,000s)	144,483	252,068	912	4,973,041
Land Value/Acre	3,454	2,348	192	22,248
Share Live Off-Farm	0.250	0.120	0.041	0.792
Elevation (ft)	436	489	0	3,043
Acres Land Area	598,253	753,171	21,107	11,916,076

N = 2,536. Counties in the continental United States with greater than 10 percent of land occupied by farms are included.

Table 2: Summary Statistics for Section-Level Sample

	Mean	SD	Min	Max
=1 if Turbine	0.055	0.227	0	1
Turbine Count	0.200	1.013	0	36
Turbine Capacity (MW)	0.344	1.715	0	33.600
Undeveloped, Private Landowners	5.888	7.253	1	377
Equal Share Undeveloped Landowners (Inverse HHI)	3.144	2.204	1	100.081
Wind Speed (m/s)	7.801	0.710	3.477	12.351
Elevation (100s ft)	6.416	4.687	0.013	31.671
Slope	1.622	1.947	0.002	26.792
Terrain Ruggedness Index	1.925	2.270	0.002	34.904
Soil Quality	12.228	3.340	1	18
Transmission $<$ 5km	0.495	0.500	0	1
Airport $<$ 5km	0.095	0.294	0	1
Distance to Rail	0.064	0.339	0	10.986
Distance to Road	3.755	2.432	0	24.722
Share Undeveloped	0.999	0.005	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	0.319	2.499	0	124

N = 90,874. Sample is limited to PLSS sections with greater than 95 percent of land privately-owned and undeveloped in counties with wind development.

Table 3: County-Level Regression Estimates

	Dependent variable:					
	Wind Farm	Turbines	IHS(Turbines)	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Avg. Farm Size)	0.035	16.978***	0.261**	22.604***	0.291**	0.042***
	(0.022)	(5.917)	(0.115)	(6.760)	(0.131)	(0.013)
Wind Speed	0.203***	28.128***	1.108***	55.606***	1.181***	0.098***
	(0.032)	(8.766)	(0.171)	(13.627)	(0.185)	(0.025)
IHS(Transmission)	0.043***	10.769***	0.255***	17.945***	0.273***	0.030***
	(0.007)	(2.263)	(0.036)	(3.532)	(0.036)	(0.006)
Log(Pop. Density)	−0.066*	−11.863**	−0.258	−22.713***	−0.370*	−0.042**
	(0.039)	(5.114)	(0.212)	(5.643)	(0.216)	(0.019)
Share Public	−0.009	−12.501	−0.067	4.496	−0.054	0.061
	(0.112)	(25.221)	(0.647)	(48.450)	(0.701)	(0.091)
IHS(Dist. Metro Area)	−0.004	−2.288	−0.033	−2.367	−0.034	0.0004
	(0.006)	(1.789)	(0.030)	(1.882)	(0.034)	(0.003)
IHS(Acres Irrigated)	−0.017***	−3.233**	−0.093***	−4.701***	−0.104***	−0.008***
	(0.003)	(1.281)	(0.015)	(1.485)	(0.016)	(0.002)
Log(Ag. Products Sold)	0.032***	6.123**	0.187***	9.416***	0.189***	0.015***
	(0.009)	(2.612)	(0.047)	(3.282)	(0.047)	(0.005)
Value/Acre	0.005	1.774	0.048	−4.782	0.059	0.011
	(0.041)	(7.552)	(0.232)	(11.799)	(0.231)	(0.027)
Perc. Live Off-Farm	0.405***	74.732**	2.145***	96.414***	2.255***	0.114***
	(0.091)	(35.056)	(0.415)	(30.668)	(0.550)	(0.041)
IHS (Elevation)	0.058***	9.826***	0.314***	13.718**	0.324***	0.023**
	(0.011)	(3.010)	(0.059)	(5.441)	(0.073)	(0.009)
Log (Land Area)	0.003	6.649	0.001	−4.991	0.030	−0.056**
	(0.024)	(12.791)	(0.131)	(12.176)	(0.142)	(0.022)
Observations	2,536	2,536	2,536	2,536	2,536	2,536
R^2	0.289	0.108	0.328	0.176	0.311	0.171

Notes: Standard errors (clustered by state) in parentheses. The dependent variable measures accumulated wind capacity as of 2018. All models include state FE's. *p<0.1; **p<0.05; ***p<0.01.

Table 4: County-Level Regression Estimates with Median Farm Size

	Dependent variable:					
	Wind Farm	Turbines	IHS(Turbines)	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Median Farm Size)	0.030	16.727**	0.189	23.388**	0.205	0.034**
	(0.024)	(6.344)	(0.127)	(9.590)	(0.138)	(0.017)
Observations	2,536	2,536	2,536	2,536	2,536	2,536
R^2	0.289	0.109	0.327	0.178	0.310	0.171

Notes: Standard errors (clustered by state) in parentheses. All models include state FEs and controls from Table 3. *p<0.1; **p<0.05; ***p<0.01.

Table 5: County-Level Regression Estimates with IV Specification

	Dependent variable:					
	Wind Farm	Turbines	IHS(Turbines)	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Mean Farm Size)	0.046*	19.715**	0.313**	24.666***	0.363**	0.045***
	(0.024)	(8.468)	(0.128)	(8.057)	(0.144)	(0.015)
Observations	2,530	2,530	2,530	2,530	2,530	2,530
R^2	0.291	0.108	0.329	0.177	0.312	0.172

Notes: Standard errors (clustered by state) in parentheses. All models include state FE's and controls from Table 3. Mean farm size is instrumented with 1997 mean farm size. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Spatial-First Differences Regressions

	Dependent variable:					
	Wind Farm	Turbines	IHS(Turbines)	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Log (Mean Farm Size)	0.016	30.579*	0.198	30.339**	0.170	0.039**
	(0.032)	(18.533)	(0.162)	(14.887)	(0.173)	(0.019)
Panel B:						
Log (Mean 1997 Farm Size)	0.057**	15.594*	0.309**	18.644*	0.336**	0.026
	(0.029)	(8.880)	(0.142)	(9.833)	(0.159)	(0.016)
Observations	1,778	1,778	1,778	1,778	1,778	1,778
R^2	0.076	0.031	0.090	0.049	0.088	0.048

Notes: Standard errors (clustered by state) in parentheses. All models include controls from Table 3. 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.

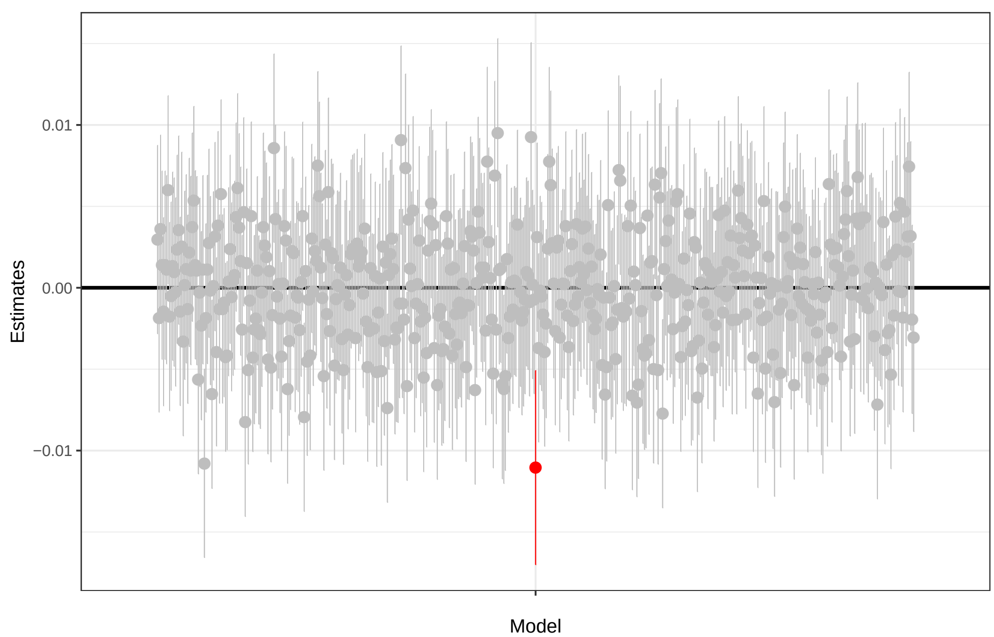


Figure 4: Randomization Inference: Section Regressions

Notes: Regression coefficients from 500 regressions in which the "treatment," the log of the number of equal-share equivalent landowners within a section, is randomized within each township. The dependent variable is the inverse hyperbolic sine of installed wind capacity in Table 7, column (5). The "true" regression coefficient appears in red in the middle.

Table 7: Section-Level Estimates with Equal Share Landowner Measure

	Dependent variable:				
	=1 if Turbine	Turbines	IHS(Turbines)	MW	IHS(MW)
	(1)	(2)	(3)	(4)	(5)
Log(Equal Share Undeveloped Landowners)	−0.001	−0.035***	−0.010***	−0.058***	−0.011***
	(0.002)	(0.008)	(0.003)	(0.014)	(0.004)
Wind Speed (m/s)	0.079***	0.308***	0.150***	0.494***	0.182***
	(0.007)	(0.036)	(0.015)	(0.058)	(0.018)
Elevation (100s ft)	0.024***	0.156***	0.060***	0.284***	0.076***
	(0.005)	(0.033)	(0.011)	(0.053)	(0.014)
Land Slope	−0.003	−0.038	−0.015	−0.093*	−0.020
	(0.006)	(0.037)	(0.013)	(0.055)	(0.016)
Terrain Ruggedness Index	0.003	0.029	0.013	0.065	0.016
	(0.005)	(0.031)	(0.011)	(0.046)	(0.014)
Soil Quality	−0.0005	0.0004	−0.0005	−0.002	−0.001
	(0.001)	(0.003)	(0.001)	(0.005)	(0.002)
Airport < 5km	−0.012***	−0.049***	−0.022***	−0.068**	−0.024**
	(0.004)	(0.018)	(0.008)	(0.031)	(0.010)
Transmission < 5km	0.018***	0.090***	0.038***	0.154***	0.049***
	(0.004)	(0.017)	(0.008)	(0.029)	(0.009)
Distance to Rail	−0.002	−0.010	−0.005	−0.017	−0.006
	(0.002)	(0.009)	(0.004)	(0.014)	(0.005)
Distance to Road	−0.002***	−0.015***	−0.006***	−0.025***	−0.007***
	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)
Share Undeveloped	0.674***	2.528**	1.178***	5.208***	1.679***
	(0.207)	(1.009)	(0.408)	(1.689)	(0.518)
Share Non-Federal	0.704***	2.873***	1.373***	4.733***	1.719***
	(0.154)	(0.700)	(0.297)	(1.258)	(0.380)
Share Non-State/Local	0.339	1.735	0.687	1.788	0.974
	(0.271)	(1.434)	(0.586)	(2.668)	(0.706)
Log (Developed Landowners)	−0.001	−0.008	−0.003	−0.013	−0.002
	(0.002)	(0.009)	(0.004)	(0.015)	(0.005)
Observations	90,874	90,874	90,874	90,874	90,874
R^2	0.433	0.376	0.420	0.375	0.430

Notes: Township FEs and land use shares omitted. Equal share equivalent landowners measured as the inverse of the Herfindahl-Hirschmann Index (HHI). All standard errors are clustered at the township level. *p<0.1; **p<0.05; ***p<0.01.

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

	Dependent variable:				
	=1 if Turbine	Turbines	IHS(Turbines)	MW	IHS(MW)
	(1)	(2)	(3)	(4)	(5)
Log(Undeveloped Landowners)	−0.002	−0.031***	−0.010***	−0.053***	−0.011***
	(0.002)	(0.007)	(0.003)	(0.013)	(0.004)
Wind Speed (m/s)	0.079***	0.307***	0.149***	0.493***	0.182***
	(0.007)	(0.036)	(0.015)	(0.058)	(0.018)
Elevation (100s ft)	0.024***	0.155***	0.060***	0.281***	0.075***
	(0.005)	(0.033)	(0.011)	(0.053)	(0.014)
Land Slope	−0.003	−0.037	−0.014	−0.091	−0.020
	(0.006)	(0.037)	(0.013)	(0.055)	(0.016)
Terrain Ruggedness Index	0.003	0.028	0.012	0.063	0.016
	(0.005)	(0.031)	(0.011)	(0.047)	(0.014)
Soil Quality	−0.0005	0.0004	−0.0005	−0.002	−0.001
	(0.001)	(0.003)	(0.001)	(0.005)	(0.002)
Airport < 5km	−0.012***	−0.048***	−0.022***	−0.065**	−0.023**
	(0.004)	(0.018)	(0.008)	(0.031)	(0.010)
Transmission < 5km	0.018***	0.090***	0.038***	0.154***	0.050***
	(0.004)	(0.017)	(0.008)	(0.029)	(0.009)
Distance to Rail	−0.002	−0.008	−0.004	−0.014	−0.005
	(0.002)	(0.009)	(0.004)	(0.014)	(0.005)
Distance to Road	−0.002***	−0.015***	−0.006***	−0.025***	−0.007***
	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)
Share Undeveloped	0.674***	2.520**	1.176***	5.194***	1.677***
	(0.207)	(1.010)	(0.408)	(1.689)	(0.518)
Share Non-Federal	0.704***	2.870***	1.372***	4.728***	1.718***
	(0.154)	(0.700)	(0.297)	(1.257)	(0.380)
Share Non-State/Local	0.340	1.733	0.687	1.787	0.975
	(0.271)	(1.434)	(0.585)	(2.669)	(0.706)
Log (Developed Landowners)	−0.0002	−0.003	−0.002	−0.004	−0.001
	(0.002)	(0.009)	(0.004)	(0.016)	(0.005)
Observations	90,874	90,874	90,874	90,874	90,874
R^2	0.433	0.376	0.420	0.375	0.430

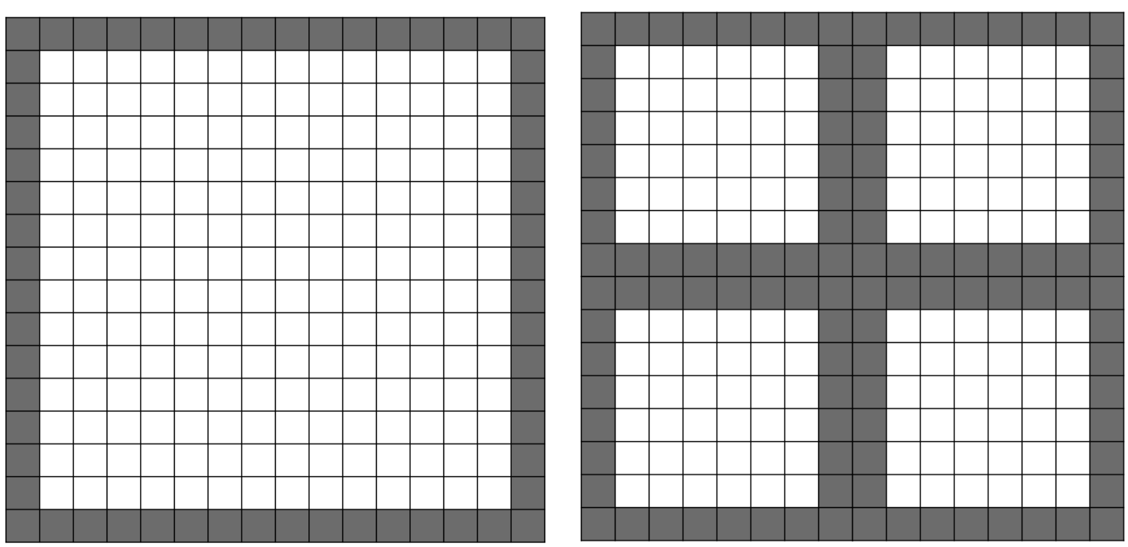
Notes: Township FEs and land use shares omitted. All standard errors are clustered at the township level. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Section-Level Spatial First Differences Regressions

	Dependent variable:				
	=1 if Turbine	Turbines	IHS(Turbines)	MW	IHS(MW)
	(1)	(2)	(3)	(4)	(5)
Panel A:					
Log (Private, Undeveloped Landowners)	-0.0003	-0.032^{***}	-0.008^{***}	-0.055^{***}	-0.008^{**}
	(0.002)	(0.008)	(0.003)	(0.015)	(0.004)
Panel B:					
Log (Equal-Share Private, Undeveloped Landowners)	0.001	-0.028^{***}	-0.007^{**}	-0.048^{***}	-0.006
	(0.002)	(0.008)	(0.003)	(0.015)	(0.004)
Observations	78,531	78,531	78,531	78,531	78,531
R^2	0.045	0.045	0.049	0.046	0.049

Notes: All variables from cross-sectional regression in Table **??** included. All models include coefficients from Table 3. 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.

Figure 5: Illustration of suitable (white) and unsuitable (gray) land for wind energy development with setback policy of one box with one landowner (panel a) and four landowners (panel b).



(a) (b)

Table 10: County-Level Regression Estimates without Texas Counties

	Dependent variable:					
	Wind Farm	Turbines	IHS(Turbines)	MW	IHS(MW)	MW/1000 Acres
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Mean Farm Size)	0.035	16.919*	0.251*	21.338**	0.233	0.050***
	(0.027)	(8.797)	(0.143)	(9.076)	(0.154)	(0.016)
Observations	2,303	2,303	2,303	2,303	2,303	2,303
R^2	0.259	0.094	0.298	0.162	0.288	0.166

Notes: Standard errors (clustered by state) in parentheses. All models include state FE's and controls from Table 3. *p<0.1; **p<0.05; ***p<0.01.

Table 11: Section-Level Estimates with and without Texas Estimates

	Dependent variable:				
	=1 if Turbine	Turbines	IHS(Turbines)	MW	IHS(MW)
	(1)	(2)	(3)	(4)	(5)
Panel A:					
Log (Equal-Share Private, Undeveloped Landowners)	−0.002	−0.035*	−0.012	−0.061*	−0.013
	(0.004)	(0.019)	(0.009)	(0.036)	(0.011)
Panel B:					
Log (Equal-Share Private, Undeveloped Landowners)	−0.001	−0.034***	−0.009**	−0.058***	−0.010**
	(0.002)	(0.009)	(0.004)	(0.015)	(0.004)
Observations	17,685	17,685	17,685	17,685	17,685
R^2	0.500	0.428	0.484	0.433	0.495

Notes: All variables from cross-sectional regression in Table 7 included.*p<0.1; **p<0.05; ***p<0.01.

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A Parcel-Level Robustness Checks

As a final robustness check, we test whether the findings hold at the most micro spatial level. We do this by examining wind turbine placement on individual parcels conditional on their surroundings. 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. Next, we count the unique number of landowners (not parcels because multiple parcels are sometimes owned by a single landowner), that appear within a radius of each parcel's boundaries. We regress the probability of each parcel hosting a turbine on the number of neighbors, conditional on other covariates.

Table 12 shows results from regressions with three different radii lengths. In column (1) the radius is one quarter mile, a half mile in column (2), and a mile in column (3).[37] The findings are similar across specifications. Parcels with more neighbors are less likely to host a wind turbine. This is conditional on parcel size, which increases the probability of hosting a turbine. Larger parcels with fewer unique neighbors are more likely to have a wind turbine, again suggesting that wind energy is drawn to landscapes with concentrated ownership. These findings support those from the county and section regressions and present further evidence that the exclusion externality dominates in wind energy siting.

[37]The number of observations decreases across regressions because we exclude parcels for which the radius intersects the county border.

Table 12: Parcel Level Regression Estimates

	Dependent Variable =1 if Turbine		
	(1)	(2)	(3)
IHS(Landowners Within Radius)	−0.002***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)
Wind Speed	0.050***	0.049***	0.042***
	(0.004)	(0.004)	(0.003)
Log(Acres)	0.014***	0.015***	0.013***
	(0.001)	(0.001)	(0.001)
Log(Perim.)	−0.004**	−0.004**	−0.003**
	(0.002)	(0.002)	(0.002)
Slope	−0.0003	−0.0001	0.001
	(0.001)	(0.001)	(0.001)
Ruggedness	0.001	0.001	−0.0001
	(0.001)	(0.001)	(0.001)
Trans. Within Radius	0.006***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)
Road Within Radius	−0.004***	−0.001	0.007***
	(0.001)	(0.002)	(0.003)
Airport Within Radius	−0.0005	−0.001	−0.001
	(0.003)	(0.002)	(0.001)
Rail Within Radius	−0.003**	−0.002**	−0.002*
	(0.001)	(0.001)	(0.001)
Soil Quality	−0.0002	−0.0003	−0.0002
	(0.0002)	(0.0002)	(0.0002)
Share Surrounding Public	−0.009***	−0.009**	−0.010*
	(0.003)	(0.004)	(0.005)
Share Surrounding Developed	0.015***	0.016***	0.022***
	(0.005)	(0.006)	(0.007)
Total Surrounding Land	0.001	0.0003	−0.002
	(0.001)	(0.002)	(0.002)
Radius (Miles)	0.25	0.5	1
Observations	504,351	482,911	536,800
R^2	0.181	0.183	0.192

Notes: Township and land use FEs omitted. All standard errors are clustered at the township level. *p<0.1; **p<0.05; ***p<0.01.