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Commercial wind turbines and residential home values: New evidence from the universe of land-based wind projects in the United States

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We augment the USWTDB database with additional information on the date of the "announcement" that a wind energy project was being developed and seeking permit approval. Data on announcement date comes from Hitachi Velocity Suite, which often corresponds to the date a transmission interconnection application is filed and necessarily would follow or be coincident with a period in which land agents are securing local landowner leases, the development company sets up a local office, and other development activity occurs, such as the erection of a meteorological tower to collect local wind speeds. Any of these could incite local conversations about the possible arrival of the project in future years. We observe non-missing announcement dates for 60% of the wind energy projects in our sample. Given that most announcement dates occur approximately four years prior to a wind energy project becoming operational, we set the announcement date equal to four years prior to the operation date in cases where we are missing the actual announcement date.

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ABSTRACT

We examine the impact of proximity to land-based commercial wind turbines on residential home values in the United States using data on the universe of commercial wind turbines and residential property transactions from 2005 to 2020. Using event study and difference-in-differences identification strategies we find that, on average, homes located within 1 mile of a commercial wind turbine experience approximately an 11% decline in value following the announcement of a new commercial wind energy project, relative to counterfactual homes located 3 to 5 miles away. Event study estimates also reveal important dynamics in the evolution of home values, with property values first declining following project announcement, and then recovering post project construction, with property value impacts becoming relatively small (∼2%) and statistically insignificant 9 years or more after project announcement (roughly 5 years after operation began). Homes located within 1–2 miles of a commercial wind turbine experience much smaller impacts and homes located farther than 2 miles away are unaffected. Our results are primarily driven by wind projects located in urban counties with populations greater than 250,000.

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1. Introduction

Over the past decade, wind energy has become one of the fastest growing energy sources in the United States, accounting for approximately 32% of U.S. electric capacity growth in 2021 (Wiser et al., 2023). Commercial wind energy generation has grown from approximately 6 billion kWh in 2000 to 380 billion kWh in 2021, with more than 70,000 turbines now accounting for 9.2% of total U.S. utility-scale electricity generation (Hoen et al., 2018; United States Energy Information Administration, 2022). The rapid growth in wind energy production has been accompanied by a large expansion in the number of counties hosting commercial wind energy projects and the number of homes located in close proximity to such projects.

The growth of commercial wind energy installations has led to opposition to the siting of new projects, particularly as those projects have moved closer to more densely populated areas. One primary concern among residents within close distances of commercial wind turbines is the potential negative impact on home values due to the noise and shadow flicker associated with turbine rotation as well as the change to the surrounding landscape (Hoen et al., 2019). A relatively large body of literature has examined how proximity to wind turbines impacts residential home values. Within the U.S. context, the evidence is mixed but the majority of studies find insignificant effects of wind turbines on home values (see reviews Brinkley and Leach, 2019; Rand and Hoen, 2017, Parsons and Heintzelman, 2022). In contrast, studies from Europe generally find that close proximity to wind turbines has a negative effect on home values with home values falling by approximately 5–10% for homes located within 2 km (~1.2 miles) of a wind turbine.

The purpose of this paper is to provide new evidence on how proximity to commercial wind turbines affects residential housing values within the U.S. context. Our analysis is based on the most comprehensive and nationally representative sample of wind energy projects and housing value transactions in the United States to date. We combine data from the U.S. Wind Turbine Database (USWTDB, Hoen et al., 2018) on the timing and exact location of the universe of wind turbine installations in the U.S. from 2005 to 2020 with data on the universe of residential housing transactions from CoreLogic including the location, attributes, and sales data from 2005 to 2020. Our final sample consists of 428 unique wind energy projects located across the United States and nearly 500,000 housing sale transactions located within five miles of a wind energy project.

To isolate the causal effect of wind turbines on residential property values, we use difference-in-differences (DiD) and event study models that allow us to examine the evolution of housing prices for homes within [0, 1], [1, 2], and [2, 3] miles from a turbine four years prior to the announcement of a new commercial wind energy project to 10 years after the announcement. Our identification strategy has several key advantages for isolating the causal impact of proximity to a wind turbine on residential home values. First, as described in more detail below, our comparison group, which consists of homes 3 to 5 miles from the nearest turbine, and our fixed effect structure enables us to use only within project variation in sale prices and distance from a wind turbine. Thus, we avoid inter-housing market (or across-jurisdiction) comparisons that may bias our estimates. Second, we control for wind project-specific nonparametric trends in housing prices over time allowing us to better model generalized housing trends in specific markets. Finally, our identification strategy directly addresses the potential biases that can arise in standard DiD and event study models in the presence of staggered timing of treatment with heterogeneous treatment effects (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021).

We find that the average home located within 1 mile of a commercial wind turbine experienced approximately an 11% decline in value following the announcement of a new commercial wind energy project, relative to homes 3 to 5 miles away from the project. Event study estimates also reveal important dynamics in the evolution of home values, with property values first declining following project announcement, and then recovering post project construction, with property value impacts becoming relatively small (~2%) and statistically insignificant 9 years or more after project announcement. Homes located within 1–2 miles of a commercial wind turbine experience much smaller impacts and homes located farther than 2 miles away are unaffected. Furthermore, we find that our results are driven by wind projects and housing markets located in populated, urban metro areas with populations of 250,000 or more.

Our paper extends the existing literature in several important ways. First, much of the existing literature is focused on specific states or regions (e.g., Dong et al., 2023). In contrast, our study is based on the full universe of housing transactions and wind turbines in the United States. Second, all but one of the existing studies within the United States rely on housing transactions that occurred prior to 2014–2015 at the latest (Hoen et al., 2015). In contrast, we examine the impact of turbines constructed in the past 15 years. Lastly, we specifically examine the impact of turbines constructed in urban areas. This second contribution is particularly policy-relevant given we find that wind projects built in urban areas (counties with populations greater than 250,000) have negative impacts on property values compared to wind projects built in more rural communities (where we find no impact on property values). We discuss potential mechanisms for this difference below.

2. Background & existing literature

Since the early 1980's when the first commercial wind turbines went into operation, wind energy has become an increasingly important energy source in the United States, accounting for over 32% of U.S. electric capacity growth in 2021 and 9.2% of total U.S. utility-scale electricity generation. Appendix Figure A1 presents the distribution of county-level wind energy capacity in 2005 and 2022. As of 2005, there were 123 counties with commercial wind energy installations that were concentrated in the southeastern part of California and the Southwest and Midwest. By 2022, the number of counties with wind energy installations had grown six-fold to 687, with wind energy installations spread across the Western, Southwestern, and Central United States and to a lesser extent the Northeast. As shown in Fig. 1, the rapid growth of wind energy projects has also resulted in a steep decrease in average distance to the nearest turbine for all transactions in our data. In 2005, the average parcel in our data was located 148.6 miles (238.2 km) away

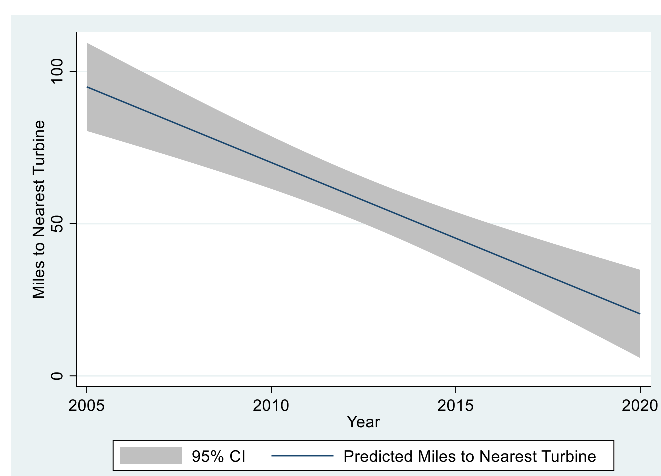

Fig. 1. Distance to Nearest Turbine for the Average House in the United States, 2005-2020

Notes: The figure represents the average distance to the nearest turbine for the average parcel in our transaction from 2005 to 2020. The average distance in 2005 was 148.6 miles (standard deviation of 367.4 miles). By 2020, the average distance was 37.1 miles (standard deviation of 25.65 miles).

from the nearest turbine. This distance decreased to 54.1 miles (86.9 km) by 2010, and then further to 37.1 miles (59.7 km) by 2020.

Despite public opinion polls showing the majority of the U.S. population supports the expansion of alternative energy sources, such as wind energy, the rapid expansion of wind energy projects, accompanied by the increase in the number of projects located in closer proximity to more densely populated areas, has led to controversy regarding the siting of wind energy projects.[1] Much of this controversy revolves around concerns over the potential impact of wind projects on residential property values. As noted by Hoen et al. (2011) and Krekel and Zerrahn (2017), concerns about the potential negative impact of wind turbines on residential property values can be categorized into three general areas: 1) the potential impact of direct views of wind turbines on property values; 2) perceptions that wind turbines will make an area appear more developed and reduce the aesthetic appeal of the areas surrounding a wind project regardless of whether wind turbines can be directly seen from residential properties; and 3) concerns over noise and shadow flicker impacts from the rotating blades of a wind turbine along with annoyance associated with aviation obstruction lights installed on top of turbines.[2]

Over the last decade a relatively large body of literature has emerged that examines the impact of wind turbines on residential property values, primarily using data from the United States and Europe. Within the U.S. context, the evidence is mixed but the majority of studies have found insignificant effects of wind turbines on residential property values. For example, using data on over 50,000 homes, including 1198 homes within 1 mile of a turbine, Hoen et al. (2015) find negative, but small and insignificant, effects of turbines on homes located in close proximity to operating turbines, and slightly larger but still insignificant effects in the period after announcement but before operation. Lang et al. (2014) and Hoen and Atkinson-Palombo (2016), examine the impact of wind turbines on residential home values in more urban settings in Rhode Island and Massachusetts, respectively, and these studies find little evidence that close proximity to turbines lowers property values. While Hoen et al. (2015) and Hoen and Atkinson-Palombo (2016) both find small and insignificant impacts on average, both studies also find that estimates in the post-announcement-pre-operation period being slightly more negative, though still insignificant. In contrast, using data on approximately 11,000 residential property transactions in three upstate New York counties, Heintzelman and Tuttle (2012) find that close proximity to wind turbines (within 0.5 miles) reduces property values in 2 of the 3 counties by between 6 and 10%.[3] Most recently, using data on wind turbines and home values in Massachusetts and Rhode Island, Dong, Gaur and Lang (2023) find that properties within 1 km of a wind turbine decrease in value by approximately 2.5%–4.6% after construction relative to properties 3–10 km away.

While the majority of U.S. studies have found small negative and insignificant effects of proximity to wind turbines on property values, the evidence from studies that use data from European countries typically finds that proximity to wind turbines reduces residential property values. For example, using data from Denmark, Jensen et al. (2014) estimate that homes where residents can see a turbine decline in value by 3%, and these homes decline by an additional 2% if residents can hear the turbines when compared to those properties outside of visible or auditory range. They also find effects fade as distance increases. Gibbons (2015) finds that English and Welsh homes with a visible wind energy project within 2 km experience approximately a 5%–6% decline in value relative to homes without a view and those located farther away. From the Netherlands and using a difference-in-differences identification strategy, Dröes and Koster (2016) find a 1.4% reduction in home prices for homes located within 2 km of a wind turbine with the effects being larger for homes located near turbines in urban areas and for larger turbines. Similarly, using data from Germany, Sunak and Madlener (2016) and Sunak and Madlener (2017) find that turbine visibility and close proximity to wind turbines reduces residential home values by approximately 9%–20% respectively. More recently, Jensen et al. (2018), Dröes and Koster (2021) and Eichholtz et al. (2023), using data from Denmark, the Netherlands, respectively, find that close proximity to wind turbines reduces residential property values by between 3%, 6% and 7%.[4]

A number of studies have found evidence of negative anticipatory effects on housing values, which begin after the announcement of the wind project and continue through operation rather than manifesting when construction begins (e.g., Dröes and Koster, 2016; Jarvis, 2021; Dong et al., 2023). Furthermore, some studies find that post project construction, housing values rebound to levels existing prior to the project's announcement (Dong et al., 2023).[5]

The stark difference in findings between studies conducted in the U. S. and those conducted in Europe raises an important question: why do European studies nearly universally find that wind turbines reduce residential property values (and in many cases by a considerable magnitude), while studies from the U.S. typically find small and statistically insignificant effects? While the existing literature provides no definitive answer to that question, there are several possibilities. First, the population density of Europe is approximately 3.5 times higher than that of the U.S. Furthermore, that figure represents average population density and most wind turbines in the U.S. are located in the less densely populated areas of the Midwest and Southwest. Thus, it is simply harder to site wind turbines farther away from residential locations in Europe than in the U.S. Second, and relatedly, European studies tend to have significantly more residential sale transactions in close proximity to a wind turbine. For example, Dröes and Koster (2016) observe 149,939 transactions within 2 km of a wind turbine while in the largest U.S. study to date, Hoen et al. (2015) observe approximately 1200 homes within 1 mile of a turbine.

As noted above, previous U.S. studies of the impact of wind turbines on residential property values contained a relatively small number of residential sales transactions within close proximity to turbines. That is not surprising given that most U.S. studies were published between 2012 and 2016. These studies tended to use data on residential housing transactions from the mid-1990s through, at most, 2015. For example,

[1] For example, a January 2022 poll by the Pew Research Center, finds that 69% of U.S. adults support the expansion of renewable energy installations such as wind and solar.

[2] Numerous studies have examined the potential health effects associated with living in close proximity to wind turbines, such as annoyance, sleep disturbance, anxiety, or depression. The consensus from the more rigorous studies (e.g., Bakker et al., 2012; Michaud et al., 2016, van Kamp and van den Berg, 2021) find links to annoyance but not health outcomes (also reviews by Knopper and Ollson, 2011; Guski et al., 2017; Freiberg et al., 2019). Annoyance has also been found to be correlated with perceptions of the planning process (Hübner et al., 2019; van Kamp and van den Berg, 2021).

[3] In related work, Heintzelman et al. (2017), examine the impact of wind turbines located on Wolfe Island, which straddles the border between New York and Canada, on property values. They find evidence of a negative effect of wind turbines on property values for homes located on the New York side of the border but no effect (and in some specification positive but insignificant effects) of wind turbines on property values for homes located on the Canadian side of the border.

[4] Appendix Table A1 provides a complete list of peer-reviewed studies examining the impact of wind turbines on residential property values along with whether those studies were conducted in the U.S. or Europe and their main finding.

[5] Although differences were not statistically significant, several studies find evidence of more negative effects on housing values in the post-announcement pre-construction period than that in the post-operation period (Hoen et al., 2011, 2015; Lang et al., 2014; Vyn and McCullough, 2014; Hoen and Atkinson-Palombo, 2016).

Hoen et al. (2015), which represents perhaps the most extensive U.S. study to date, utilizes data on residential sale transactions from 1996 to 2011, which, as shown in Fig. 1 predates the time period when wind turbines increasingly began to be sited closer to more densely populated areas. Further, over the last decade commercial wind turbines have grown in size, which likely has increased the visual impacts associated with turbines.[6] Given the trend in the U.S. toward larger wind turbines located closer to areas with great population and more active housing markets over the last 10 years, the purpose of this paper is to revisit the relationship between residential property values and proximity to commercial wind turbines using data on the universe of commercial turbines and residential home transactions in the U.S. between 2005 and 2020. Relative to existing U.S. studies, we observe over 20,000 residential sales transactions within 1 mile of a wind turbine, compared to the approximately 1200 transactions observed by Hoen et al. (2015).

3. Empirical framework

To examine the relationship between proximity to wind turbines and residential property values we utilize a difference-in-differences (DiD) identification strategy that relates the timing of treatment (being close to a wind turbine post the announcement of a wind project) to home prices for homes located [0 to 1], [1 to 2], and [2 to 3] miles away from the closest turbine within a given wind energy project. Specifically, we first created 428 unique datasets, each representing a unique commercial wind project and the residential home transactions that occurred within 5 miles of the project and transacted within 4 years prior to project announcement and 10 years post project announcement. We call each of these unique datasets a "project." We then stacked the 428 projects to create our final analytic dataset and specify a stacked difference-in-differences specification of the following form:

$$ln\left(P_{icdjt}\right) = \beta\, \boldsymbol{D}_{idt} + \boldsymbol{X}_i\alpha + \delta_{dc} + \lambda_{tc} + \varphi_{jc} + \varepsilon_{icdjt}, \tag{1}$$

where $ln(P_{icdjt})$ is the natural log of the sales price of residential home transaction i that belongs to project c within distance bin d and census block group j, that transacted in quarter and year t. D_{idt} is a vector consisting of 3 distance bin indicators for homes located [0 to1], [1 to 2] and [2 to 3] miles from the closest turbine in the wind energy project and where each distance bin is interacted with an indicator for whether the home sale occurred after the announcement of the wind project. The omitted category for the distance bin indicators is homes located 3 to 5 miles from the closest wind turbine in the project. δ_{dc}, λ_{tc} and φ_{jc} are, respectively, distance bin-by-project fixed effects (FEs), transaction quarter-by-year-by-project FEs and census block group-by-project FEs, and ε_{icdjt} is a random disturbance term. Finally, $\boldsymbol{X}_i$ is the vector of individual home characteristics including: parcel size building living area square feet, the age of the building at the time of sale, age squared, the number of stories, bedrooms, and full and half bathrooms, . The standard errors in equation (1) are clustered at the project level, and we use STATA/MP v17 to estimate the regressions and event studies.

The coefficients of primary interest in (1) are the β s which represent the DiD estimates of the effect of treatment (being close to a wind turbine post announcement of the project) on home prices for homes located [0 to1], [1 to 2], and [2 to 3] miles away from the closest wind turbine in a project, respectively. Note that each of the 428 projects represents a unique quasi-experiment where the DiD treatment group is homes located within [0 to1], [1 to 2], and [2 to 3] miles from the closest turbine in a wind project, which is compared to the control group, homes located 3 to 5 miles away, both before and after announcement of the wind project.

The inclusion of distance bin-by-project FEs, δ_{dc} and transaction quarter-by-year-by-project FEs, λ_{tc}, imply that our estimates are identified based only on within project variation in sale prices and distance from a wind turbine. Thus, our coefficients of primary interest, β s, represent the average treatment effect over the 428 quasi-experiments for homes located within each of our specified distance bins. Furthermore, note that the inclusion of quarter-by-year-by-project FEs allows for very localized (project-specific) nonparametric trends in housing prices over time. Finally, our stacked DiD framework avoids the potential biases that can arise in standard DiD and event study models in the presence of staggered timing of treatment with heterogeneous treatment effects. Specifically, several recent studies have shown that DiD specifications relying on the staggered timing of treatment for identification may be biased in the presence of heterogeneous treatment effects due to the contamination of treatment effects from early versus later adopters from other relative time periods (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). As discussed by Cengiz et al. (2019) and Goodman-Bacon (2021) our stacked DiD model avoids this potential source of bias by ensuring that treatment effects are based only on within project comparisons.

To examine the evolution of property values over time, we complement the DiD model with an event-study model of the following form:

$$ln\left(P_{icdjt}\right) = \sum_{k=-4}^{10} \boldsymbol{T}_{k,idt}\gamma_k + \boldsymbol{X}_i\alpha + \delta_{dc} + \lambda_{tc} + \varphi_{jc} + \eta_{icdjt}, \tag{2}$$

where $\boldsymbol{T}_{k,idt}$ represents a series of lead and lag indicators for when a wind energy project is announced for each of the three distance bins, η_{icdjt} is a random disturbance term and all other terms are as defined in equation (1). We re-centered $T_{k,idt}$ so that $T_{0,idt}$ always equals one in the year a project was announced. We included a series of indicators from 2 to 4 years prior to a project being announced ($T_{-4,idt}$ to $T_{-2,idt}$), and a series of indicators for the year the project was announced and 1–10 years after announcement ($T_{0,idt}$ to $T_{10,idt}$). Note that $\boldsymbol{T}_{k,idt}$ is a vector consisting of 14 indicators for the four years prior to a wind project being announced and the ten years after announcement for each of the three distance bins outlined in equation (1). Thus, $\boldsymbol{T}_{k,idt}$ includes 42 indicators all together (14 temporal indicators for each of the three distance bins). The omitted category for our treatment indicators (i.e., the reference year for all estimates) is the year prior to the announcement of a project ($T_{-1,idt}$).

The coefficients of primary interest in equation (2) are the $\gamma_k^{'}s$. The estimated coefficients on the lead treatment indicators (γ_{-4} to γ_{-2}) indicate whether the parallel trends assumption appears to hold. Specifically, if wind turbines induce exogenous changes in home values, these lead treatment indicators should be small in magnitude and statistically insignificant, implying that the price of homes located close to a turbine (within 1, 2 or 3 miles) were trending in a similar way to homes located farther away (3–5 miles) prior to the announcement of a wind energy project. The lagged treatment indicators ($\gamma_1, \ldots, \gamma_{10}$) allow the effect of distance to a wind turbine on home prices to evolve nonparametrically over time in the post treatment period.

4. Data

We construct an original dataset that combines data on the universe of residential property transactions from CoreLogic with data from the U.S. Wind Turbine Database (USWTDB) on the timing and exact location of the universe of wind energy installations and turbines in the U.S. from 2005 to 2020. The complete CoreLogic housing transaction data consists of over 260 million residential property transactions in the United States from January 2005 to December 2020 and contains property-level characteristics including address, latitude-longitude coordinates, property type, and many property characteristics (e.g., living area, number of

[6] According to the U.S. Office of Energy Efficiency & Renewable Energy, the hub height of commercial wind turbines has increased 66% since 2000 from approximately 190 feet–322 feet in 2021. Furthermore, the diameter of turbine rotor blades has also increased substantially, up 104% since 1999 to 432 feet (Wiser et al., 2023).

bedrooms, baths, etc.), as well as transaction-specific data, including sale amount and sale date for each transaction.

The USWTDB provides information on the universe of land-based and offshore wind turbines in the United States including the year each wind turbine became operational, the installed capacity of each turbine measured in kilowatts (kW), turbine technical specifications, and the latitude and longitude of each turbine which we use to geocode each property transaction to the nearest utility-scale wind turbine.

We restrict the property transaction data in several ways. First, we restrict the sample to property transactions within 5 miles of the nearest utility-scale turbine (i.e., greater than 600 kW). We further restrict the sample to arm's length transactions of residential properties that had complete information on their sale date and sale amount along with several other restrictions that are detailed in Appendix Table A2. Finally, we restrict the sample by removing transactions that do not contribute to our identification strategy due to insufficient observations within our distance bins. Our final analytic sample consists of 428 unique wind projects, across 34 states, and 496,054 transactions that occurred within 5 miles of a utility-scale turbine.

Fig. 2 illustrates the density of housing transactions in each of our pre-specified distance bins. The majority of these transactions are in our control group—homes located greater than 3 miles but within 5 miles of a turbine. We have approximately 20,000 transactions within 1 mile of a turbine, 61,000 transactions greater than 1 mile but within 2 miles of the nearest turbine, and over 90,000 transactions greater than 2 miles but within 3 miles of the nearest turbine. As noted above, we treat each of our 428 wind projects in our sample as unique quasi-experiments. Appendix Figure A2, provides an example of one such project in Herkimer County, New York.

In Table 1, we provide descriptive statistics on the full sample (Column 1), transactions within 3 miles (Column 2), and the control group (Column 3), and, in Table 2, we conduct a series of balancing tests that compare the characteristics of homes located within three miles of a utility-scale turbine to homes located 3 to 5 miles from the nearest turbine. Specifically, we regress the pre-determined characteristics of homes on an indicator that takes the value one if the transaction occurred within 3 miles of a turbine, and we include census block group, transaction quarter-by-year, and project fixed effects. We cluster standard errors at the project level. As shown in Table 2 the treatment and control sample display remarkable balance: none of the property characteristics of homes located within 3 miles of the nearest turbine (treatment group) are statistically different from the characteristics of homes located 3 to 5 miles from the nearest turbine (control group).

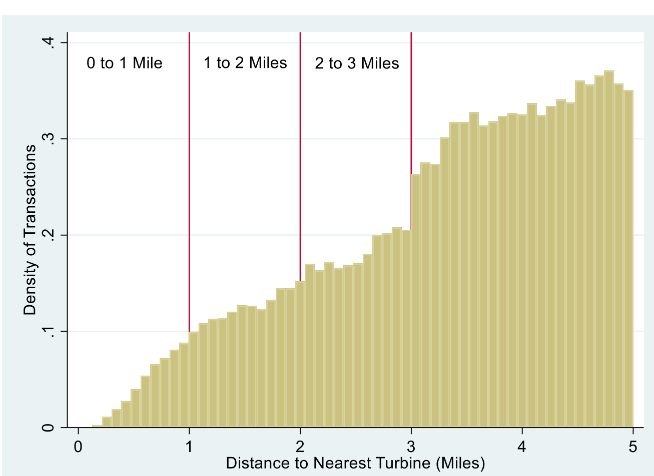

Fig. 2. Density of Transactions within 5 miles of a Turbine
Notes: Figure presents the density of housing transactions within our three main distance bins of [0, 1], [1, 2] and [2, 3] miles from the nearest wind turbine and transactions in our control group consisting of homes located [3, 5] miles from the nearest turbine.

Table 1
Descriptive statistics.

	Full Sample	Within 3 Miles	Greater than 3
Parcel Size (Acres)	0.43	0.44	0.43
	[1.32]	[1.25]	[1.35]
Building Square Feet	1817.56	1792.96	1830.67
	[1171.48]	[1012.17]	[1247.88]
Age of Building	54.72	59.81	52.01
	[37.53]	[39.71]	[36.02]
Number of Stories	1.54	1.58	1.52
	[0.58]	[0.57]	[0.58]
Number of Bedrooms	3.39	3.40	3.39
	[1.43]	[1.44]	[1.43]
Number of Full Baths	1.82	1.79	1.84
	[0.99]	[0.97]	[1.00]
Number of Half Baths	1.08	1.08	1.07
	[0.69]	[0.39]	[0.80]
Adjusted Sale Price ($)	186,050	178,774	189,927
	[169,734]	[167,709]	[170,677]
Total Transactions	496,054	172,423	323,631

Notes: Table presents summary statistics for housing transactions where Column 1 presents summary statistics for the full sample, column 2 presents summary statistics for homes located within 3 miles (being close to a wind turbine), and column 3 presents summary statistics for the control sample of homes located 3 to 5 miles from the nearest turbine.

In Table 3, we present results similar to those reported in Table 2 except we now include separate indicators for homes within 1 mile, homes located greater than 1 but within 2 miles, and homes located greater than 2 but within 3 miles of the nearest turbine. We find that 3 of these balancing tests (out of 24) are statistically significant at the 10%-level or less. Two of these tests (on the number of half baths) are small in magnitude (~0.1 fewer half-baths), and 2 of the 3 tests are on the "1 to 2 miles" indicator. Overall, based on the results in Tables 2 and 3, we find relatively little evidence of meaningful differences between transactions within 3 miles of the nearest turbine (treatment group) and those between 3 and 5 miles of the nearest turbine (control group), which provides us with further confidence that our identification strategy can isolate the causal impact of proximity to a wind turbine on housing values.

5. Results

5.1. Event study estimates

We begin by presenting the impact of proximity to a utility-scale wind turbine on property values by plotting the estimated $\gamma_k^{'}s$ and associated 90% and 95% confidence intervals from our event study specification given by Equation (2). For ease of presentation, and to clearly visualize the dynamic treatment effects for home sales in each respective distance bin, we present separate event study estimates for each of our three treatment distance bins ([0 to1], [1 to 2] and [2 to 3] miles from the closest turbine) in Figs. 3–5 respectively. We note however, that the estimates reported in Figs. 3–5 are all from the same regression model given by Equation (2).

Fig. 3 presents event study estimates for homes within 1 mile of the closest turbine and reveals important dynamics in the effect of wind turbines on home values. Immediately following the announcement of a wind energy project, property values begin to decline, falling by approximately 15% two years after the announcement and remaining depressed until project construction is generally complete (approximately 4 years after announcement). Following the beginning of operation of a wind project, property values begin to stabilize and then rise. Nine years or more after the announcement of the project (i.e., 5 years after the project begins operating), any impact of wind turbines on property values becomes relatively small (~2%) and statistically insignificant. Thus overall, Fig. 3 reveals a measurable, but ephemeral,

Table 2
Balance tests on unit-level characteristics with fixed effects.

	Adjusted Sale Price ($)	Parcel Size (Acres)	Building Square Feet	Age of Building	Number of Stories	Number of Bedrooms	Number of Full Baths	Number of Half Baths
Within Distance (=1 if < 3 miles)	-5162	0.0539	-21.0369	0.0639	0.0005	0.0096	0.0104	-0.0179
	(4948)	(0.057)	(29.75)	(1.242)	(0.022)	(0.031)	(0.032)	(0.017)
Control Mean	$189,927	0.425	1830.67	52.01	1.52	3.40	1.84	1.72

Notes: This table presents balancing tests for housing transaction attributes. Each column represents a separate regression where the listed housing attribute is regressed on an indicator that equals one if the housing unit is within 3 miles of the nearest wind turbine. All specifications include census block group fixed effects, sale year-quarter fixed effects, and project fixed effects. Robust standard errors in parentheses, clustered at the project level.

Table 3
Balance tests within distance bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Adjusted Sale Price ($)	Parcel Size (Acres)	Building Square Feet	Age of Building	Number of Stories	Number of Bedrooms	Number of Full Baths	Number of Half Baths
0 to 1 Mile	3086	-0.0820	-46.9664	2.0015	0.0258	-0.0006	0.0027	-0.0948*
(tx1)	(8891)	(0.2700)	(60.1986)	(4.2381)	(0.0371)	(0.0732)	(0.0739)	(0.0488)
1 to 2 Miles	-5782	0.4324*	-49.9998	-2.3200	-0.0202	-0.0666	-0.0057	-0.1034**
(tx2)	(5676)	(0.2580)	(45.9568)	(2.9173)	(0.0300)	(0.0488)	(0.0456)	(0.0424)
2 to 3 Miles	-5376	-0.0033	-14.7521	0.5499	0.0049	0.0302	0.0111	0.0043
(tx3)	(5343)	(0.0465)	(32.7739)	(1.2786)	(0.0223)	(0.0345)	(0.0357)	(0.0167)
Control Mean	$189,927	0.425	1830.67	52.01	1.52	3.40	1.84	1.72

Notes: Table presents balancing tests for housing transaction attributes. Each column and row represents a separate regression where the listed housing attribute is regressed on an indicator that equals one if the housing unit is within 1 mile (Panel 1), 1 to 2 miles (Panel B) or 2 to 3 miles (Panel C) of the nearest wind turbine. All specifications include census block group fixed effects, sale year-quarter fixed effects, and project fixed effects. Robust standard errors in parentheses, clustered at the project level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

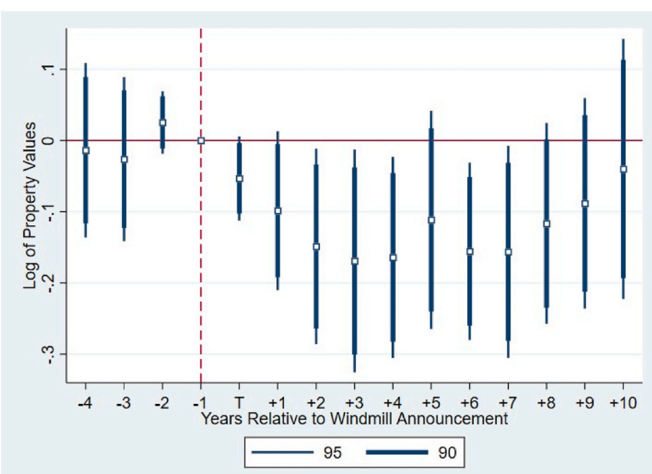

Fig. 3. Stacked Event Study Estimates for Homes located within 0–1 Miles of a Turbine
Notes: Figure presents estimated coefficients from the stacked event study specification given by Equation (2). Estimates are for home located within 1 mile of the nearest wind turbine. Specification includes distance-bin-by-project, census-block-group-by-project, and quarter-by-year-by-project fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

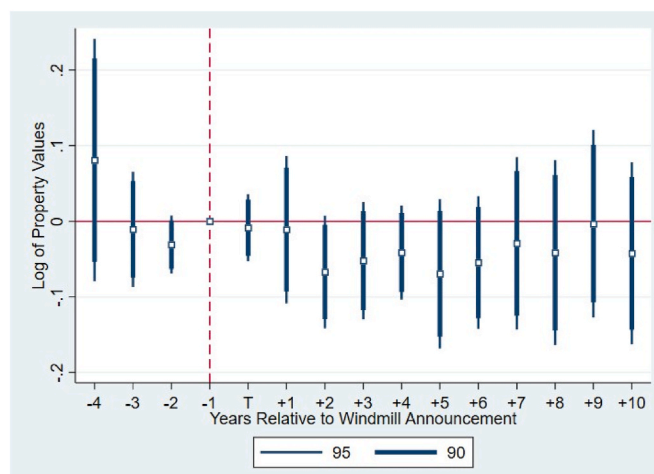

Fig. 4. Stacked Event Study Estimates for homes located within 1–2 Miles of a Turbine
Notes: Figure presents estimated coefficients from the stacked event study specification given by Equation (2). Estimates are for home located within 1–2 miles of the nearest wind turbine. Specification includes distance-bin-by-project, census-block-group-by-project, and quarter-by-year-by-project fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

negative impact of wind turbines on property values following announcement of a wind project for properties within a mile of the turbine. Importantly, Fig. 3 provides little evidence that property values within 1 mile of a turbine were trending either higher or lower relative to property values 3 to 5 miles from a turbine prior to the announcement of a wind project: the estimated coefficients on two, three, or four years prior to announcement indicators are small in magnitude and close to zero.

Figs. 4 and 5 present event study estimates for homes located more than 1 mile but within 2 miles of a turbine and homes located more than

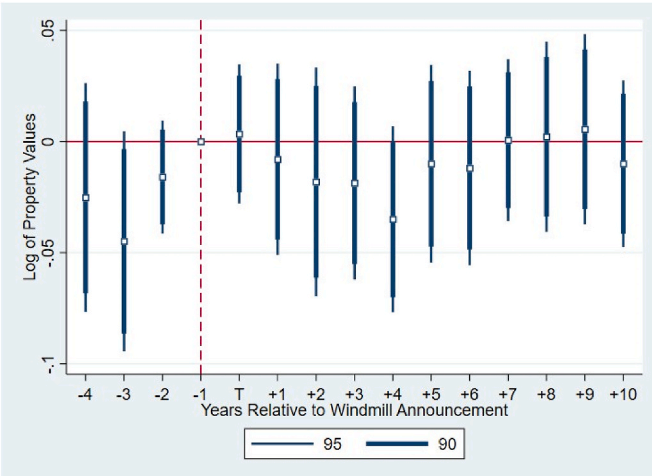

Fig. 5. Stacked Event Study Estimate for homes located 2 to 3 Miles of a Turbine
Notes: Figure presents estimated coefficients from the stacked event study specification given by Equation (2). Estimates are for home located within 2–3 mile of the nearest wind turbine. Specification includes distance-bin-by-project, census-block-group-by-project, and quarter-by-year-by-project fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2 miles but within 3 miles of a turbine, respectively. For homes located within 1–2 miles of a turbine (Fig. 4), the estimated treatment effects follow a similar pattern to those shown in Fig. 3, except the estimated treatment effects post project announcement are much smaller in magnitude and noisier. Specifically, 2–5 years post project announcement, property values decline by approximately 6 percent but then begin to rebound 6–10 years post announcement. Furthermore, we once again find no evidence of pre-trending prior to the announcement of a wind project. In contrast, for homes located 2 to 3 miles from the nearest turbine (Fig. 5), there is some evidence of a small decline in property values (~3%) 2–4 years post project announcement but in general we see no meaningful pattern in the estimated treatment effects and very few of the coefficients are economically meaningful (coefficients are between −0.04 and 0.00) or statistically significantly different from zero.

We test the robustness of all our stacked DiD event study estimates using an alternative event study estimator developed by Sun and Abraham (2021), which is also free from contamination and bias that may arise in event study models with staggered timing of treatment and heterogeneous treatment effects. We report these event studies in Appendix Figure A3 through A5, and they are substantively and economically similar to our main event studies.

5.2. Difference-in-differences estimates

In Table 4, we present DiD estimates based on Equation (1). All specifications in Table 4 include our core fixed effect structure, namely distance-bin-by-project fixed effects and transaction quarter-by-year-by-project fixed effects. The estimates represent the average treatment effect after project announcement, through construction and into project operation. Columns 1–8 then present estimated treatment effects based on specifications with and without controls and with different locational fixed effects. Specifically, columns 1 and 2 present estimated treatment effects with and without controls from specifications that include census-tract fixed effects. Columns 3 and 4 replace the census tract fixed effects with census-tract-by-project fixed effects. Finally, columns 5 and 6 replace the census tract fixed effects in columns 1 and 2 with census block group fixed effects while columns 7 and 8 report results from our preferred specification which replaces the block group fixed effects with block-group-by-project fixed effects.

We begin by noting that the estimated treatment effects reported in Table 4 are remarkably robust regardless of the locational fixed effects we employ or whether or not we include controls: none of the estimated coefficients for each distance bin are statistically different from one another across each specification. While the coefficient on the "1–2 mile" indicator oscillates between being marginally statistically significant (in Columns 1–5 and 7) and statistically insignificant (in Columns 6 and 8), the magnitudes of the coefficients are all similar, i.e., varying between 3.06% and 4.36%. The "0–1 mile" indicator remains highly statistically significant and large in magnitude regardless of the specification. Moreover, the fact that the estimates reported in Table 4 are insensitive to the inclusion or exclusion of a host of controls for the physical characteristics of homes, provides further evidence that our event study and DiD estimates have a causal interpretation and that our identification strategy mimics a randomized control trial. Nevertheless, given the potential precision gains from including controls, our preferred specification includes the full set of controls for the attributes of transacted properties.

We present the results of our preferred specification from Equation (1) in Column 8. On average the announcement, construction and operation of a wind project causes a 10.91% decline in property values for homes that are within one mile of the nearest turbine. This is a meaningful, though as noted above, ephemeral, decline following project announcement. For homes located within 1–2 miles from the nearest turbine, we find a statistically insignificant 3.06% decline in sales price, which is approximately one-third the size of the impact on homes within one mile of the turbine. This suggests that the negative effects of proximity to turbines on home values dissipates rather quickly with distance. Consistent with that notion, for homes located 2 to 3 miles from the nearest turbine, we consistently find no negative impacts on home values—all the estimated coefficients are positive in sign but small in magnitude and statistically insignificant.[7]

Using our preferred specification, rather than using a somewhat arbitrary bandwidth of one mile, we estimate the impact of a wind turbines on home values using quarter-mile distance bins, and we plot these coefficients in Fig. 6.[8] Consistent with Table 4, we find that the impact of wind turbines on home values decays quickly with distance. In fact, we find no statistically significant impacts after 1.25 miles. In this figure, the comparison group is properties more than 3.25 miles from the nearest turbine. However, these results are robust to altering the comparison group to properties at least 2.5 miles from a turbine or those greater than 4 miles from a turbine. Note that the estimated coefficient on the [0 to 0.5) mile indicator bin is negative but statistically insignificant, likely because there are very few transactions within 0.5 miles of a turbine (hence the large standard errors).

5.3. Falsification tests, Robustness Checks, and heterogeneity analysis

To provide further evidence that our core results have a causal interpretation, we conduct a falsification test in which we randomly assign placebo wind energy projects to the centroid of census tracts located in counties *without* wind energy projects but with wind speeds

[7] Although not included in this paper for reasons of brevity we estimated effects within 1 mile of homes in four separate U.S. Census designated regions—the Northeast, Midwest, South, and West, finding similar temporal trends as the full sample but insignificant differences between the regions. These results are available upon request.

[8] Given the relatively few observations between 0 and 0.25 miles that are not properties that directly host wind turbines, we aggregate 0 to 0.5 miles together. The remaining indicators are quarter-mile bins.

Table 4
Main effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price
0 to 1 Mile (tx1)	-0.1288***	-0.1267***	-0.1283***	-0.1270***	-0.1120***	-0.1101***	-0.1102***	-0.1091***
	(0.0389)	(0.0406)	(0.0368)	(0.0383)	(0.0367)	(0.0390)	(0.0367)	(0.0388)
1 to 2 Miles (tx2)	-0.0436*	-0.0400*	-0.0423*	-0.0400*	-0.0382**	-0.0305	-0.0383**	-0.0306
	(0.0233)	(0.0241)	(0.0224)	(0.0231)	(0.0192)	(0.0204)	(0.0191)	(0.0203)
2 to 3 Miles (tx3)	0.0187	0.0152	0.0173	0.0134	0.0180	0.0141	0.0177	0.0138
	(0.0232)	(0.0223)	(0.0220)	(0.0211)	(0.0197)	(0.0180)	(0.0196)	(0.0179)
Observations	479,841	479,841	475,607	475,607	496,215	496,215	496,054	496,054
R-squared	0.7952	0.8255	0.8072	0.8337	0.7188	0.7781	0.7193	0.7784
Distance Bin-Project FE	Y	Y	Y	Y	Y	Y	Y	Y
Tract FE	Y	Y	N	N	N	N	N	N
Tract-by-Project FE	N	N	Y	Y	N	N	N	N
Block Group FE	N	N	N	N	Y	Y	N	N
Block Group-by-Project FE	N	N	N	N	N	N	Y	Y
Year-Quarter-by-Project FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y

Notes: Table presents estimates or the impact of proximity to wind turbines on housing values based on Equation (1). All specifications include distance-bin-by-project fixed effects and year-by-quarter-by-project fixed effects. Specifications with controls include the full list of housing attributes reported in Table 1. Robust standard errors in parentheses, clustered at the project level. ***p < 0.01, **p < 0.05, *p < 0.1.

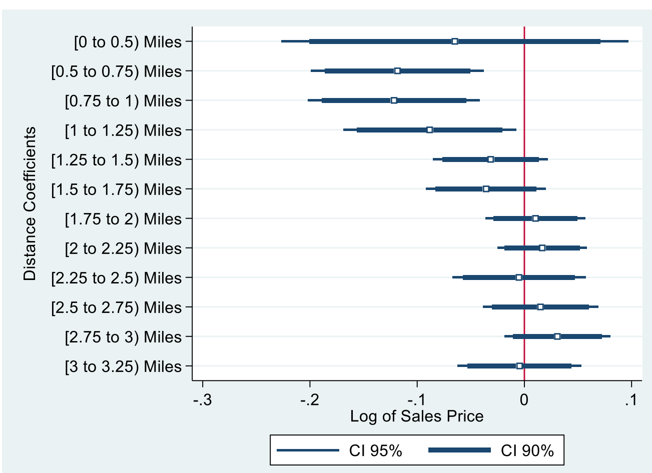

Fig. 6. Differences in Treatment Effect by Bin Distance
Notes: Figure presents estimated coefficients from a version of Equation (1) where we include indicator terms by the half-mile rather than the one-mile indicators presented in Equation (1). The specification includes distance-bin-by-project, census-block-group-by-project, quarter-by-year-by-project fixed effects, and control. The thin part of the blue lines denotes the 95% confidence interval, and the thicker part of the blue lines denotes the 90% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

and other characteristics that resemble counties with wind energy ("the matched sample"). Specifically, we first identify a sample of comparison counties, or counties that observationally resemble counties with wind projects, measured by socio-demographics and wind capacity, using propensity score matching. We use data on county income and demographic characteristics from the 2000 U.S. Decennial Census and measures of average county wind speed to estimate a propensity score using a nearest neighbor matching algorithm without replacement. We include controls for wind speed, wind speed squared, household income, population density, percent college educated, fraction homeowner, and share non-white. We exclude counties that have installed wind projects prior to 2005 from the falsification exercise.

We randomly sample census tracts from the matched sample and randomly assign project announcement dates to these placebo wind energy projects from the probability distribution function of announcement dates we observe in our analytic sample. We then re-estimate our DiD models 1100 times and plot the estimated coefficients, as well as the lower and the upper bounds of a 95% confidence interval for each coefficient, in Fig. 7 through 9. In Fig. 7, we see that our estimated effect from Table 4 for transactions within 1 mile lies significantly to the left of the estimated coefficients from this placebo test, which are normally distributed around zero. For transactions within 1–2 miles of a turbine, the estimated treatment effect from Table 4 is once again in the left tail of the distribution of estimated coefficients, while

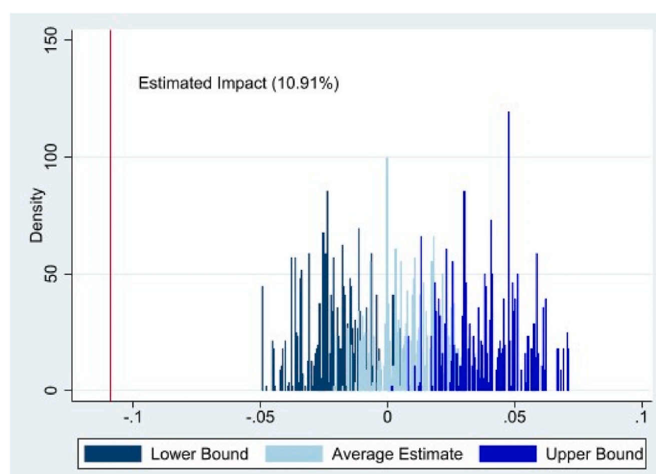

Fig. 7. Falsification Tests for within 1 Mile (N = 1100)
Notes: Figure presents estimates from falsification tests where we randomly assign pseudo wind energy projects to the centroid of census tracts located in counties without wind energy projects and randomly draw from the empirical distribution of actual project start dates. Red line depicts actual treatment effect estimate from column 8 of Table 4 for homes located within one mile of the nearest wind turbine. The lower bound is the lower bound of the 95% Confidence Interval for each of the average estimates, whereas the upper bound is the upper bound of the 95% Confidence Interval for each average estimate. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

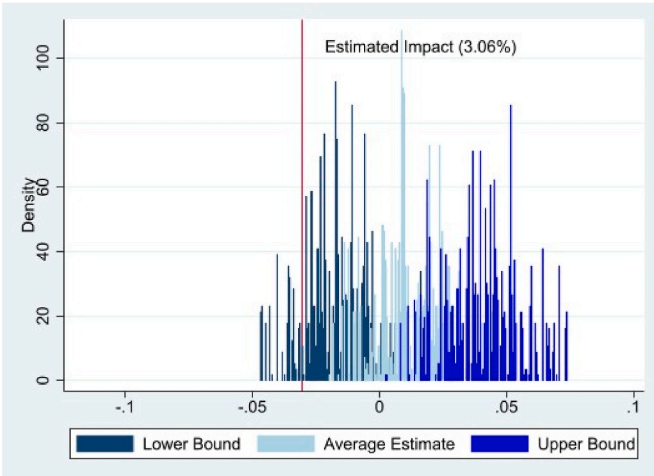

Fig. 8. Falsification Tests for homes located 1 to 2 Miles (N = 1100)
Notes: Figure presents estimates from falsification tests where we randomly assign pseudo wind energy projects to the centroid of census tracts located in counties without wind energy projects and randomly draw from the empirical distribution of actual project start dates. Red line depicts actual treatment effect estimate from column 8 of Table 4 for homes located within 1–2 miles of the nearest wind turbine. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

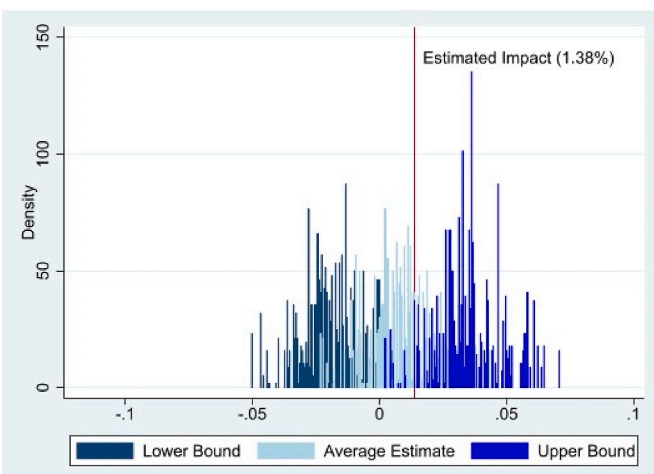

Fig. 9. Falsification Tests for homes located 2 to 3 Miles (N = 1100)
Notes: Figure presents estimates from falsification tests where we randomly assign pseudo wind energy projects to the centroid of census tracts located in counties without wind energy projects and randomly draw from the empirical distribution of actual project start dates. Red line depicts actual treatment effect estimate from column 8 of Table 4 for homes located within 2–3 miles of the nearest wind turbine. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

the estimated effect on homes between 2 and 3 miles from a turbine is within the distribution of the estimated coefficients, consistent with the results in Table 4 showing no impact of turbines on housing values for homes located 2 to 3 miles from the nearest turbine. Overall, the falsification tests provide robust evidence that our estimated impact of proximity to wind turbines on home values is not being driven by chance or idiosyncratic market factors.

As noted previously, we restrict our sample by trimming potential outliers which we define as transactions in the top and bottom percentile of sales amount, land area, or living area, as well as foreclosed properties. Trimming these potential outliers, which some studies define as the top/bottom percentile (see Hoen et al., 2011; Hoen et al., 2015) or the top/bottom 5th percentile (see Dong et al., 2023), is common in the existing literature. Moreover, foreclosed properties frequently sell for below-market rates in non-competitive or non-traditional sales, and thus we drop these observations as well (Mian et al., 2015). To ensure that these sample restrictions are not significantly affecting our analysis, Appendix Table A3 presents the results of our preferred specification (Column 8 of Table 4) for our analytic sample in Column 1, for the full sample with the bottom and top percentile observations and the foreclosed properties included in Column 2, for the sample where we drop the top/bottom percentile observations but include foreclosed properties in Column 3, and for the sample where we drop foreclosures but keep the top/bottom percentile in Column 4. The estimated coefficients are qualitatively, economically, and statistically similar across all samples.

Given results by Dröes and Koster (2016) and Dong et al. (2023), which find greater impacts of wind farms in urban areas, in Columns 1 and 2 of Table 5, we re-estimate equation [1] except we restrict our sample to projects located in counties in metro areas with populations of 250,000 or more. In column 3 and 4, we restrict our sample to projects located in metro counties with a population of less than 250,000 and non-metro counties.[9] Given that our identification strategy requires active housing markets with sufficient number of within-project housing transactions before and after the announcement of a project, 72.3% of our sample is located in highly urban counties with populations greater

Table 5
Results by urbanicity.

	Urban Sample (Counites with Pop ≥250,000)		Non-Urban Sample (Counites with Pop <250,000)	
	(1)	(2)	(3)	(4)
	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price
0 to 1 Mile (tx1)	-0.1471***	-0.1494***	-0.0157	-0.0071
	(0.0407)	(0.0423)	(0.0432)	(0.0473)
1 to 2 Miles (tx2)	-0.0467**	-0.0427*	-0.0099	0.0059
	(0.0231)	(0.0240)	(0.0227)	(0.0185)
2 to 3 Miles (tx3)	0.0134	0.0094	0.0344	0.0324
	(0.0246)	(0.0220)	(0.0233)	(0.0229)
Observations	358,734	358,734	135,874	135,874
R-squared	0.7294	0.7801	0.6020	0.7128
Distance Bin-Project FE	Y	Y	Y	Y
Tract FE	N	N	N	N
Tract-by-Project FE	N	N	N	N
Block Group FE	N	N	N	N
Block Group-by-Project FE	Y	Y	Y	Y
Year-Quarter-by-Project FE	Y	Y	Y	Y
Controls	N	Y	N	Y

Notes: Table presents estimates or the impact of proximity to wind turbines on housing values based on Equation (1) for the sample of transactions located in counties in metro areas with population of 250,000 or more people, i.e., urban-rural continuum 2003 codes of 1 or 2. All specifications include distance-bin-by-project fixed effects and year-by-quarter-by-project fixed effects. Specifications with controls include the full list of housing attributes reported in Table 1. Robust standard errors in parentheses, clustered at the project level. ***p < 0.01, **p < 0.05, *p < 0.1.

[9] Specifically, we restrict our sample to counties with a 2003 urban-rural continuum classification of "1," which is "county in metro area with 1 million population or more" and "2", or a "county in a metro area of 250,000 to 1 million population." These urban-rural continuum codes are available from the Economic Research Services at the U.S. Department of Agriculture.

than 250,000. We find that our results are entirely driven by this urban sample. As shown in Columns 1 and 2, on average the announcement, construction, and operation of a wind project in an urban county causes a 14.94% decline in property values for homes that are within one mile of the nearest turbine. We also find a marginally statistically significant decline of 4.27% for homes located within 1–2 miles from the nearest turbine. We continue to find no impact on properties beyond 2 miles. In Fig. 10, we examine differences in treatment effects by quarter-mile distance bins, and we find statistically significant and negative effects of wind turbine announcement, construction, and operation on homes within 1.5 miles but no measurable impact beyond that distance.[10] The estimated effects of proximity to turbines in less urban and non-metro counties (Columns 3 and 4 of Table 5) are near zero and statistically insignificant. These results are similar (i.e., much smaller than the highly urban sample and statistically insignificant) if we restrict exclusively to non-metro counties that have an urban population of 20,000 people or fewer. Overall, these results suggest that the negative effects of proximity to turbines on home values dissipate quickly with distance, and most of these negative effects are driven by transactions in urban areas.

6. Conclusion and policy implications

Over the past 40 years, wind energy in the United States has grown from a relatively novel energy source in rural counties in the plains of North Dakota and the deserts of Southern California to now representing almost 40% of all new commercial energy installations in the United States (United States Energy Information Administration, 2022). This trend is expected to continue, with over 15 GW (GW) of land-based wind energy projects currently under construction, 9 GW in advanced development stages, and more than 170 GW of land-based wind projects with active grid interconnection requests across the U.S at the end of 2022 (ACP, 2022; Rand et al., 2022). As wind energy has become an increasingly common energy source, wind turbines have, by extension, been sited increasingly closer to more populated areas and in proximity to more residential homes. While previous research examining the impact of wind turbines on property values in the United States has generally found small and statistically insignificant impacts of wind turbines on home prices (see Appendix Table A1), these studies have examined wind projects in relatively rural areas with comparatively fewer homes sales proximate to the wind turbines. Given the increasing encroachment of wind projects on residential areas, this study revisits this question using the most comprehensive dataset to date on wind turbines and nearby home sales.

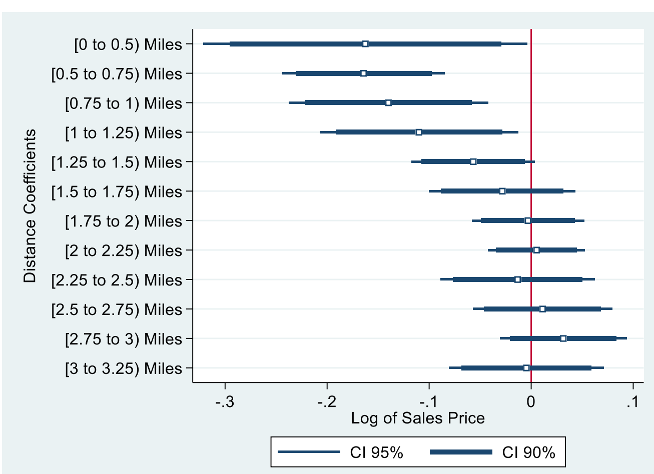

Fig. 10. Differences in Treatment Effect by Bin Distance for Urban Counties
Notes: Figure presents estimates from equation [1] for transactions belonging to wind project constructed in urban counties with populations greater than 250,000. This urban classification is based on 2003 Rural-Urban Continuum Codes available from the Economic Research Services at the U.S. Department of Agriculture. The Urban restriction in this figure are counties with a "1" or "2" urban classification. The thin part of the lines is the edge of the 95% confidence interval, and the thicker part of the lines are the 90% confidence interval.

We find that homes located within one mile of a commercial wind turbine experience on average approximately an 11% decline in value following the announcement of a new commercial wind energy project, relative to counterfactual homes located 3 to 5 miles away. This impact is dynamic —it is largely driven by declines in sale prices following the announcement and during the construction of a wind project. Once a wind project becomes operational, home prices tend to rise with property value impacts becoming small and statistically insignificant 9 years or more after the announcement of the project (about 5 years after project operation). This suggests that the housing market is reacting negatively to the expectation of likely impacts (after announcement) and the heightened activity during construction, but after operation begins, those negative perceptions and related home price impacts appear to fade. These results align with previous hedonic analysis (Dong et al., 2023) and qualitative research finding that attitudes toward wind projects are the most negative after announcement yet prior to operation (Devine-Wright, 2005; Ellis et al., 2023), which might be capitalized into home values, at least in some cases (Mills et al., 2019). It also might be explained by sorting (Tiebout, 1956), as individuals with more favorable attitudes toward the wind project move into the area, which has been found elsewhere (Hoen et al., 2019). Finally, a third possibility is that, during the pre-construction period, the actual (i.e., long-term) impacts to home prices cannot be determined because the turbines are not yet constructed and operational, so home buyers are internalizing that risk with lower offers.

We find the negative capitalization effect is localized to homes proximate to the wind projects and any negative effects decay quickly beyond 1.25 miles and these results are driven primarily by projects in highly urban counties, i.e., counties with a population greater than 250,000 people. What is unique about projects or the neighbors of those projects in counties with higher population densities? Wind projects are not located in urban areas, but, in these counties, might be nearer to then, i.e., in the urban fringe. We find in our own sample they have, on average, fewer turbines than the projects in more rural counties, indicating they have less land area to fit into. It might be the case that landowners who live in these urban fringe areas place greater value on the aesthetic qualities of the land than those who live in more rural areas, and therefore are averse to changes to those qualities (see Janhunen et al., 2014; Devine-Wright, 2009; Bessette and Mills, 2021).

We find the declines in property values induced by a wind project are borne by a geographically identifiable group of residents, suggesting policy mechanisms may exist to remedy these impacts.[11] Brunner et al. (2022) and Brunner and Schwegman (2022a), demonstrate that wind energy installations lead to significant increases in local government revenues due to the property tax payments and payments in lieu of taxes

[10] In results available upon request, we examine potential heterogeneity in our average treatment effects by size or scale of wind energy projects, the height of the turbines, and by population and housing density. We find no evidence that the impact of wind turbines on property values varies by the size of wind projects, whether measured by number of turbines or nameplate capacity, the height of the turbines, or the density of the local area.

[11] Further, property value impacts represent a potential distributive injustice, where the neighbors of a project are being disproportionately burdened as compared to homes further away from the project (Schlosberg, 2007; Jørgensen et al., 2020), though, Dong et al. (2023) theorize those impacted are more affluent.

that wind energy developers pay. One possible way to compensate homeowners located near a wind energy installation would be to provide them with a property tax abatement for a period after announcement and continuing for a period of years after operation begins, funded with the revenue generated from the wind project, that might offset any reduction in the value of their homes. Alternatively, compensation could be offered by developers directly to homeowners during this period as suggested by others (Jacquet, 2012; Walker et al., 2014; Garcia et al., 2016; Fast et al., 2016).[12]

On the other hand, because effects are found to begin prior to construction (and then fade), and therefore logically represent the pricing of future risk into the market (that is later not fully realized), possibly better efforts to describe the actual effects on communities can be employed. For example, simulations of the future views of turbines from individual homes are rarely, if ever, available. Instead, photo simulations from a relatively small set of prominent viewpoints in communities are provided, and, therefore, home buyers and sellers are left to speculate what views of turbines from their homes might look like. Similarly, the sounds of turbines, especially those at night when the background sounds dissipate (Müller et al., 2023), are not ever simulated at individual home locations, though they are often regulated at those locations (Haac et al., 2019). Providing views, both day and night, from many more viewpoints including homes throughout the community, and simulated sounds from different locations, might help to alleviate the practice of pricing in this risk. Opportunities for individuals to visit nearby projects and talk to existing homeowners near those projects might additionally help provide greater certainty of actual effects during this period. Finally, much has been written about the connection between local attitudes and perceptions of the planning process (e.g., see review by Rand and Hoen, 2017), and those perceptions and property values (Vyn, 2018). Therefore, if greater efforts are made to improve that process to give local stakeholders more say in the process, property values might be less impacted.

Further, the results of Brunner et al. (2022) and Brunner and Schwegman (2022a) suggest that local jurisdictions use the property tax revenue and PILOTS from wind energy installations to increase spending on public services, reduce property taxes, or both. A large literature starting with Oates (1969) demonstrates that reductions in local taxes and/or increases in public services are capitalized into housing values. Consistent with that notion Brunner and Schwegman (2022a) and Brunner and Schwegman (2022b) find that property values in counties with large wind energy installations tend to rise after the turbines become operational. This suggests another avenue through which wind energy installations may increase the local tax base and hence provide another stream of revenue to compensate homeowners in close proximity to turbines for any property value losses. Because this study compares values of sets of homes all within 5 miles of the same wind project, this capitalization effect, if it exists, would be experienced by all homes in the local jurisdiction. These potential positive effects are, therefore, not exhibited in our results.

Given these results, a number of areas of further research are encouraged. Conducting an analysis where views of turbines are explicitly accounted for would be valuable, building on the previous literature (e.g., Lang et al., 2014; Jensen et al., 2018; Gibbons, 2015; Sunak and Madlener, 2016; Hoen et al., 2011). Further, examining positive impacts wind energy projects might have, such as within school district and county boundaries, would be valuable. Finally, qualitative work, with an attempt to unpack housing preferences among a large set of buyers and sellers, especially those in urban areas, would provide more insight into the largely heterogenous set of findings in this literature and this paper. Combining that with longitudinal data collection would be particularly valuable to further investigate how and why sentiment toward local projects evolves over time in different locations.

CRediT authorship contribution statement

Eric J. Brunner: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. **Ben Hoen:** Conceptualization, Funding acquisition, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Joe Rand:** Software, Data curation. **David Schwegman:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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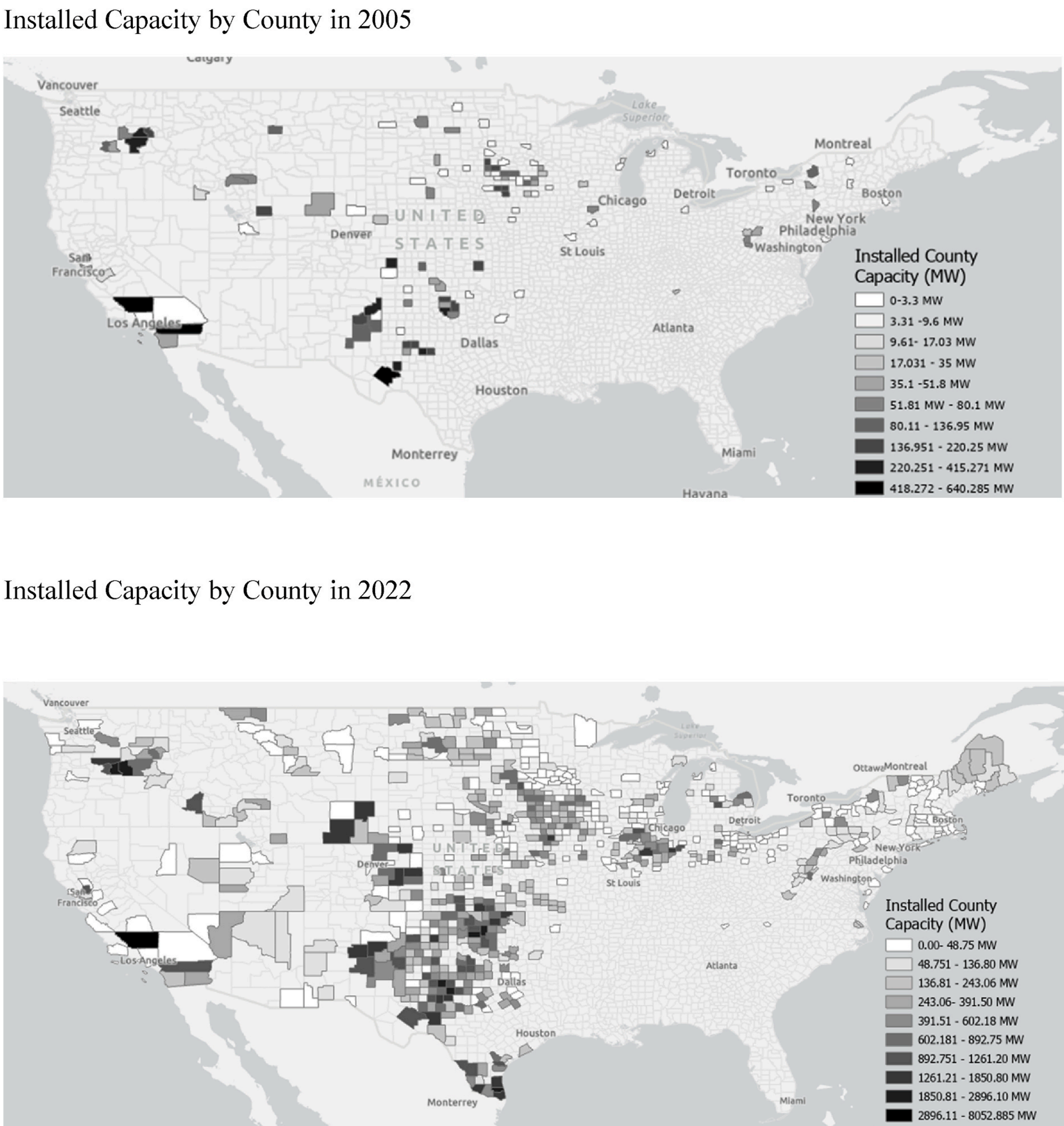
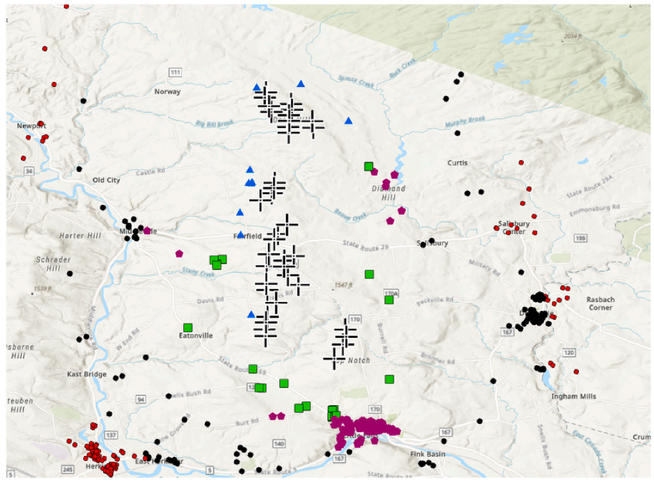
Appendix Figures and Tables

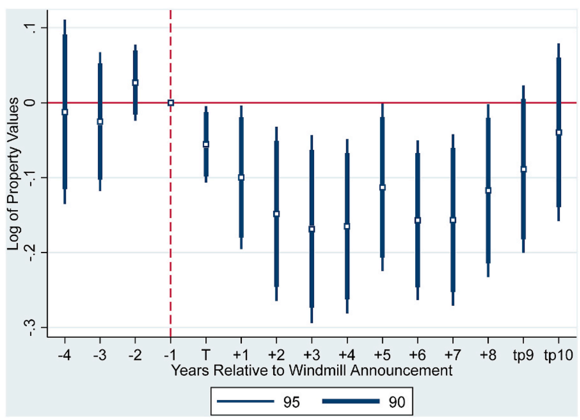
[12] One anonymous reviewer suggested a property value guarantee similar to the one offered in Denmark. Though, this approach has been criticized as not addressing key concerns (Jørgensen et al., 2020) and would require an appraisal of individual properties, which is highly susceptible to spurious results because of the small sample sizes.



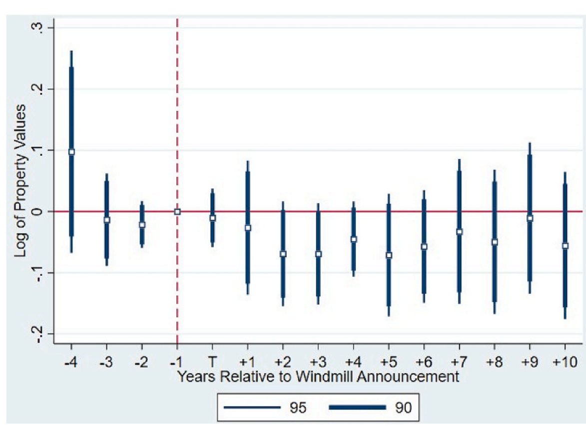
Appendix Fig. A1. County-Level Installed Wind Energy Capacity in 2005 and 2022 (MW).



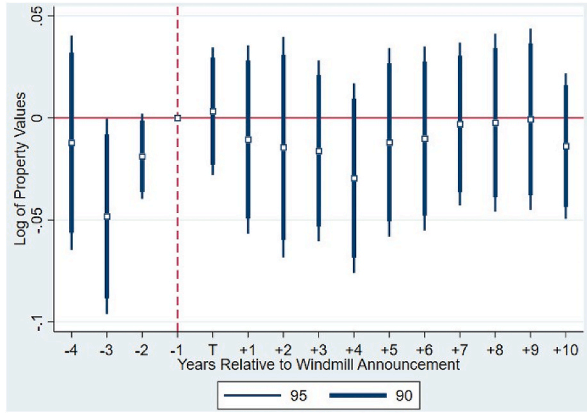
Appendix Fig. A2. Example Project (Herkimer County, New York)
Notes: Figure presents a representative wind energy project from our analytic sample. Black crosses represent wind turbines, blue triangles denote homes located within 1 mile of the nearest wind turbine, homes within 1–2 miles are depicted using green squares, and homes within 2–3 miles are depicted as purple pentagons. Our comparison homes are represented by black dots while transactions greater than 5 miles (excluded observations) are depicted as red dots.



Appendix Fig. A3. Sun and Abraham (2021) Event Study Specification, 0 to 1 Mile
Notes: Figure presents event study estimates based on the estimator developed by Sun and Abraham (2021). Estimates are for homes located within 1 mile of the nearest wind turbine. Specification includes distance bin, census block-group, and quarter-by-year fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals.



Appendix Fig. A4. Sun and Abraham (2021) Event Study Specification, 1 to 2 Mile
Notes: Figure presents event study estimates based on the estimator developed by Sun and Abraham (2021). Estimates are for home located within 1–2 miles of the nearest wind turbine. Specification includes distance bin, census block-group, and quarter-by-year fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals.



Appendix Fig. A5. Sun and Abraham (2021) Event Study Specification, 2 to 3 Mile
Notes: Figure presents event study estimates based on the estimator developed by Sun and Abraham (2021). Estimates are for home located within 2–3 miles of the nearest wind turbine. Specification includes distance bin, census block-group, and quarter-by-year fixed effects. Dotted red line denotes year prior to the announcement of a wind project. The thin vertical blue lines denote the 95% confidence intervals, whereas the thicker vertical blue lines denote the 90% confidence intervals.

Appendix Table A1
Wind Energy Studies
Notes: All studies citations can be found in the reference list. North American studies are in the top panel, while non-North American (primarily European) studies are in the bottom panel. All studies that find a negative impact (or association) between wind projects and home values are colored in red under the findings column. Studies that find no significant impacts or minimal impacts are colored black.

Study	Location	Sample Size (distance)	Findings
		North American Studies	
Grover (2002)	USA	n/a (2-25 miles)	No impact on property assessments
Laposa and Miller (2010)	USA	2,910 (n/a)	Insignificant and minimal impacts
Hoen et al. (2011)	USA	2,500 (0-3 miles); 7,500 (0-5 miles)	No significant impact on property values
Heintzelman and Tuttle (2012)	USA	1,1659 (0-1 mile); 11,331 (0-10 miles)	Significant decline in sale price (-8% - -15% for homes within 1 mile)
Lang et al. (2014)	USA	3,254 (0-1 mile); 48,554 (0-5 miles)	No significant impact on property values
Hoen et al. (2015)	USA	1,198 (0-1 mile); 50,000 (0-10 miles)	No significant impact on property values
Castleberry and Greene (2018)	USA	23,000	No significant impact on property values
Hoen & Atkinson-Palombo (2016)	USA	1,503 (0-1 mile); 122,000 (0-5 miles)	No significant impact on property values
Dong, Gaur, & Lang (2023)	USA	369,260 (0 – 3 KM)	Significant decline in in sales prices (-2.5 to -4.6 % for homes within 2 miles)
Vyn and McCullough (2014)	Canada	32 (0-2km); 106 (0-10 km)	No significant impact on property values (2.5 to 4.6% for homes within 1km)
Vyn (2018)	Canada	Unknown	WTs have negatively impacted property values in “unwilling host” municipalities, while no significant impacts are found in unopposed municipalities.
		Non-North American Studies	
Jensen et al. (2014)	Denmark	12,640 (0-2.5 km)	Significant reduction in sale price (-3% for homes with a view and -6.7% for homes with significant noise exposure)
McCarthy & Balli (2014)	New Zealand	945	No significant impact on property values
Gibbons (2015)	UK	38,000 (0-2 km)	Significant reduction in sale price (-5-6% within 2 km with larger effects for visible areas)
Droes and Koster (2016)	Netherlands	80,000 (0-2 km)	Significant reduction in sale price (-1.4% within 2 km)
Sunak and Madlener (2016)	Germany	2,141 (0-3 km)	Significant reduction in price (-9-14% if turbine visible). No impact if no or marginal view.
Jensen et al. (2018)	Denmark	4,932 (0-3 km)	Significant negative effect to a distance of 3 km.
Droes and Koster (2021)	Netherlands	171,500 (0-2 km)	Large turbines decrease house prices within 2 km by 5.4%.
Jarvis (2021)	UK	~8 million transactions; includes failed wind projects (0-5 km)	The median wind project causes a 4-5% reduction in residential property values at 2km. Effects increase at closer distances and for larger projects.
Sims and Dent (2007)	UK	1,052 (0.5-4 miles)	No significant impact on property values
Sims et al. (2008)	UK	201 (0-0.5 mile)	No significant impact on property values

Appendix Table A2
Retention criteria for transactions

Condition for retention	Rationale
Coordinate values are populated	Coordinates are needed to obtain distances between homes and wind turbines.
Land area, year built, and home square footage are populated	Land area, year built, and home square footage are essential property characteristics to control for in analysis
Coordinates appear 20 times or less	Repeated, identical coordinates for multiple properties may indicate data quality issue

(*continued on next page*)

Appendix Table A2 (*continued*)

Condition for retention	Rationale
Property type is residential (including single family residence, condominium, duplex, apartment)	Analysis only considers homes (i.e. residential properties) sold in arms-length transactions after the year 2000
Transaction is categorized as arms-length	
Year of sale between 2000 and December 2020	
Sale amount is greater than $5000 or the 1st percentile of sale price (whichever value is higher) and less than the 99th percentile of sale amount values within a given state	Removing outliers from analysis
Sale amount per unit area of living space is greater than the 1st percentile and less than the 99th percentile of sale amount per unit area of living space values within a given state	
Land area is greater than the 1st percentile and less than the 99th percentile of land area values within a given state	
Property was built before 2020, and after the 1st percentile of values for year built within a given state	
Sale amount is greater than the mortgage amount, or mortgage amount is missing	Any other relationship (between sale amount & mortgage amount, land area & living space area, sale year & year built, set of variables representing land area) may indicate data quality issues
Land area is greater than living space area	
Age of property (sale year minus year built) is non-negative	
Both variables representing land area converge within 0.01 acres	
Deed is not categorized as foreclosure	Sale amount in a foreclosure may not accurately represent the value of a home
Sale occurred over one year after last recorded sale for that property	Removes potentially "flipped" homes, or homes that undergo a rapid renovation and are re-sold, from dataset; for those homes, characteristics in CoreLogic dataset may not be representative of characteristics after renovation
Property address was not determined from mail	Address determined from mail may reflect the address of an absentee owner, not of the physical property location

Appendix Table A3
Robustness Checks to Sample Restrictions

	(1)	(2)	(3)	(4)
	Log of Sale Price	Log of Sale Price	Log of Sale Price	Log of Sale Price
0 to 1 Mile (tx1)	-0.1091***	-0.1036***	-0.1073***	-0.0978**
	(0.0388)	(0.0380)	(0.0379)	(0.0395)
1 to 2 Miles (tx2)	-0.0306	-0.0239	-0.0329*	-0.0228
	(0.0203)	(0.0226)	(0.0199)	(0.0217)
2 to 3 Miles (tx3)	0.0138	0.0154	0.0123	0.0165
	(0.0179)	(0.0180)	(0.0175)	(0.0184)
Sample	Analysis Sample	Full Sample – Including Top and Bottom 1% and Foreclosures	Dropping Top and Bottom 1% Sample	Dropping Foreclosures
Observations	496,054	537,929	516,898	515,895
R-squared	0.7784	0.7698	0.7764	0.7868

Notes: Table presents separate estimates by different sample restrictions of the impact of proximity to wind turbines on housing values based on Equation (1). All models include distance-bin project fixed effects, block-group by project fixed effects, year-quarter-by-project fixed effects, and controls (i.e., the same model as Column 8 of Table 4). Standard errors clustered at the project level. ***p < 0.01, **p < 0.05, *p < 0.1.

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