Journal of Agricultural and Resource Economics 45(3):410–427 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.302463

The On-Farm and Near-Farm Effects of Wind Turbines on Agricultural Land Values

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We estimate the effects of utility-scale wind turbines on agricultural land values in Kansas using parcel-level transaction data from 2001 to 2017 in a hedonic price model. By matching transaction data and wind turbine data at the common land units scale, we are able to ascertain on-farm effects as well as near-farm effects. Across all our analyses, the preponderance of results suggests that wind turbines do not affect agricultural property values, either on-farm or nearby, in a statistically significant way. Thus, our results cannot confirm that wind turbines will increase land values when installed on a parcel.

Key words: farmland, hedonic, land values, turbines, valuation, wind

Introduction

Wind power constitutes an important component of renewable power portfolios. From 2000 to 2013, wind power capacity in the United States grew from 2.5 gigawatts to over 60 gigawatts. The U.S. Department of Energy projects total wind capacity to expand to over 220 gigawatts by 2030. Despite the alleged benefits of wind power for mitigating carbon emissions and reducing reliance on nonrenewable fuel sources, there are a number of unresolved controversies over the placement of wind turbines and their potential influence on property values (e.g., Khatari, 2004; Groothuis, Groothuis, and Whitehead, 2008; Heintzelman and Tuttle, 2012; Sunak and Madlener, 2017). The projected future growth of the wind energy industry is likely to exacerbate these controversies.

This paper combines a rich set of agricultural land sale transaction data with location-specific data on utility-scale wind turbines in Kansas to analyze the effects of wind turbines on agricultural land values. By matching land sale transaction data and wind turbine data at the common land units (CLU) scale, we are able to estimate two types of effects: (i) the effect of having one or more turbines on the value of a parcel (i.e., the on-parcel impact) and (ii) the effect of having one or more turbines on the value of *nearby* parcels (i.e., off-parcel impacts).

The literature examining the impacts of wind turbines on property values is still relatively new and has produced mixed conclusions. Wind turbines have been characterized as having disamenity effects on property values (Vyn and McCullough, 2014, review the literature). These effects include concerns over noise generation, possible health effects, bird deaths, ice throw, and negative visual effects. However, despite widespread concerns that negative public perception about wind turbines is capitalized into property values (Ladenburg and Dubgaard, 2007; Krueger, Parsons, and Firestone, 2011; Heintzelman and Tuttle, 2012; Sunak and Madlener, 2017; Jensen et al., 2018), a number of studies suggest that proximity to wind turbines has no impact on land values (Laposa and Mueller, 2010; Hoen et al., 2011, 2013; Lang, Opaluch, and Sfinarolakis, 2014; Vyn and McCullough, 2014;

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Review coordinated by Richard T. Woodward.

Center for Economic Development and Business Research, 2019) or may have differential impacts depending on whether communities support or oppose wind energy (Vyn, 2018; Boyle et al., 2019).

Previous studies have largely focused on how turbines impact residential properties rather than agricultural properties (two exceptions are Vyn and McCullough, 2014; Shultz, Hall, and Strager, 2015). Residential land studies provide useful information, but many wind farms are located in agricultural regions and there are reasons that wind farms may have different effects on agricultural land values. For example, recent research has shown that wind farms can alter local temperature and precipitation (Li et al., 2018) as well as increase nearby crop yields (Chen, 2019; Kaffine, 2019).[1] Thus, in contrast to residential property values, there is the possibility that agricultural land values may actually *increase* in response to placement of nearby wind turbines if the crop yield effects are large.

An additional consideration specific to agricultural properties is the *on-farm* effects of having a wind farm. Specifically, for agricultural landowners that contract with wind energy companies to lease land use rights, a natural question that arises is what the presence of turbines implies for the value of their land. In promoting their Wind Powering America program, the U.S. Department of Energy (2004) estimated that wind energy would provide \$1.2 billion in new income to agricultural and rural landowners. There is some recent evidence that wind lease payments can raise the value of one's land (Myrna, Odening, and Ritter, 2019). However, turbines can negatively impact irrigability and farmability factors such as equipment maneuverability and drainage (Baker et al., 2018).

Kansas is a leading state in agricultural production and also ranks highly in wind energy potential. However, stakeholder opinion is starkly divided over the prospect of wind energy expansion (Dodge, 2019; Lefler, 2019; Shorman, 2019). Analyzing the impacts of wind energy projects on agricultural land values can therefore assist policymakers in conducting cost–benefit analysis of wind energy expansion. Moreover, understanding how on-farm land values are affected by wind turbine installations can provide information to landowners interested in diversifying their farm incomes and wealth portfolios.

A unique aspect of our research is the use of parcel-level sales data of every agricultural land transaction in Kansas from 2001 to 2017. In addition, we have data on all 2,506 utility-scale wind turbines constructed in Kansas between 2001 and 2017. We spatially match the turbine data layer to 14,196 total agricultural land transactions occurring in counties with at least one wind turbine for the years 2001 through 2017. Of these 14,196 transactions, 1,530 parcels were sold at least twice.

Methodologically, this paper takes the hedonic price model approach to estimate the effect of proximity to wind turbines on land values. The treatment groups are defined by various measures of proximity, including the inverse distance of a parcel to the nearest turbine, a set of dummies representing whether a parcel belongs to a set of concentric rings about a turbine, and a dummy for whether a parcel has turbines directly on it. To control for the possibility that placement of wind turbines is correlated with omitted variables, we include a rich set of spatial dummies up to the resolution of township-level (461 total). Year and month dummies are also included to control for idiosyncratic temporal factors influencing land sales (e.g., commodity price fluctuation, interest rates). Lastly, we are able to exploit a subsample of 1,530 repeat sales in a parcel-level fixed effects framework (i.e., the finest level of controls possible).

While we do find positive land value effects in certain specifications, the preponderance of our hedonic estimates provides little to no evidence of statistically significant impacts of wind turbines on agricultural land values.[2] Thus, our results cannot confirm that wind turbines will increase land values when installed on a parcel. One interpretation of this result is that the lease payments negotiated between wind energy companies and land owners are on average approximately equal to

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[1] Producers in Harper County, Kansas, have reported more rainfall and less hail measured on weather gauges that are closer to wind turbines (Davis, 2018).

[2] The positive effects are restricted to the inverse distance treatment group. However, the positive effect goes away when parcel-level fixed effects are included.

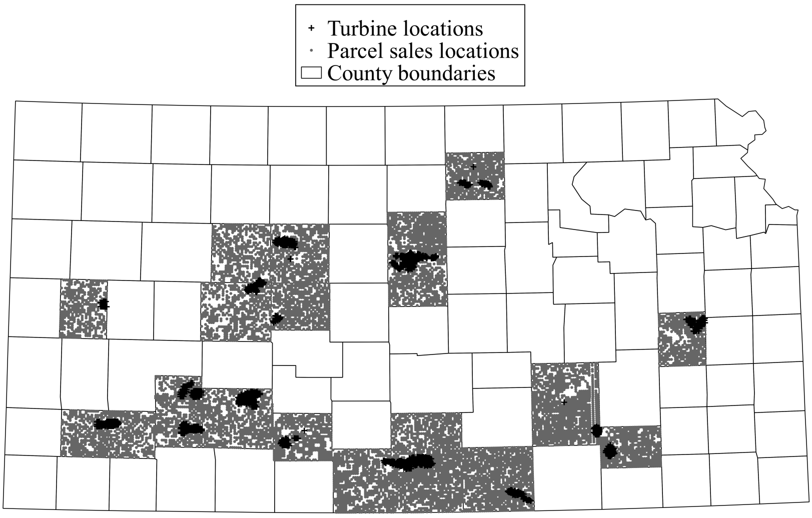

Figure 1. Location of Wind Turbines and Parcel Sales Data

land owners' minimum willingness to accept (i.e., the compensation offsets any disamenity values).[3] Additionally, our results suggest that wind turbines have not produced statistically significant negative external effects for agricultural property values in Kansas.

This paper is most closely related to the studies by Vyn and McCullough (2014), who estimate agricultural property value impacts using 1,590 farmland sales in southern Ontario, and Shultz, Hall, and Strager (2015), who use a cross-section of 2,912 assessed agricultural land values in Pennsylvania. Both studies find little evidence of wind farm impacts. The present study not only uses a much larger dataset (over 14,000 sales) across a longer time horizon but is also the first to consider both the on-farm and near-farm land value impacts in the United States using arms-length transaction data (rather than assessed values).[4]

Background and Study Area

In 2017, Kansas ranked among the top five states in wind energy generation and in future wind energy potential (U.S. Energy Information Administration, 2018). Over one-third of Kansas' electricity was generated from wind power in 2017. As of 2018, total installed wind capacity was over 5,500 megawatts (MW) generated by 2,996 wind turbines. An additional 1,600 MW of wind capacity is under construction or in development (American Wind Energy Association, 2019). However, landowners are divided in their opinion over wind energy expansion in Kansas (Dodge, 2019; Lefler, 2019; Shorman, 2019). One faction views wind energy as a boon due to job creation, tax revenues, and lease payments to landowners. Another faction is concerned with possible impacts to neighboring livestock, noise pollution, loss of enjoyable viewsheds, and depressed land values. In fact, Sedgwick County (home of Wichita—the largest city in Kansas) recently banned the development of large-scale wind turbines (Lefler, 2019), while commissioners in Reno County rejected a permit for a new 220 MW wind farm (Shorman, 2019).

The wind power project data used in this study include the location and specification of all utility-scale wind turbines installed and operational up through the year 2017 (Figure 1). We therefore limit

[3] The most common compensation structure is a royalty or fixed-fee arrangement made to the landowner on a monthly or yearly basis. Such structures tie the value of the wind project to the land. Lump-sum payments are the least common and would result in the value of the wind project not being tied to the land (Windustry, 2009).

[4] Ma and Swinton (2012) demonstrate that hedonic estimates can be downward biased when assessed values are used instead of arms-length transactions.

Table 1. Study Area Wind Facilities and Land Transactions

County	2017 Capacity (MW)	2017 Turbines	Startup Year	2010 Population	Parcel Sales	Average Sales ($/acre)	Corn and Soybean Acres (thousands)
Barber	183.2	92	2009	4,861	670	4,134	5.4
Butler	151.0	101	2005	65,880	1,299	3,142	80.0
Clark	429.0	208	2016	2,215	378	2,828	1.4
Cloud	201.4	70	2008	9,533	530	2,417	48.0
Coffey	199.0	95	2015	8,601	524	2,099	96.6
Elk	199.8	111	2011	2,882	571	3,246	14.2
Ellis	206.5	115	2013	28,452	524	1,948	3.5
Ellsworth	186.0	124	2008	6,497	460	1,890	3.6
Ford	417.2	235	2006	33,848	767	2,255	53.7
Grant	112.9	61	2013	7,829	705	3,013	49.1
Gray	507.8	342	2001	6,006	867	3,193	93.7
Harper	281.6	176	2012	6,034	745	1,930	5.7
Haskell	136.9	74	2013	4,256	622	4,557	108.4
Kingman	104.0	65	2012	7,858	586	2,071	19.0
Kiowa	116.6	76	2010	2,553	414	2,796	36.3
Lincoln	264.3	165	2008	3,241	632	2,168	12.3
Marshall	72.0	36	2016	10,117	605	3,194	168.0
Ness	168.3	94	2015	3,107	504	1,923	4.3
Pratt	208.3	121	2016	9,656	529	2,265	73.2
Rush	46.0	20	2015	3,307	453	1,148	9.0
Sumner	150.0	75	2015	24,132	1,153	2,170	68.0
Trego	30.4	17	2015	3,001	356	1,603	8.9
Wichita	99.0	33	2009	2,234	354	2,094	34.9

the analysis to land sale transaction data for the years up to 2017. In total, 23 counties had active wind energy projects in 2017 (see Table 1), including 2,506 active wind turbines, ranging in size from 0.05 MW to 3.0 MW, with a total wind energy capacity of 4,471 MW. Projects range in size from 0.07 MW to 419 MW, with an average capacity of 124 MW.

Table 1 summarizes the number and average value of the land transactions across the 23 counties with wind energy projects, along with 2010 census populations and thousands of acres planted to corn or soybeans, obtained from the USDA National Agricultural Statistics Service. Average land values range from about $1,148/acre in Rush County to over $4,500/acre in Haskell County. Average land values are generally larger for counties having more corn- and soybean-planted acres. The notable exceptions are Barber and Elk Counties, which are likely influenced by their proximity to Wichita.

Data

The data used in the analysis are taken from a variety of sources, at the finest resolution possible.

Land Transactions

To conduct the analysis, we leverage parcel-level sales data for every agricultural land transaction of at least 40 acres in size in Kansas from 2001 to 2017. The data were obtained from the Property Valuation Division (PVD) of the Kansas Department of Revenue (Figure 1). In order to be characterized as a farmland transaction, a parcel must be at least 75% cropland by area. We restrict

Table 2. Summary Statistics

Variable (units)	Mean	Std. Dev.	Min.	Max.
Price per acre ($/acre)	2,604.9	2,734.2	139.3	16,854.0
Total agricultural acres	172.2	128.1	40.0	1,429.8
Percentage of parcel irrigated (%)	8.2	23.8	0.0	100.0
Commute time to 10,000 population (hrs)	0.8	0.4	0.0	2.0
Commute time to 40,000 population (hrs)	1.7	0.9	0.4	3.8
Root zone available water storage (mm)	232.2	58.8	50.0	330.0
Soil organic carbon (kg/m^2)	9.7	3.0	1.8	25.4
Percentage of parcel with acidic soils (%)	0.8	6.3	0.0	100.0
Percentage of parcel with basic soils (%)	50.3	43.0	0.0	100.0
Slope (%)	3.5	2.5	0.0	21.5
Elevation (ft)	605.6	228.8	205.0	1,448.0
Growing season precipitation (inches)	19.8	4.1	13.1	29.0
Evapotranspiration (inches)	34.8	1.6	30.8	38.1
Degree days between 10° and 32° Celsius (degrees × days)	2,074.8	104.8	1,798.7	2,332.1
Degree days over 32° Celsius (degrees × days)	46.0	10.3	20.3	80.5

the analysis to arms-length transactions to ensure accurate reflections of fair market values and to the 23 counties having at least one turbine by 2017. We drop parcels having multiple sales within the same year because these are unlikely to represent separate competitive transactions (about 470 transactions dropped). In total, we have data on 14,196 transactions. Our PVD sales data include information on total amount of sale, estimates of dollar amount improvements to land, and acres of the parcel that are dryland or irrigated.[5] We exclude the value of improvements from the price because this usually reflects the value of storage barns and outbuildings (but not turbines).[6,7] All prices are converted to 2017 dollars using the Consumer Price Index. Table 2 provides summary statistics for land transactions and characteristics included in our analysis.

Two main concerns when working with agricultural land sales data are sparseness of transactions reflecting fair market value and whether the decision to list or purchase land is endogenous to land characteristics. The former concern is not an issue in this setting because we have over 14,000 arms-length transactions covering 23 counties over a 17-year period. The latter concern can be characterized as a sample-selection problem and has been empirically documented in cases where rural land has competing agricultural and non-agricultural uses (Koundouri and Pashardes, 2003). Sample selection is unlikely to be a problem in this setting because there is little exurban development pressure in Kansas, which would drive wholly competing uses of the land (White, Morzillo, and Alig, 2009). Additionally, we are able to control for nonagricultural development pressure by including variables on commute times to cities of various size (described below) and by including a rich set of spatial dummies (up to the township level).

Soils

Soil characteristics likely to affect rents from agriculture are obtained from the SSURGO soil survey on the website of the USDA Natural Resource Conservation Service (NRCS). The PVD data contain information on the acres of the parcel represented by each soil type. We link these soil types to the SSURGO data, which provide information on the characteristics of each soil type and aggregate

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[5] Additional details of the PVD transaction data are described in Tsoodle, Golden, and Featherstone (2006) and Sampson, Hendricks, and Taylor (2019).

[6] According to conversations with land appraisers, wind turbines are not included in the value of improvements. This is because wind turbine capital is owned by the wind energy utility rather than the landowner.

[7] In later subsections, we investigate differential impacts across parcels that have residential value and those that do not. In short, we find no evidence of statistically significant differential impacts.

the characteristics to the parcel level. The following soil characteristics are used as controls in regressions: percentage of parcel with pH less than 6 (acidic soils), percentage of parcel with pH greater than 7.5 (basic soils), plant available water storage, and soil organic carbon in the top 150 cm of the soil horizon.

Climate

Daily gridded weather data are obtained from PRISM and are linked to sections of the Public Land Survey System, which are then merged to the parcels. We construct four climate variables (1981–2012 average) for each section: average growing season precipitation, average number of annual degree days between 10° and 32° Celsius, average number of annual degree days greater than 32° Celsius (i.e., heat levels detrimental to crop growth, Schlenker, Hanemann, and Fisher, 2006), and average reference growing season evapotranspiration. The climate variables are expected to capture average climate conditions related to agriculture at the section level.

Urban Influence

We control for urban influence by using data on the commute time to a city with a population of 10,000 or more and commute time to a city with a population of 40,000 or more. Commute times from each parcel are calculated using Google Maps.

Wind Turbines

We obtain the locations and technical specification of utility-scale wind turbines in Kansas from the U.S. Wind Turbine Database, jointly operated by the U.S. Geological Survey, Lawrence Berkeley National Laboratory, and American Wind Energy Association. Turbine locations are obtained from high-resolution aerial imagery. Technical specifications for the turbines are obtained from the make and model, as provided by the manufacturer. Utility-scale turbines are characterized as turbines capable of generating power to feed into the grid to supply a utility. Turbine locations are judged to be within a 10-meter error tolerance. In total, we obtain the location and specification of all 2,506 utility-scale turbines in Kansas that became active up to the year 2017. Table 1 provides turbine summary statistics.

The locations of each turbine and land parcel were matched using QGIS. To determine whether a parcel contained a wind turbine, we spatially merged the turbine and parcel locations to CLU files for each of the 23 study counties. A CLU is an individual contiguous farming parcel, defined as the smallest unit of land having a permanent, contiguous boundary and is used by the USDA Farm Service Agency when linking farm records to maps or images. We overlay the parcel and turbine coordinates to the CLU files and label any CLU sharing a parcel coordinate and turbine coordinate as being a parcel with a turbine on it. Figure 2 provides an example.

Methodology

This paper estimates the direct effect of wind turbines on the value of an agricultural parcel and the indirect effects on the value of nearby parcels. Fundamentally, we are interested in estimating the treatment effect of either (i) having a wind turbine on the parcel or (ii) having a turbine *in nearby proximity to* the parcel (but not on the parcel).

There are a number of challenges in measuring the effect of turbines. The first is the date at which the turbine begins to exist. We assume that the relevant existence date is the year that the turbine becomes operational (we explore sensitivity to this assumption in a later section). The second challenge is how to measure the effects of wind turbines. Because we match parcel locations and

Figure 2. Sample Parcel and Turbine Locations Together with CLUs

Notes: Parcel locations are for any parcel having a sales transaction during the period of analysis and not necessarily subsequent to a turbine installation.

turbine locations at the CLU level, we can reasonably ascertain whether a parcel had a turbine on it when it sold.

There are multiple reasons why a turbine might affect land value when it is installed on a parcel. Foremost, the landowner obtains lease payments from granting the wind energy company the rights to install and operate the turbine(s). Typically, the terms of the lease are 20–30 years, with payments most often being made to the landowner over scheduled intervals (e.g., annually). A recent survey of lease contracts revealed compensation payments ranging from $1,500 to $9,500 per turbine per year (Windustry, 2009).[8] Interviews with farmers have demonstrated that a leading motivator for pursuing on-farm wind turbines is diversification of income (Sutherland and Holstead, 2014). However, turbines also have a number of potentially adverse effects, such as compromising viewsheds, annoyance from noise, bird deaths from the rotary blades, landscape impacts such as compression of soils and soil erosion, annoyance to livestock, taking land out of production for access roads and turbine pads, and disruption of farm equipment (e.g., harvesters, irrigation structures) (Khatari, 2004; Heintzelman and Tuttle, 2012; Vyn and McCullough, 2014).

In theory, the terms of the lease agreement and the amount of compensation will emerge from a bargaining process between the landowner and wind company (Coase, 1960; Libecap, 1993). The landowner's minimum willingness to accept is *ex ante* expected to be the amount that approximately covers the opportunity cost of turbine installation (i.e., any disamenity cost and revenues forgone from taking land out of production). For the wind company, the maximum offer will depend on the power purchase agreement with the power plant. According to the Lawrence Berkeley National Laboratory, recent wind power purchase agreements in the Midwest range from about $20 per megawatt-hour (MWh) to $40/MWh (Berkeley Lab, 2019). Assuming an average annual electricity generation of 2,000 MWh/MW and evaluating at our sample average turbine size of 1.8 MW implies average annual gross revenue of $72,000–$144,000 per turbine to the wind company.

[8] For parcels having wind energy installments, the average number of turbines is 1.3, with an average capacity of 2.4 MW. Using the lease payment ranges above and assuming a 20-year lease term and 5% discount rate, the average capitalized value would range from about $25,000 to $161,000. This represents about 6%–40% of the value of the average parcel in our sales data.

Table 3. Summary Statistics for Wind Turbine Variables

Turbine Proximity Measure	Mean	Std. Dev.	Max./Count
Average distance to nearest turbine (km)	97.0	100.0	438.7
Turbine on parcel	0.003	0.056	44
Turbine 0–2 km away	0.013	0.111	178
Turbine 2–4 km away	0.014	0.116	193
Turbine 4–6 km away	0.022	0.147	314

Thus, whether land values increase in response to a new stream of wind lease payments will depend on the extent to which those lease payments exceed a landowner's *ex ante* expected opportunity costs. It is also worth noting that *even if* the lease payments exceed such costs, if similar properties without turbines retain the option of readily and costlessly adding turbines at some future date, then prospective buyers would not necessarily place greater value on properties with turbines compared to those without. More specifically, in a competitive bidding market, if turbines were not completely exclusive to the properties on which they reside, we would not expect to observe a significant premium for such properties.[9]

For parcels having a turbine *nearby*, potential adverse effects include the loss of enjoyable viewsheds (Sunak and Madlener, 2017), noise, disturbing livestock, and shadow flickers (Khatari, 2004; Groothuis, Groothuis, and Whitehead, 2008). Potential positive effects include more beneficial weather (Li et al., 2018) and even an increase in crop yields (Chen, 2019; Kaffine, 2019). Additionally, there is the potential for a positive network effect if lease payments or the ability to "opt in" to a wind energy lease are affected by having existing turbines in place nearby. Indeed, the wind turbine data exhibits some clustering in the location of turbines (Figures 1 and 2), suggesting there may be incentives to agglomerate (e.g., Moreno-Cruz and Taylor, 2017). The various potential negative and positive impacts of having turbines nearby mean that the net impact could be offsetting.

To account for proximity effects of a parcel to a turbine, we use two distance measures that have been used in previous hedonic analyses of wind turbines in residential settings. The first is the inverse of the linear distance to the nearest turbine. The reasoning behind using the inverse distance measure is that parcels closer to a turbine are most likely to experience adverse environmental effects or, alternatively, positive agglomeration effects (see, e.g., Heintzelman and Tuttle, 2012). To compute the inverse distance, we calculate for each year the linear distance between the location of a parcel that sold and the nearest turbine that is active in that year. The second distance measure is a set of dummies representing whether a parcel belongs to a set of spatial rings around a turbine. We define the rings at 0–2 km, 2–4 km, and 4–6 km around the turbine.[10] Using spatial bands set at 2 km permits more observations to be exploited in the treatment groups (i.e., compared to narrower, 1 km bands). Additionally, the cutoff of 6 km was chosen based on visual extents used in previous hedonic studies (e.g., Vyn and McCullough, 2014). Together, these dummy variables capture potential nonlinear effects in proximity to a turbine.

Descriptive Statistics

Table 3 presents summary statistics for the wind turbine distance measures. The number of post-turbine installation sales are relatively few, largely because wind capacity grew slowly between 2001 and 2009 and turnover of agricultural land is generally low. We observe 44 land transactions with an active turbine located on the parcel. This represents about 0.3% of our total observations. Sales of parcels that are located 0–2 km (178 total), 2–4 km (193 total), or 4–6 km (314 total) away

[9] Consider an example: Suppose there are two identical parcels for sale: one with turbines and one without. Suppose the parcel without turbines retains the option to contract with a wind company at any future time. In this case, potential buyers might not bid more for the parcel with turbines because they could readily trigger that option on the alternative parcel when/if they desire.

[10] Analyses using 0–3 km and 3–6 km rings produce similar results (Table S1 in the Online Supplement [www.jareonline.org]).

Table 4. Farm Characteristics for Parcels That Install Turbines and Those That Do Not

Variable	Turbine on Parcel	Turbine Not on Parcel
Price per acre ($)	2,475.8	2,602.7
	(198.40)	(23.00)
Commute time to 10,000 population (hrs)	0.7	0.8**
	(0.02)	(0.00)
Commute time to 40,000 population (hrs)	1.7	1.6
	(0.06)	(0.01)
Proportion of parcel irrigated	5.5	8.3*
	(1.40)	(0.20)
Root zone available water storage (mm)	236.6**	228.1
	(4.40)	(0.50)
Soil organic carbon (kg/m^2)	9.6	9.6
	(0.17)	(0.03)
Acidic soils (proportion of land)	0.0	0.8*
	(0.03)	(0.06)
Basic soils (proportion of land)	58.3***	50.2
	(3.20)	(0.40)
Slope (%)	3.5	3.5
	(0.17)	(0.02)
Elevation (ft)	584.8	591.7
	(13.40)	(1.93)
Growing season precipitation (inches)	17.7	17.9
	(0.27)	(0.03)
Evapotranspiration (inches)	34.6	34.4
	(0.11)	(0.01)
Degree days between 10° and 32° Celsius (degrees × days)	2,054.6	2,051.7
	(6.04)	(0.92)
Degree days over 32° Celsius (degrees × days)	42.1	42.9
	(0.56)	(0.09)

Notes: Mean values are shown and standard errors appear in parentheses. Parcels that choose to install turbines are compared with those that do not install turbines using a t-test. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

from an active turbine each represent about 1%–2% of our total observations. A potential limitation of this study is therefore the low number of post-turbine observations in the data.

Before discussing the econometric analysis, it is useful to contextualize the setting by summarizing the key farm characteristics and land values from the data. Table 4 presents summary statistics across parcels that have turbines and those that do not. Mean values are compared using a t-test. We find no statistically significant difference in the real market price per acre for parcels with turbines and parcels without turbines. We do find that parcels with turbines are statistically more likely to be located closer to towns with populations of 10,000 or more, to have less irrigation, to have a higher proportion of basic soils, and to have greater root zone water storage. There is no statistically significant difference in climate characteristics for parcels with and without wind turbines. However, a more detailed econometric analysis is required to determine whether these differences are truly the result of wind turbines (rather than coincidental correlation).

Empirical Approach

We use the hedonic approach to measure the effects of wind turbines on agricultural land values. Following Rosen (1974), any parcel i can be expressed as a bundle of observable attributes, with the market price for parcel i being determined by these attributes. In competitive markets, agricultural land parcels having desirable attributes will be bid up by potential buyers. The amount by which parcel i is bid up depends on how much potential buyers value the attribute. The estimated price premium associated with a particular attribute of agricultural land thus provides evidence of how the market values that attribute.

Formally, the models we estimate can be described by two regression equations. The first uses spatial dummies of varying resolution:

$$\ln \frac{price}{acre}_{i,t} = w_{i,t}\boldsymbol{\beta} + x_i\boldsymbol{\alpha} + \tau_t + \eta_m + \lambda_l + \mu_{i,t}, \tag{1}$$

where $\ln \frac{price}{acre}_{i,t}$ is the log of the real price per acre for parcel i in year t, $w_{i,t}$ represents the treatment variables, which are defined as the different measures of turbine proximity at the time of the sale (Table 3), x_i is a set of other property attributes (e.g., irrigation, soil organic carbon), τ_t captures unobserved temporal heterogeneity using year dummies, η_m is a set of month-specific dummies, λ_l is a set of spatial dummy variables ranging from no controls to controls for the 461 townships (6-mile-square) in our study region, and $\mu_{i,t}$ is the error term, which is clustered at the township. Thus, when township dummies are specified, the effects of wind turbines on land values in equation (1) are identified through cross-sectional and time-series variation within townships that is not common to all Kansas parcels.

Two main concerns in the identification of the effects of wind turbines on land values are omitted variable bias and endogeneity. If unobserved factors impact land values and are also correlated with the treatment variables, then estimates of the regression parameters will be biased. Similarly, if the location of wind turbines is driven in part by the value of land in that location, then this relationship would result in endogeneity bias. For example, if wind turbines are strategically located in areas that have lower land values, then one might erroneously conclude that wind turbines negatively affect land values. These issues are addressed by the spatial dummy variables, which absorb any time-invariant heterogeneity that affects land values (i.e., land endowment effects). In this way, any heterogeneity that is clustered (e.g., at the township level) will no longer be omitted in the regression. Likewise, any time-variant heterogeneity that affects all land values will be controlled for using the year and month dummies. Controlling for endogeneity bias in this setting therefore relies upon the assumption that wind turbines are located at random within the unit of spatial control (e.g., township).

A final concern is spatial autocorrelation in land values. That is, it may be the case that the market price for parcel i is driven to some degree by the value of nearby parcel j via neighborhood effects. Additionally, factors that are unobserved for parcel i may correlate with the unobserved factors for parcel j. One way to address spatial autocorrelation is to develop an empirical model that explicitly accounts for the particular structure of spatial dependence (e.g., Elhorst, 2003; Schnier and Felthoven, 2011; Sampson, 2018).[11] However, the particular specification of the spatial weighting matrix is often arbitrary, making it difficult to determine which model of spatial dependence best represents the true data-generating process (Gibbons and Overman, 2012). In this paper, we correct for spatial correlation in land values through the use of spatial controls. To control for correlation in remaining unobserved factors, we cluster the model errors at the township level. Thus, if certain geographies have higher or lower land values on average, then this will to a large extent be controlled for by the spatial dummies. Additionally, we allow for arbitrary correlation in the error term within each township.

Our second model exploits data from repeated sales of parcels. We have data on 1,530 parcels that sold at least twice from 2001 to 2017, for a total of 3,263 repeat transactions. The regression model in equation (1) can be adapted as

$$\ln \frac{price}{acre}_{i,t} = w_{i,t}\boldsymbol{\beta} + \tau_t + \eta_m + \lambda_i + \mu_{i,t}, \tag{2}$$

[11] In this context, the township dummy variables can be viewed as analogous to a spatial weighting matrix, where 1 is assigned to parcel pairs within a township and 0 otherwise.

where λ_i is a parcel fixed effect and all other variables are as described previously. In equation (2), parcel characteristics will drop out because they do not vary over time. Identification of the effect of wind turbine proximity is thus achieved from parcels that transact more than once during the period of analysis and vary in their situational exposure to turbines over time. While repeat sales data are statistically powerful, it is worth noting that the reduction in observations is likely to reduce the precision of the estimates, while inclusion of parcel-level fixed effects may exacerbate any attenuation bias resulting from measurement error.

Results

We first present results for the analysis using equation (1) as the regression model. Columns 1–3 of Table 5 show coefficient estimates for the model specifying the log of the inverse distance to the nearest turbine while columns 4–6 show estimates for the model specifying a set of dummies indicating proximity to the nearest turbine. In columns 1–3, the coefficient is positive and statistically significant at 0.10 or better and similar in magnitude across specifications. Because the main variable of interest is specified using a log-log, the coefficient on the log of the inverse distance can be interpreted as an elasticity of land price with respect to the inverse of the distance to the nearest turbine. In particular, the coefficient value indicates that a 10% increase in the inverse distance results in a 0.26%-0.65% increase in land value. Thus, this implies that proximity to a turbine increases land values.

Looking at columns 4–6 of Table 5, we find that the coefficient for having a turbine *on* the parcel switches between negative and positive, though the effect is not statistically significant in any of the specifications. For the 0–2 km and 2–4 km treatment groups, we find positive but statistically insignificant effect on land values. For the 4–6 km treatment group, the coefficient is negative in columns 4 and 5 and marginally statistically significant in column 5. In column 6, which includes spatial controls at the township level, the effect is very small in magnitude and not statistically significant, implying that the use of township controls absorbs some of the effect previously attributed to the 4–6 km treatment group. As mentioned previously, it is possible that the null effect for turbines near the parcel stems from offsetting positive and negative impacts. In said cases, a more detailed set of data and empirical approach would be necessary to decompose the total effect. Taken together, columns 1–6 of Table 5 suggest that the impacts of turbines on farmland values range from positive to statistically insignificant.

With respect to the other model covariates, we find that irrigation, soil organic carbon, and the number of degree days favorable to growing conditions positively impact agricultural land values (as expected). In particular, a 10% increase in the percentage of the total parcel that is irrigated increases land value by about 7%–9%, and this effect is significant at 0.01, which is consistent with previous studies of irrigation premiums (Sampson, Hendricks, and Taylor, 2019). An additional kg/m^2 of soil organic carbon increases land values by about 1%–3%, and the effect is statistically significant at 0.10 or better. An additional degree day between 10° and 32° Celsius increases land values by about 0.1%–0.3%, in certain specifications (i.e., columns 1, 3, and 4).

Heterogeneity in Turbine Size

Regression estimates thus far have grouped all turbine sizes together. If turbine disamenity value is driven by factors related to visibility, then it stands to reason that taller turbines would have a relatively greater effect. Turbine hub heights in the data (distance from platform to center of rotor) range from about 65 m to about 95 m, with an average of 73 m. Table S2 in the Online Supplement presents results for a subset of the data based on turbines that have hub heights of

Table 5. Regression Results

Variable	1	2	3	4	5	6
ln(Inverse distance to nearest turbine)	0.0452***	0.0264*	0.0651***			
	(0.014)	(0.014)	(0.015)			
Turbine on parcel				−0.0452	−0.0772	0.1130
				(0.1400)	(0.1460)	(0.1580)
Nearest turbine 0–2 km				0.0536	0.0411	0.0911
				(0.0906)	(0.0849)	(0.0689)
Nearest turbine 2–4 km				0.0667	0.0036	0.0732
				(0.0837)	(0.0779)	(0.0823)
Nearest turbine 4–6 km				−0.0935	−0.126*	0.0012
				(0.0710)	(0.0737)	(0.0668)
Proportion of parcel irrigated	0.0091***	0.0078***	0.0074***	0.0091***	0.0078***	0.0074***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
Root zone available water storage (mm)	−0.0005	−0.0007*	−0.0004	−0.0005	−0.0007*	−0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Soil organic carbon (kg/m^2)	0.0246***	0.0279***	0.0110*	0.0242***	0.0278***	0.0112*
	(0.0064)	(0.0059)	(0.0059)	(0.0064)	(0.0058)	(0.0059)
Acidic soils (proportion of land)	−0.0031*	0.0001	0.0004	−0.0030*	0.0001	0.0004
	(0.0018)	(0.0017)	(0.0015)	(0.0018)	(0.0016)	(0.0015)
Basic soils (proportion of land)	−0.0008	−0.0002	−0.0003	−0.0007	−0.0003	−0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Slope (%)	0.0264***	0.0189***	−0.0120	0.0274***	0.0190***	−0.0114
	(0.0074)	(0.0073)	(0.0076)	(0.0073)	(0.0072)	(0.0075)
Elevation (ft)	−0.0001	−0.0002	−0.0002*	−0.0002	−0.0002	−0.0003*
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Growing season precipitation (inches)	−0.0151	0.0475*	0.0011	−0.0250	0.0429*	−0.0024
	(0.0164)	(0.0250)	(0.0409)	(0.0162)	(0.0248)	(0.0409)
Evapotranspiration (inches)	−0.0548	0.0638	0.0955	−0.0369	0.0723	0.0874
	(0.0503)	(0.0790)	(0.1480)	(0.0510)	(0.0788)	(0.1470)
Degree days between 10° and 32° Celsius (degrees × days)	0.0011***	0.0001	0.0034*	0.0013***	0.0001	0.0033
	(0.0004)	(0.0009)	(0.0020)	(0.0004)	(0.0009)	(0.0020)
Degree days over 32° Celsius (degrees × days)	−0.0069	0.0008	−0.0202	−0.0111**	−0.0008	−0.0198
	(0.0056)	(0.0106)	(0.0234)	(0.0054)	(0.0106)	(0.0234)
Commute time to 10,000 population (hrs)	0.1660***	−0.0049	0.1210	0.1540***	−0.0127	0.1160
	(0.0545)	(0.0877)	(0.1840)	(0.0542)	(0.0868)	(0.1850)
Commute time to 40,000 population (hrs)	0.1540***	0.0721	0.0419	0.1380***	0.0669	0.0368
	(0.0504)	(0.0748)	(0.1590)	(0.0507)	(0.0744)	(0.1600)
Spatial controls	None	County	Township	None	County	Township
Adjusted R^2	0.23	0.26	0.35	0.22	0.26	0.35
No. of obs.	12,157	12,157	12,153	12,189	12,189	12,185

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies.

at least 73 m, which is approximately the cutoff between small- and large-scale wind turbines.[12] That is, the regressions in Table S2 use only turbines having hub heights of 73 m or larger. Note that analysis of heterogeneity in turbine size in this approach may exacerbate attenuation bias from measurement error due to the reduction in observations. Looking across columns 1–4 of Table S2, the results provide no evidence that taller turbines have greater effects on agricultural land values than smaller turbines.

Impacts over Time

Previous work highlights the possibility that over long enough periods of time, the hedonic price coefficients may vary (Kuminoff, Parmeter, and Pope, 2010). Given the relatively long period of analysis (2001–2017) there is potential for this issue here. One main concern is the real estate market crash and economic downturn of 2007–2009. To test the impact of the real estate market crash, we run the models after excluding observations from 2007–2009. Estimates are reported in columns 1 and 3 of Table S3 in the Online Supplement. In short, the results are consistent with Table 5.

A parsimonious way to test temporal variance over the full sample period is to specify a linear time trend and interact the various treatment groups with the trend. We report these estimates in columns 2 and 4 of Table S3 for specifications including township dummies. For the model using the log of the inverse distance to the nearest turbine, the baseline coefficient is 0.116 and is statistically significant at $p < 0.01$ (consistent with column 3 of Table 5). Additionally, the linear trend interaction indicates the magnitude of the effect declined by about 0.6 percentage points per year on average. For the model with the 0–2 km, 2–4 km, and 4–6 km treatment groups, we detect that the baseline impacts of on-farm and near-farm wind turbine proximity are not statistically significant (consistent with column 6 of Table 5). Additionally, the linear trend interacted with the treatment groups is not statistically significant.

Repeat Sales

Table 6 presents coefficient estimates when the sample is restricted to only sales occurring more than once for the same parcel. In the repeat sales data, there are 8 transactions with a turbine on-parcel, 44 transactions in the 0–2 km group, 40 transactions in the 2–4 km group, and 72 transactions in the 4–6 km group. The smaller sample size and inclusion of parcel fixed effects may reduce precision and/or exacerbate measurement error. Column 1 of Table 6 presents estimates for the model specifying the log of the inverse distance to the nearest turbine with parcel-level controls. Column 2 of Table 6 presents estimates for the model specifying the set of dummies indicating proximity to the nearest turbine with parcel-level controls.

In column 1, we find a negative and statistically insignificant coefficient on the log of the inverse distance to the nearest turbine. In column 2, we also find that the coefficients on all treatment groups are negative and statistically insignificant. The point estimates on some of the treatment groups in column 2 go up in absolute magnitude relative to the pooled model estimates in Table 5, but the uncertainty also increases because less variation is exploited in the smaller sample. Consistent with the earlier estimates from columns 4–6 of the pooled cross section in Table 5, the model estimates in Table 6 provide no evidence of statistically significant proximity effects of wind turbines on agricultural land values. Thus, our results do not confirm that parcels that opt to have turbines installed capitalize a premium compared to similar parcels. Additionally, parcels that have turbines installed nearby do not suffer any systematic disamenity value.

We also investigate different definitions of the on-parcel effects of turbines in the repeat sales data. Table S4 in the Online Supplement presents estimates using the number of total turbines

[12] For example, Vaisala Energy defines a large-scale turbine (> 1 MW) as typically having hub heights of 80 m or larger (https://www.3tier.com/en/support/wind-online-tools/what-prospecting-hub-height/).

Table 6. Effects of Turbine Proximity to a Parcel Using Repeat Sales

Variable	1	2
ln(inverse distance to nearest turbine)	−0.0091	
	(0.0280)	
Turbine on parcel		−0.0983
		(0.0760)
Nearest turbine 0–2 km		−0.1490
		(0.1060)
Nearest turbine 2–4 km		−0.1940
		(0.1450)
Nearest turbine 4–6 km		−0.0957
		(0.1490)
Spatial dummies	*Parcel*	*Parcel*
Within R^2	0.26	0.26
No. of obs.	3,250	3,263

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies.

installed on the parcel (column 1) and the total installed capacity (in MW) on the parcel (column 2). In both cases, the effect of turbines is not statistically significant.

Sensitivity to Existence Date

As mentioned previously, we assume the relevant existence date for the turbines began at the time the turbines became operational. However, impacts to property values could precede the turbine operation date if awareness of the turbine locations is known by buyers and sellers. To investigate this possibility, we define an alternative existence date as the full calendar year prior to the turbine's operation date. Estimates on turbine construction times range from 2 to 6 months, so a full calendar year setback should capture pre-construction-phase impacts (European Wind Energy Association, 2016). We report estimates using the pooled sample with township dummies in columns 1 and 3 of Table S5 in the Online Supplement. Columns 2 and 4 of Table S5 present estimates from the repeat sales subsample with parcel-level controls. Generally, the point estimates are robust to the alternative existence date. One exception is the 2–4 km treatment group in the repeat sales subsample, which changed from −0.19 and was not statistically significant using the operation date to −0.31 and marginally statistically significant ($p < 0.10$) using the alternative existence date.

Residential versus. Nonresidential Farmland

We investigate whether parcels having a residence are affected differentially from parcels without a residence. To do this, we factor in the value of residence in the real price per acre and create an indicator variable if the parcel has a positive residential value associated with it. We then interact the indicator with the treatment variables. Note that we could not estimate differential effects for on-parcel turbines because there is only one transaction having both a turbine and a residence. Results are presented in Table S6 in the Online Supplement. In short, post-estimation F-tests do not reject the null hypothesis of no differential impacts between parcels with and without residential value.

Land Value Impacts of Electricity Production

The on-farm hedonic price impact of having wind turbines can be converted to a value per unit of electricity production. To this end, we conduct a back-of-envelope analysis of the largest dollar value of a MWh of electricity that cannot be rejected given the econometric estimates. The following calculations are meant as first-order approximations only. Focusing on the on-farm impact of wind turbines, our preferred coefficient estimate is 0.113, with an upper 95% confidence interval of 0.424 using the pooled data (Table 5). Using the pooled sample average of $2,605/acre and 172 acres per transaction (Table 2) implies an average parcel value of $448,060. Assuming 1.3 turbines per parcel (following footnote 8) and an average size of 1.8 MW with average capacity factor of 0.35 implies annual electricity production of 7,174 MWh. The upper 95% confidence interval estimate equates to a 53% increase in parcel value. Dividing this premium by 7,174 MWh gives $33/MWh, which is in the range of recent power purchase agreements in the Midwest (Berkeley Lab, 2019). Thus, the largest on-farm impact that we cannot reject from the econometric analysis is about $33/MWh.

Conclusion

For many agricultural producers, the value of their land constitutes the largest component of their wealth (U.S. Department of Agriculture, 2019). Fluctuations in that value can therefore have major implications for well-being and even for solvency. In this paper, we leverage a large dataset on agricultural land transactions to estimate the impact of wind turbines on nearby land values and on-farm land values. Across all our analyses, the preponderance of results suggests that wind turbines do not affect agricultural property values, either on-farm or nearby, in a statistically significant way. This contrasts with some recent studies that find economically significant disamenity effects for residential properties, but it supports recent related studies on agricultural land values (Vyn and McCullough, 2014; Shultz, Hall, and Strager, 2015) and rural residential land values in Kansas (Center for Economic Development and Business Research, 2019).

While the preponderance of our results indicates no statistically significant impacts to agricultural land values, this does not strictly rule out any positive or negative impacts from occurring on a case-by-case basis. Some of the treatment group estimates in our regression analysis have large standard errors, which may suggest that some properties have experienced large positive or negative impacts from turbine proximity. In fact, community opposition to turbines has arisen over time in some regions of Kansas (Lefler, 2019; Shorman, 2019) and community sentiment can shape the ways in which turbines affect property values (Vyn, 2018; Boyle et al., 2019). Thus, our study cannot strictly refute that some properties have been impacted by proximity to turbines. Rather, our analysis indicates that any such impacts have not occurred on a systematic basis across the 23 Kansas counties with utility-scale turbines.

Our findings have several implications for policy makers and agricultural landowners. As previously noted, the number of wind farms are slated to increase by nearly 4 times over the next 10 years. Additionally, the size and energy generation capacity of wind turbines are increasing, which has the potential to increase lease payments to landowners but also strengthen any external effects to neighboring parcels in the future. Our results indicate that, at least so far, such effects have not materialized on a systematic basis for agricultural properties in Kansas. Concerning landowners, for those that already have turbines on their property, our findings cannot confirm that the value of their land will increase. Similarly, landowners interested in contracting with a wind firm should not expect a wind farm to raise (or lower) the value of their land. One interpretation of the absence of any on-farm effect is that the bargaining process between landowners and wind energy companies has resulted in lease payments that approximate landowners' minimum willingness to accept on average across Kansas. Another possibility is that properties with turbines are still not exclusive enough to warrant a significant premium. Indeed, Myrna, Odening, and Ritter (2019) note that suitable land for turbine installation is highly scarce in Germany, which may explain their finding of positive on-farm impacts.

There are several potential directions for future research. Here we have focused on agricultural properties, but it would be interesting to extend the analysis to exurban properties, as in Vyn and

McCullough (2014) and the Center for Economic Development and Business Research (2019).[13] A second possibility is to compare the impacts across state borders or across different types of agricultural producers (e.g., field crops vs. pasture). Both a limitation of the present study and a possibility for the future concerns the breadth of the data. Wind turbines have only been in operation for less than 20 years in Kansas, and thus data on land sales with and near turbines, particularly repeat sales data, are still somewhat limited. Thus, it will be important to revisit the results of this analysis, particularly the on-farm analysis, as more data are collected.

[First submitted July 2019; accepted for publication January 2020.]

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Journal of Agricultural and Resource Economics 45(3):S1–S4 ISSN 1068-5502

doi: 10.22004/ag.econ.302463

Online Supplement: The On-Farm and Near-Farm Effects of Wind Turbines on Agricultural Land Values

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Table S1. Regression Results Using 0–3 km and 3–6 km Treatment

Variable	**1**	**2**	**3**
Turbine on parcel	−0.0463	−0.0787	0.1170
	(0.1400)	(0.1460)	(0.1570)
Nearest turbine 0–3 km	0.0756	0.0578	0.1270
	(0.0776)	(0.0752)	(0.0776)
Nearest turbine 3–6 km	−0.0644	−0.112*	−0.0035
	(0.0662)	(0.0660)	(0.0605)
Proportion of parcel irrigated	0.0091***	0.0078***	0.0074***
	(0.0006)	(0.0007)	(0.0006)
Root zone available water storage (mm)	−0.0005	−0.0007*	−0.0003
	(0.0004)	(0.0004)	(0.0004)
Soil organic carbon (kg/m^2)	0.0241***	0.0277***	0.0111*
	(0.0064)	(0.0058)	(0.0059)
Acidic soils (proportion of land)	−0.0030*	0.0001	0.0004
	(0.0018)	(0.0016)	(0.0015)
Basic soils (proportion of land)	−0.0007	−0.0003	−0.0003
	(0.0005)	(0.0005)	(0.0005)
Slope (%)	0.0277***	0.0192***	−0.0113
	(0.0073)	(0.0072)	(0.0075)
Elevation (ft)	−0.0002	−0.0002	−0.0003*
	(0.0002)	(0.0001)	(0.0001)
Growing season precipitation (inches)	−0.0251	0.0427*	−0.0016
	(0.0162)	(0.0248)	(0.0410)
Evapotranspiration (inches)	−0.0378	0.0719	0.0874
	(0.0510)	(0.0787)	(0.1470)
Degree days between 10° and 32° Celsius	0.0013***	0.0001	0.0033*
(degrees × days)	(0.0004)	(0.0009)	(0.0020)
Degree days over 32° Celsius (degrees × days)	−0.0110**	−0.0007	−0.0200
	(0.0054)	(0.0106)	(0.0234)
Commute time to 10,000 population (hrs)	0.1530***	−0.0144	0.1120
	(0.0542)	(0.0865)	(0.1840)
Commute time to 40,000 population (hrs)	0.1390***	0.0679	0.0401
	(0.0508)	(0.0744)	(0.1600)
Spatial controls	None	County	Township
Adjusted R^2	0.22	0.26	0.35
No. of obs.	12,194	12,194	12,190

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies.

Table S2. Heterogeneity of Impact by Turbine Hub Height

	Hub Height > 73 m			
Variable	**1**	**2**	**3**	**4**
ln(inverse distance to nearest turbine)	−0.00428	0.0239		
	(0.0180)	(0.0190)		
Turbine on parcel			−0.0247	0.0644
			(0.1480)	(0.1820)
Nearest turbine 0–2 km			−0.0472	0.0507
			(0.0770)	(0.0818)
Nearest turbine 2–4 km			0.0237	0.0453
			(0.0830)	(0.0790)
Nearest turbine 4–6 km			−0.0676	0.00557
			(0.0670)	(0.0680)
Spatial dummies	*County*	*Township*	*County*	*Township*
Adjusted R^2	0.22	0.32	0.22	0.32
No. of obs.	5,808	5,789	5,840	5,821

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies.

Table S3. Regression Results for Time-Variant Models

Variable	**1**	**2**	**3**	**4**
ln(inverse distance to nearest turbine)	0.0738***	0.116***		
	(0.0176)	(0.0260)		
Turbine on parcel			0.1880	−0.8530
			(0.1500)	(1.1800)
Nearest turbine 0–2 km			0.0780	0.1620
			(0.6880)	(0.2940)
Nearest turbine 2–4 km			0.0410	0.1420
			(0.0788)	(0.3980)
Nearest turbine 4–6 km			−0.0070	−0.0080
			(0.0680)	(0.1770)
Linear trend		0.0100		0.0410***
		(0.0104)		(0.0050)
ln(inverse distance to nearest turbine) (linear trend)		−0.0060**		
		(0.0024)		
Turbine on parcel (linear trend)				0.0670
				(0.0770)
Nearest turbine 0–2 km (linear trend)				−0.0060
				(0.0212)
Nearest turbine 2–4 km (linear trend)				−0.0060
				(0.0291)
Nearest turbine 4–6 km (linear trend)				0.0005
				(0.0138)
Sample	Excludes 2007–2009	Full	Excludes 2007–2009	Full
Adjusted R^2	0.37	0.38	0.37	0.38
No. of obs.	9,818	12,162	9,848	12,194

Notes: : Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models include township, year, and month dummies.

Table S4. Effects of Total Number of Turbines and Installed Capacity on a Parcel

Variable	1	2
Number of turbines installed on parcel	−0.0214	
	(0.0210)	
Installed capacity on parcel (MW)		−0.0144
		(0.0130)
Spatial dummies	Parcel	Parcel
Within R^2	0.26	0.26
No. of obs.	3,263	3,263

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Also includes year and month dummies.

Table S5. Regression Results If Turbine Existence Date Is Pushed Back One Calendar Year

Variable	1	2	3	4
ln(Inverse distance to nearest turbine)	0.0547***	−0.0140		
	(0.0145)	(0.0293)		
Turbine on parcel			0.0693	−0.0961
			(0.1530)	(0.0749)
Nearest turbine 0–2 km			0.0675	−0.1680
			(0.0746)	(0.1330)
Nearest turbine 2–4 km			0.0942	−0.3130*
			(0.0815)	(0.1720)
Nearest turbine 4–6 km			−0.0290	0.0895
			(0.0655)	(0.1790)
Spatial dummies	Township	Parcel	Township	Parcel
R^2	0.35	0.26	0.35	0.26
No. of obs.	12,155	3,250	12,190	3,263

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies. Columns 1 and 3 report adjusted R^2. Columns 2 and 4 report within R^2.

Table S6. Regression Investigating Differential Effects by Residence Status

Variable	1	2
Residence	0.1680**	0.1740***
	(0.0535)	(0.0270)
ln(inverse distance to nearest turbine) (no residence)	0.0591***	
	(0.0150)	
ln(inverse distance to nearest turbine) (residence)	0.0572**	
	(0.0226)	
Turbine on parcel		0.1090
		(0.1600)
Nearest turbine 0–2 km (no residence)		0.0642
		(0.0700)
Nearest turbine 2–4 km (no residence)		0.0494
		(0.0810)
Nearest turbine 4–6 km (no residence)		−0.0172
		(0.0670)
Nearest turbine 0–2 km (residence)		0.2670
		(0.2310)
Nearest turbine 2–4 km (residence)		−0.0989
		(0.2650)
Nearest turbine 4–6 km (residence)		−0.0396
		(0.1790)
Spatial dummies	Township	Township
Adjusted R^2	0.36	0.35
No. of obs.	12,159	12,191

Notes: Standard errors clustered at township in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. In all specifications, the dependent variable is the log of real price per acre. Models also include year and month dummies.

[Received July 2019; final revision received January 2020.]