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Uplifting winds: The surprisingly positive community-wide impact of wind energy installations on property values

Ben Hoen [a,*], Eric Brunner [b], David Schwegman [c]

[a] Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA, 94720, USA
[b] University of Connecticut, 10 Prospect Street Hartford, CT, 06103, USA
[c] American University, 4400 Massachusetts Avenue, NW Washington, DC, 20016, USA

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ABSTRACT

A primary concern of stakeholders when considering a new wind project is the potential negative effects wind turbines may have on home values. Yet, what has been surprisingly overlooked in the literature and general discourse around wind energy is that the well-researched positive economic development and fiscal and amenity benefits of wind energy (e.g., increased tax base, tax revenue, better public services and employment gains) might positively affect jurisdiction-wide housing values. With a focus on school districts in the United States, we compare home values in school districts with wind energy installations, before and after a wind energy installation becomes operational, to home values in other school districts located in the same county but without a wind energy installation to provide some of the first causal evidence on the relationship between wind energy projects and district-wide property values. We find that wind projects lead to economically meaningful increases in district-wide housing values of approximately 3 %, when those values are compared to similar homes located in school districts in same-county without wind energy. The effect is strongly correlated with wind project size. The mechanisms, our research suggests, are likely related to relatively large increases in school district per-pupil revenues and expenditures, which are also correlated with wind project size. We suggest other possible mechanisms for the increased values as well.

1. Introduction

In 2024, 4 GW of wind energy was installed in the United States, which is historically low, but as of spring 2025, >16 GW were currently under construction, and 12 GW was in “advanced development” [1,2]. Changes in federal incentive and permitting policies in 2025 will likely result in significant headwinds for the industry, but wind energy, even without incentives, remains one of the least expensive forms of energy, especially given the increasing costs of gas-fired generation [3]. Therefore, there is likely to be continuing annual installed capacity in the US over the next decade and beyond [2,4]. While wind energy installations in the U.S. were historically sited in less populated rural areas, the growth of wind energy has led to more installations being sited in higher population density areas and hence closer to residential homes [5].

A top concern of stakeholders in prospective host communities, and one of the leading causes of opposition to wind energy projects, is the potential negative impact wind projects may have on nearby residential property values due to the noise and visual pollution associated with turbine rotation as well as the impact on the surrounding landscape [6–12]. Given that homes are the most valuable asset in the majority of household portfolios, this concern is justifiable [13].

Property values provide a trusted source of information on the revealed preferences of individuals [14,15]. Economic theory, which is the classic tool used to understand market interactions, including real estate markets, assumes market participants are rational actors who weigh the costs and benefits to maximize their utility given the information available to them [16,17]. Further, it is well-researched that individuals self-sort across communities based on buyer preferences, called Tiebout Sorting [18–20]. Therefore, property values near wind energy projects, as well as the property values within a community that hosts these projects, can be a useful source of information as to how buyers of homes, and to a broader extent, community members, weigh

* Corresponding author.
E-mail address: bhoen@lbl.gov (B. Hoen).

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the costs and benefits of various aspects of the community, including the real or perceived effects of wind turbines on community members, the local economy, and sense of place in that community. As such, analyses of property values can inform stakeholders (e.g., decision makers, community members, developers, researchers) considering future wind projects.

Over the last decade, a large body of literature has emerged that examines the impact of wind turbines on residential property values [21]. Studies from Europe consistently find that homes located within 2 km (1.2 miles) of wind turbines experience approximately a 5 % to 10 % decline in value following the construction and operation of turbines [21–25]. While evidence from the U.S. tends to be more mixed [26–30], three of the most recent studies have all found adverse effects for homes within 2.4 km of a turbine, with home values falling by approximately 5 % to 10 % post project announcement and then slowly recovering once the project becomes operational [5,30,31]. The methodological approach used in nearly all these studies involves comparing homes within close proximity or view of wind projects to similar homes slightly further away [5,27,28,30,32,33] or outside of sightlines [22,31]. This approach exposes differences between these comparative set of homes but would mask any effects experienced by all homes in proximity to wind projects, such as those in the same school district as the wind project.

A smaller set of studies from the U.S. have also examined the impact of wind energy projects on local economic development and the revenues and expenditures of local communities. In general, these studies find that wind energy projects deliver substantial economic benefits to host communities including increases in local employment and income [34–36], increases in school district and county revenue and expenditures [32,33,37,38], reductions in local property tax rates [37], and even improvements in county credit ratings [39]. Researchers have found, for example, that wind energy installations lead to significant increases in school district revenues and expenditures, which school districts have used to modernize and improve school facilities, reduce class sizes, and in some instances, lower property taxes [35,40,41].

Surprisingly, what has been largely overlooked in the literature is whether the local economic development and fiscal and amenity benefits of wind energy development increase (i.e., are capitalized into) property values within the broader community (i.e., "community-wide property values"). Starting with Oates [42], a large body of literature has found that community property tax rates and service quality (broadly defined to include local revenues and expenditures and outcomes such as crime rates and test scores) are capitalized into housing values [41,43].[1] The mechanism underlying this capitalization is simple: as development spurs additional employment in a community, and/or allows a community to lower property tax rates and increase spending and services, demand and willingness to pay for housing in the community also increase, driving up home values. However, despite the substantial literature finding positive impacts of wind energy installations on local employment and community revenues and expenditures, the possible community-wide capitalization of these wind energy-driven changes in local fiscal and economic conditions has received surprisingly little attention.

As such, the purpose of this paper is to provide some of the first evidence on whether wind energy installations impact community-wide property values. We hypothesize that such an effect exists and have assembled a large dataset to explore this question. Specifically, we combine data on the timing, location, and capacity of the universe of wind energy installations in the U.S. with data on the universe of residential housing transactions from 2005 to 2021 from Cotality (formerly CoreLogic). With a focus on school districts in the United States, we estimate difference-in-differences and event study models that compare home values in school districts with wind energy installations, before and after a wind energy installation becomes operational, to home values in other school districts located in the same county but without a wind energy installation. Using other datasets, we also examine school district revenue and expenditures, and classroom outcomes in the form of student-teacher ratios across districts with various levels of wind deployment to provide a plausibly causal mechanism driving changes in home values. We believe this is the first analysis to combine these datasets of wind deployment, real estate, and school district outcomes, all in one analysis.

Finally, we focus on the U.S. exclusively because the many different types of data are readily available, including detailed wind turbine information, real estate data, school district revenues and expenditures, and class sizes. This analysis, though, could be performed in other locales. There is, indeed evidence that tax revenues do accrue, though apparently at lower levels, in EU countries such as Germany [44,45] and Spain [46]. It is unclear if the composite datasets exist though to duplicate this type of analysis.

What follows, respectively, are discussions of data, empirical strategy, results, and discussion.

2. Materials and methods

2.1. Data

We construct our main analytic dataset using data from four main sources. Data on the universe of large-scale (>100 kW) wind energy installations in the U.S. comes from the United States Wind Turbine Database (USWTDB) [47]. The database is updated quarterly and contains the location and characteristics of all wind energy projects in the US. These data include the geographic coordinates of each turbine (10-m resolution), the turbine's nameplate capacity, and operation year.[2] Lawrence Berkeley National Laboratory (LBNL) separately supplied the "announcement" year for projects where available, which is defined as the year in which substantial local activity began occurring for the project (see Brunner et al. [5], for more details on these dates). We use school district geographic shapefiles from the National Center for Education Statistics (NCES) to place each wind turbine in a unique school district and then collapse the data to the school district-by-year level by summing the installed wind energy capacity in each school district in each year [48].

We obtain data on home sales between 2005 and 2021 from Cotality (formerly CoreLogic) [49]. The Cotality housing transaction database consists of over 21 million residential property transactions in the United States from January 2005 to December 2021 and contains property-level characteristics, including address, latitude-longitude coordinates, property type, and property characteristics, including living area in square feet and the number of bathrooms. Most importantly, the database contains transaction-specific data, including the sale amount and sale date for each transaction. We restrict the sample to arm's length transactions of residential properties that had complete information on their sale date and sale amount. We then collapse the Cotality data to the school district-by-year level and create annual measures of the average sale price of homes and the number of transactions in each school district. Our main analysis is based on a "donut hole" sample where we drop any homes located within 3.2 km of a turbine prior to aggregating

[1] Also see Bartik [50] for a review of the positive impacts of local economic development on home values, which in our case could arise from the employment impacts associated with wind energy development within a school district.

[2] We examine installed capacity's correlation with key outcomes because it is the most common unit of wind energy taxation. But in some locales, production (i.e., output) is taxed either in addition to or in place of installed capacity. Installed capacity is correlated with output ($\rho = 0.6$, when fixing temporal and geographic effects), and thus we posit it is an effective proxy when output is the unit of taxation.

to the district level. However, we also present results based on specifications that include all transactions and, separately, where we drop homes located within 1.6 km of a turbine. We also examine transactions of just homes within 1.6 and 3.2 km of a turbine.

We then merge in annual data from the NCES on school district: 1) enrollment; 2) pupil-teacher ratios; 3) local revenue; 4) total expenditures; and 5) current operating expenditures. We deflate all the financial outcomes to constant 2021 dollars using the Consumer Price Index and divide these measures by annual enrollment to obtain per pupil outcomes.

Finally, we merge in a set of school district demographic variables from the 2000 census and housing characteristics from the Cotality dataset to use as controls. Those variables are: 1) the average living area of residential homes; 2) the average number of baths of residential homes; 3) the share of the population age 25 or older with a college education; 4) median household income; 5) the share of the population that is nonwhite; 6) the share of the population age 55 or older; and 7) an indicator if a school district is classified by the NCES as rural.[3]

We restrict the data in several ways. First, we drop nontraditional school districts such as charter schools, magnet schools and regional centers keeping the universe of unified (K-12 districts) and elementary districts in the U.S. We also drop school districts with a maximum wind energy capacity of under 2 MW since these districts represent places with a single, or small number of, wind turbine(s) rather than a commercial wind energy installation. Finally, we create a balanced temporal window with data both 5 years prior to a wind energy installation becoming operational and 10 years after.

Table 1A in the Appendix contains the means and standard deviations of variables used in our analysis, both overall and separately for districts with a wind energy installation and those without. As expected, school districts with a wind energy installation tend to be substantially more rural when compared to districts without a wind installation. Furthermore, on average, there are approximately 11 school districts per county with slightly fewer in counties that contain at least one wind energy installation. Finally, among counties with at least one school district that hosts a wind energy installation, on average 37 % of the districts have wind energy installations.

2.2. Empirical strategy

To examine the impact of wind energy installations on residential housing values, school district financial outcomes, and pupil-teacher ratios, we begin by estimating nonparametric event study models of the following form:

$$y_{ijt} = \sum_{k=-5}^{10} \gamma_k T_{k,it} + X_i\theta_t + \delta_i + \lambda_{j,t} + \eta_{ijt}, \quad (1)$$

where, y_{ijt} is a measure of school district resources or the log of district housing values in district i, located in county j, in year t,[4] $T_{k,it}$ is a series of lead and lag indicators around the year a commercial wind installation became operational in district i, $X_i\theta_t$ is a vector of school district housing and socio-demographic control variables measured in 2000 and interacted with a linear time trend, δ_i and $\lambda_{j,t}$ are vectors of school district and county-by-year fixed effects, respectively, and η_{ijt} is a random disturbance term. In all specifications we cluster standard errors at the school district level to allow for arbitrary within-school-district autocorrelation of the disturbance term. When the outcome is the average sale price of homes in a district, we weight these regressions by the total number of transactions that occurred in a given district and year.

The coefficients of primary interest in (1) are the $\gamma_k's$ that trace out the annual evolution of our outcomes for districts with a wind energy installation relative to districts located in the same county but without a wind energy installation. We include yearly indicators for 1 to 5 years prior to a wind energy installation becoming operational ($T_{-5,it} - T_{-1,it}$) and 1 to 10 years after an installation becomes operational ($T_{1,it} - T_{10,it}$). The omitted, or reference category, for these treatment effect indicators is the year an installation becomes operational. The indicators for the years prior to operation allow us to examine whether our outcomes of interest were trending higher (relative to districts without a wind energy installation) prior to an installation becoming operational. Such trending would violate the parallel trend assumption of DiD models and call into question the causal interpretation of our results. The post-operation indicators capture the nonparametric post-treatment evolution of our outcomes of interest. Note that the county-by-year fixed effects in (1) allow for county-specific arbitrary time trends in our outcomes of interest, which allows us to better model the localized nature of housing markets when the dependent variable is residential sale prices. Also, note that the county-by-year fixed effects ensure that we identify the effect of wind energy installations on our outcomes of interest using only within-county variation in treatment. Thus, eq. (1) uses only non-treated school districts (i.e., districts with no wind energy) in the same county as the comparison, or counterfactual, group.

Given the staggered timing of treatment associated with wind energy installations and the potential for heterogeneous treatment effects, we employ the event study estimator developed by Sun and Abraham to estimate eq. (1) [51]. Specifically, it is now widely understood that with staggered timing of treatment and heterogeneous treatment effects, event study and standard DiD estimates are potentially biased by the effects from other relative time periods. The Sun and Abraham estimator directly addresses this issue and produces unbiased treatment effect estimates.

To improve precision, we augment the event study models given by (1) with standard DiD models that collapse the vector of treatment indicators in (1) into a single post-treatment indicator:

$$y_{ijt} = \alpha_1 Operation_{it} + X_i\theta_t + \delta_i + \lambda_{j,t} + \varepsilon_{ijt}, \quad (2)$$

where $Operation_{it}$ is an indicator that takes the value of one in all years after a wind energy installation becomes operational, ε_{ijt} is a random disturbance term and all other terms are as defined in eq. (1). The coefficient of primary interest in (2) is α_1 that is the standard DiD estimate of the impact of wind energy installations on our outcomes of interest.

Finally, to allow for heterogeneity in the capacity of different wind energy installations across locations and time, we augment eq. (2) by replacing the post-treatment indicator, $Operation_{it}$, with a continuous measure of treatment, namely capacity per pupil measured as total annual installed capacity in a given year in kilowatts divided by district enrollment. This measure takes the value of zero in all years prior to a wind energy installation becoming operational and then the total installed capacity per pupil in all years post-operation. It also takes the value of zero for all school districts without a wind energy installation.

We estimate both the binary and continuous version of eq. (2) using a stacked DiD estimator to once again account for the staggered timing of treatment in our data and the potential for heterogeneous treatment effects. Specifically, following Cengiz et al. [52] and Goodman and Bacon [53] we create a set of datasets that include observations from a cohort of school districts where wind energy development becomes operational in the same year and other school districts that never had a

[3] See https://nces.ed.gov/programs/edge/Geographic/LocaleBoundaries

[4] We do not use a repeat sales model for two reasons. First, given our limited time period, restricting our analysis to properties that sell multiple times within this time period introduces a particular type of endogeneity given that properties that sell frequently over a short period are likely a distinct type of property (or a property that attracts a particular type of buyer) that is not similar to the average home (or buyer) in the neighborhood. Second, most energy installations are located in less densely populated communities where housing stocks tend to be thinner, and homes transact less frequently. Thus, we have limited statistical power to do repeat sales.

wind energy installation during our sample timeframe. We then stack these datasets together and replace the district and county-by-year fixed effects in eq. (2) with district-by-cohort and county-by-year-by-cohort fixed effects.

3. Results

Using the school district-by-year panel described above, we estimate event studies from 5 years before a wind project's operation to 10 years after, as well as standard difference-in-difference (DiD) models, each for the various outcomes.

3.1. Housing value outcomes

We begin our analysis by describing the impact of wind energy installations on school district-wide housing values. As noted previously, recent studies from the U.S. have found that homes located within 1.6–3.2 km (one or two miles) of wind turbines experience declines in value in the time period following the announcement of a wind project, when compared to values 3 to 5 miles away from those same projects. Fig. 1 presents event study estimates based on specifications where the dependent variable is the log of the average sale price of homes in a school district. To ensure that our capitalization estimates are independent of the potential negative effects on homes located near a turbine, in Fig. 1A we exclude (leave a donut hole for) home sales within 3.2 km of the nearest wind turbine. Fig. 1B is based on a specification that includes those sales within 3.2 km.[5] In these figures, the horizontal axis measures the years relative to when a wind energy installation becomes operational (denoted by the vertical red line), while the vertical axis measures the percent change in home values. Both figures show clear evidence of a jump up in home values of approximately 3 % to 5 % after a wind energy installation becomes operational, although the estimates are noisy. In support of the parallel trend assumption underlying DiD models, there is no evidence that home values were trending higher (or lower) before wind projects became operational.

As noted above, event study estimates tend to be statistically noisy because treatment effects must be estimated for each year prior to and after an installation becomes operational. Thus, to improve precision, in Table 1 we present standard DiD estimates of the combined post-operation effect of wind energy installations on district housing values, and also include a specification excluding sales within 1.6 kms. In the binary treatment specification that excludes homes within 3.2 km of a turbine, home values increase by 2.9 % on average for districts with any wind energy (Row 1 column 1). Columns 2 and 3 show effects with a 1.6 km donut hole and with all data included (i.e., no donut hole) at 2.7 % and 2.8 % (see first row). These results imply that home prices in school districts with wind energy increase by approximately 2.7 % to 2.9 % relative to home prices in the same county but in school districts without wind energy. Estimates accounting for the heterogeneous distribution of installed wind energy capacity across school districts are shown in the third row of Table 1. Using 3.2 km, 1.6 km, and no donut holes, home prices are respectively approximately 0.073 %, 0.061 %, and 0.075 % higher for each additional kilowatt of installed wind capacity per pupil. Therefore, although increases in home values appear to be slightly smaller when proximate homes are included, overall, school districts see a net increase in home values, whether estimated as a binary or continuous effect. Finally, comparing the estimates in the 1st and 2nd rows or the 3rd and 4th rows of Table 1, we note that our estimates are robust and quite stable to the inclusion or exclusion of a host of controls for the physical characteristics of transacted homes and the socio-economic characteristics of school districts, which provides further evidence that our DiD estimates have a causal interpretation and that our identification strategy mimics a randomized control trial.[6]

3.2. School district outcomes

To examine possible mechanisms for the increases in home prices we present event study results for school district per pupil revenues, expenditures and pupil-teacher ratios in districts with wind energy as compared to school districts without any wind energy projects but located in the same county. While there are clearly other potential mechanisms for the increases in home prices including reductions in local property taxes or employment impacts induced by wind energy development, we focus on the impact of wind energy installations on school district revenues and expenditures because, unlike other potential mechanisms, there is annual detailed data available on revenues and expenditures. Results are shown in Figs. 2A-2D. Per pupil local revenue increases by roughly $1000 three years following the operation of a wind project and is maintained out to 9 years following (2A). This represents approximately a 13 % increase in local revenue per pupil for the average school district in our sample. As shown in Fig. 2B and C, we see a corresponding increase in real total (instructional plus capital) expenditures of roughly $1500 to $2000 per year per pupil 4 to 7 years after project operation begins (1B), and an increase in real current (instructional) expenditures of roughly $500 per pupil 6 to 9 years following the beginning of operations (2C). For the mean school district, these estimates correspond to approximately a 12 % increase in total expenditures per pupil and a 3.7 % increase in current expenditures per pupil. Consistent with current expenditures being used to increase the number of staff and/or reduce class sizes, Fig. 2D shows a significant decline in the student-teacher ratio of approximately 0.2 to 0.3 students per teacher approximately 4 years after operations begin. There is no evidence in any of the event studies of pre-trends before a wind project begins operation, consistent with these estimates having a causal interpretation.

The event studies shown in Fig. 2 describe the evolution of school district revenues, expenditures, and pupil teacher ratios over time among school districts that host a wind energy installation relative to those districts in the same county without a wind energy installation. However, the event studies, which estimate binary effects, do not account for various project sizes that might be coming online. Given standard ad valorum taxation practices, which collect higher taxes on higher valued assets, or production taxation of wind project output, which collects higher taxes on increased output, higher capacity projects with more output should, on average, result in larger economic benefits, all else being equal. Therefore, estimating effects using a continuous measure of installed capacity can provide further nuance. See Brunner et al. [34] for a detailed summary of state wind energy tax practices.

We estimate standard DiD models to examine these binary and continuous relationships. Table 2 presents results for the combined post-operation period for each of the four outcome variables described in Fig. 2. The top two rows present estimates based on a single binary indicator that takes the value of one in all years after a wind energy installation becomes operational. The top row includes school district-

[5] The results restricted to homes within 3.2 kms (i.e., just inside the donut hole) are discussed later; see Table 4.

[6] We also examined whether the adoption of a wind energy installation in one school district had spillover effects on adjacent districts, potentially due to the jobs created by the wind energy development but the people with those jobs living outside of the school district. Specifically, we first created an indicator variable that takes the value of one if a district is adjacent to a treated district and zero otherwise. We then interacted that indicator variable with an indicator that takes the value of 1 in all years after a wind energy installation becomes operational in the focal district. Hence, this interaction term captures the effect of treatment on neighboring districts. We then augmented the DiD models presented in Table 1 by adding this new variable to the model. The estimated coefficient on the spillover variable was small and statistically insignificant in all specifications, providing little evidence of any spillover effects. Results are available upon request.

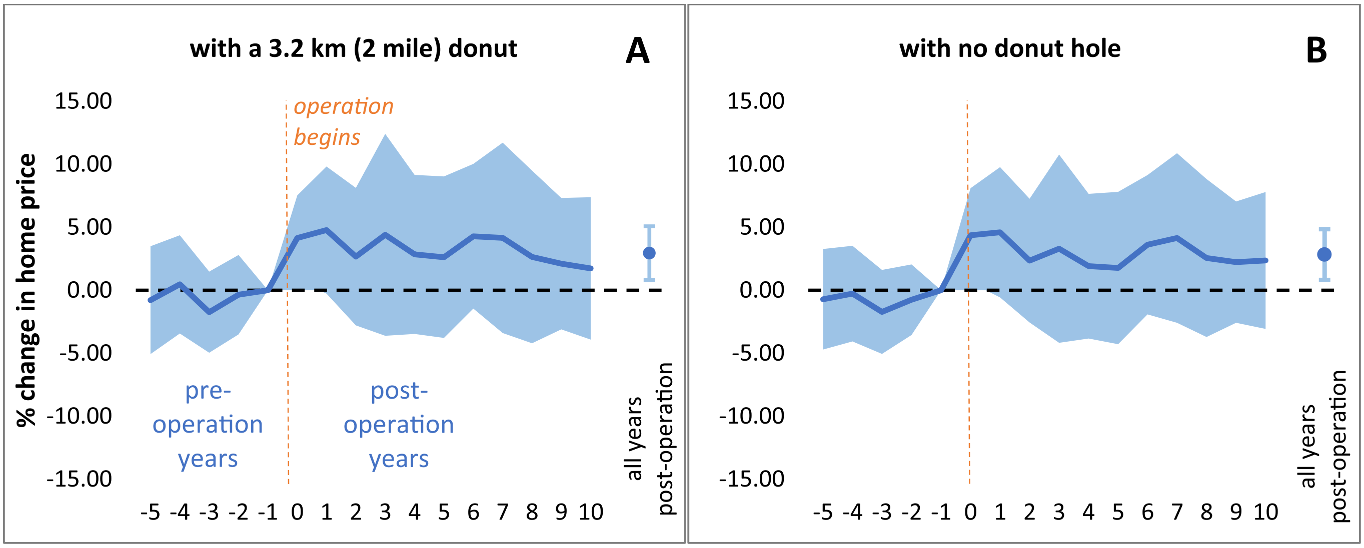

Fig. 1. Event studies showing effects on home values before and after wind project operation. A) with all sales within 3.2 km (2 miles) from the nearest turbine removed (i.e., 3.2 km donut hole), and B) with sales within 3.2 km included (no donut hole). Dark lines represent point estimates, and shaded areas represent 95 % confidence intervals, and vertical orange lines represent when wind project operations began. The DiD average "all years post-operation" estimate from Table 1 is shown as a point to the right in each figure. Event study model specifications are described in eq. (1) of the Methods section and are based on the estimator developed by Sun & Abraham (2021). Dollars are expressed in real 2021 dollars.

Table 1
Difference-in-differences estimates for home prices following commencement of wind project operation.Table 1 presents estimated treatment effects from stacked DiD specifications of the impact of wind energy installation operation on school district housing prices. Estimates shown for home prices (1) within 3.2 km (2 miles) from the nearest turbine removed (i.e., 3.2-km donut hole), (2) within 1.6 km (1 mile) removed, and (3) with them included (no donut hole). Top panel presents estimates with and without housing and district controls based on a binary treatment indicator that equals one in all years after a wind energy installation becomes operational. Bottom panel presents estimates with and without controls based on a continuous measure of treatment, namely capacity per-pupil measured in kilowatts. All specifications are weighted by the number of housing sale transactions in a given year and school district. Housing controls include average square footage of home and average number of baths. District controls include district median income, percent of the population that is college educated, over 55, nonwhite, as well as a rural location indicator, all interacted with linear time trend. All specifications include school district-by-cohort fixed effects and county-by-year-by-cohort fixed effects. Robust standard errors clustered at district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)
Treatment	3.2 km Donut Hole	1.6 km Donut Hole	No Donut Hole
	With Controls		
Binary	0.0294**	0.0271**	0.0283**
	(0.0130)	(0.0125)	(0.0123)
	Without Controls		
Binary	0.0267**	0.0250**	0.0262**
	(0.0131)	(0.0115)	(0.0113)
	With Controls		
kW of Capacity Per-Pupil	0.000738**	0.000615**	0.00075**
	(0.000318)	(0.000242)	(0.000241)
	Without Controls		
kW of Capacity Per-Pupil	0.000734**	0.000615**	0.00075**
	(0.000318)	(0.000243)	(0.000243)
Observations	1,812,875	1,812,875	1,812,875

level controls measured in the year 2000 for median household income, percent college-educated, fraction of the population over 55, fraction nonwhite, and a rural location indicator, each interacted with a linear time trend. The second row presents results based on specifications without any controls. The third and fourth rows present results based on specifications where we replace the binary treatment indicator with installed capacity, measured as kilowatts of capacity per pupil and the fifth and sixth rows weight the models in rows 3 and 4 by the number of students in a district.

In the binary treatment specifications, all the estimated revenue and expenditure coefficients on the treatment indicator are positive, statistically significant, and similar in magnitude for specifications with and without controls. In terms of magnitude, the results in the first row imply that, on average, wind energy installations lead to approximately an \$800 increase in local revenue per pupil, a \$703 increase in total expenditures per pupil, and a \$203 increase in current expenditures per pupil. As shown in column 4, wind energy installation leads to a decline in the pupil-teacher ratio but the estimate is noisy. In the continuous treatment specifications (3rd and 4th rows) all the estimated coefficients are of the expected sign and statistically significant at the 5 % level or better, except pupil-teacher ratio, which is significant at the 10 % level. In terms of magnitude, each additional kW per pupil of installed capacity increases real per pupil local revenue and per pupil total expenditures by approximately \$20, current expenditures by approximately \$7, and decreases class size by 0.002 pupils per teacher. Also note that as shown in rows 5 and 6, that the models that weight by the number of students are quantitatively and qualitatively similar to the unweighted results shown in rows 3 and 4.[7]

3.3. *Outcomes for large projects*

To further examine the relationship between housing values and school district resources, we examine if greater installed capacity

[7] We have also considered using an instrumental variable (IV) framework where we use the results reported in Tables 1 and 2 to compare the implied impact of \$1000 increase in school spending on housing values to other estimates from the literature based on school district spending increases. See detail on this in the Appendix.

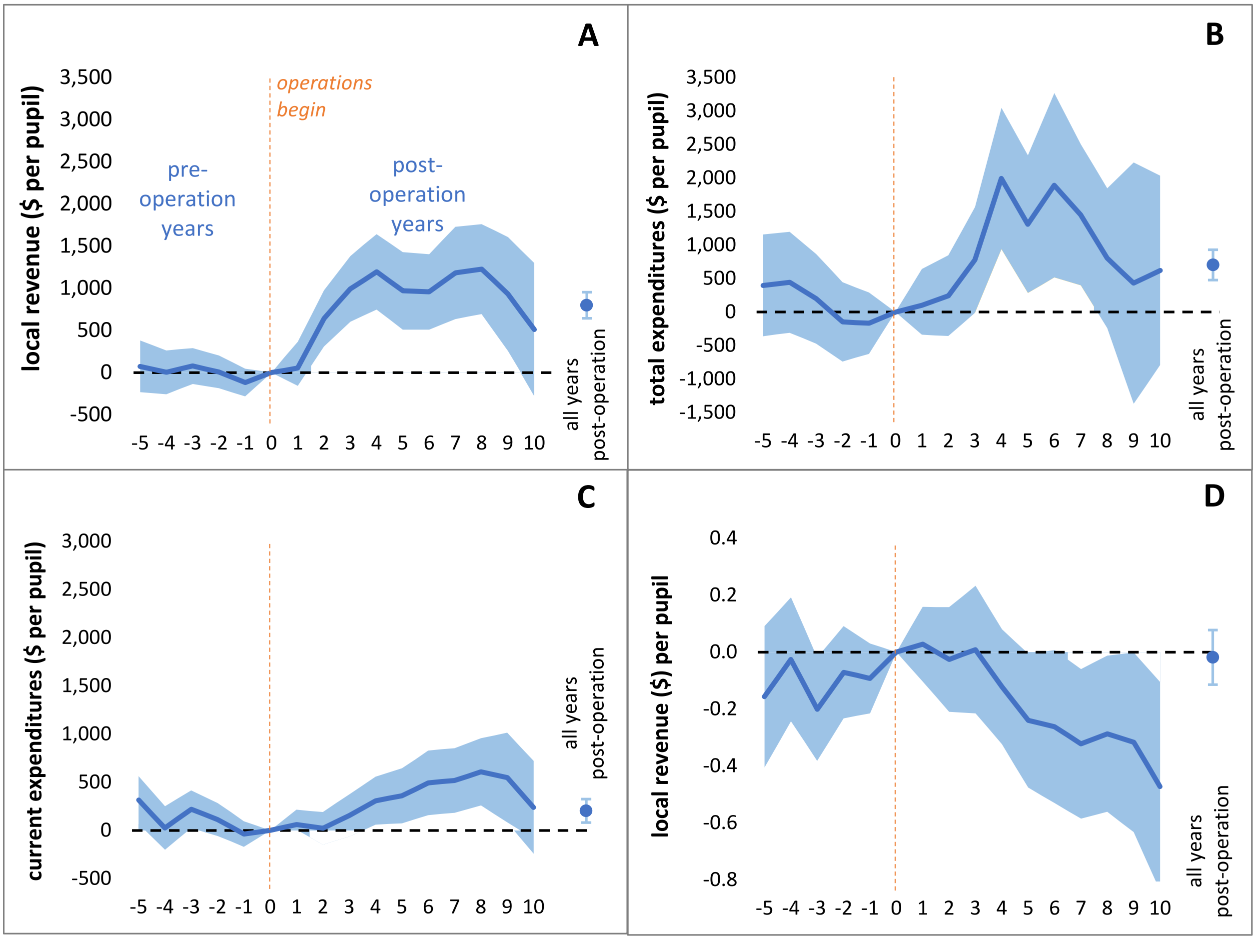

Fig. 2. Event studies showing effects on school district outcomes before and after wind project operation. A) per pupil local revenue, B) per pupil total expenditures, C) per pupil current expenditures, and D) student-teacher ratio. Dark lines and shaded areas represent point estimates and 95 % confidence intervals, respectively, and vertical orange lines represent when wind project operations began. The DiD average "all years post-operation" estimate from Table 1 is shown as a point to the right in each figure. Event study model specifications are described in the Methods section and are based on the estimator developed by Sun & Abraham (2021). Dollars are expressed in real 2021 dollars.

(defined as installed wind capacity per pupil, or kilowatts per pupil) results in both greater school district resources and higher home prices. To examine how our outcomes vary with the level of installed capacity, in Fig. 3, we plot the effect of wind energy installations on per pupil local revenues (B), total expenditures (C), current expenditures (D), and housing values (A) by ventiles (20th) of installed capacity per pupil. The impact of per pupil wind energy capacity remains small for all outcomes up to the 50th percentile of capacity but then increases at an increasing rate. Furthermore, the effect of capacity per pupil is similar across all outcomes, including housing values. This implies that the impact of wind energy on school district revenues and expenditures and the resulting positive impact on home values are correlated and are concentrated in communities with greater amounts of installed wind energy per pupil.

Table 3 presents additional evidence that the impact of wind energy installations on housing values and district resources is concentrated among districts with the highest installed capacity per pupil. School districts with wind energy are split according to being either above or below the median installed per pupil capacity of 20 kW, and models for each outcome variable are estimated for the two sub-samples. The 20 kW/pupil median might apply to a school district with a median number of students (~500) and the median installed capacity (~10 MW), but it could also apply to relatively small school districts with lower installed capacity (e.g., 25th percentile levels of ~200 pupils and 4 MW) or larger districts with more capacity (e.g., 75th percentile levels of ~1000 students and 20 MW). Alternatively, the effect might be limited to larger districts with more capacity rather than smaller districts with less capacity. Whichever is the case, significant increases in revenue, expenditures, and home prices are on average, evident for the cohort of school districts above the median of installed capacity per pupil. Although mostly positive, none of the estimates in the below median sample are statistically significant.

The results presented in Fig. 3 and Table 3 strongly suggest that the positive capitalization effects we observe are correlated with the increase in school district resources that occurs after a wind energy installation becomes operational. Specifically, if greater installed capacity within a district results in higher-levels of school district resources and services (as we show in Fig. 3 and Table 3), then demand and willingness to pay for housing within the district should also increase, leading to increases in property values district-wide. To provide further evidence that our results might be driven by the impact of wind energy installations on school district resources and home values, we conducted two falsification tests. In the first test, we drop all observations after a wind installation becomes operational. We then assign a placebo date of operation by moving the actual year a wind installation becomes operational back 5 years. In the second test, we move the date back 8 years. Since we hypothesize that the positive capitalization effects we observe are caused, by the local economic development, property tax reductions and fiscal benefits that occur after the operation of a wind energy installation, we should find no evidence of positive capitalization in these falsification tests. Results are reported in Table 2A of the Appendix. The top panel of the table reproduces our core results

Table 2
Difference-in-differences estimates for school district outcomes following commencement of wind project operation. Estimates shown for per pupil local revenues (1), total expenditures (2), current expenditures (3), and pupil-teacher ratios (4). Top panel presents estimates with and without controls based on a binary treatment indicator that equals one in all years after a wind energy installation becomes operational. Middle panel presents estimates with and without controls based on a continuous measure of treatment, namely capacity per-pupil measured in kilowatts. Bottom panel weights the models by the number of students in a district. Controls include district median income, percent college educated, percent of population over 55, and percent nonwhite and a rural location indicator, all interacted with linear time trend. All specifications include school district-by-cohort fixed effects and county-by-year-by-cohort fixed effects. Robust standard errors clustered at district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Treatment	(1) Local Revenue	(2) Total Expenditures	(3) Current Expenditures	(4) Pupil-Teacher Ratio
	With Controls			
Binary	799.0***	702.9***	203.3*	−0.0183
	(154.4)	(227.5)	(122.4)	(0.0960)
	Without Controls			
Binary	820.8***	714.9***	221.0*	−0.0269
	(156.0)	(228.0)	(123.5)	(0.0963)
	With Controls			
kW of Capacity Per-Pupil	20.25***	19.94***	6.691***	−0.00182*
	(3.078)	(5.488)	(1.992)	(0.00107)
	Without Controls			
kW of Capacity Per-Pupil	20.66***	20.20***	6.829***	−0.00202*
	(3.071)	(5.512)	(1.995)	(0.00106)
	Enrollment Weights with Controls			
kW of Capacity Per-Pupil	22.69***	21.60***	6.871***	−0.00182
	(3.419)	(5.517)	(1.908)	(0.00127)
	Enrollment Weights Without Controls			
kW of Capacity Per-Pupil	23.01***	21.23***	7.438***	−0.00230*
	(3.432)	(5.486)	(1.965)	(0.00127)
Observations	1,687,924	1,687,975	1,687,958	1763,020

for comparison purposes. The next two panels present results from the falsification tests. As expected, all the estimated coefficients in panels 2 and 3 are statistically insignificant and small in magnitude.

3.4. Proximate property value impacts

We also examine if development periods before operation might exhibit unique effects on the value of homes located in close proximity to turbines. As shown in Table 4, we restrict the sample of homes located in districts with a wind energy installation to include only homes within 1.6–3.2 km (1 or 2 miles) from the nearest turbine. We then estimate DiD models based on eq. (2) for three different development periods: after project announcement but before operation, within the first four years after operation, and five or more years after operation. As others have found [30,32], we see evidence of an adverse effect after the announcement and before operation begins within 1.6 km of the nearest turbine. We find no evidence of effects on home prices once the wind project becomes operational, when, presumably, positive impacts related to school district spending and improvements begin to be capitalized (see Fig. 1).[8]

[8] Although it might seem appropriate to compare home prices within the donut hole to those outside but in the same school district, this would make both sets "treated" (i.e., affected by school-district wide impacts), and therefore is not appropriate if the goal is to examine school district wide effects.

4. Discussion

One of the primary concerns of local elected officials and residents when considering the approval of a proposed commercial wind energy installation is the potential negative effects that wind turbines may have on home values due to their impact on the surrounding landscape and the noise and shadow flicker from the turbines themselves. Yet, what has surprisingly been overlooked in the academic literature and the general discourse around commercial wind energy siting, is the potential positive impact wind energy projects may have on jurisdiction-wide housing values. These positive effects may arise because of the impact of wind energy projects on employment, the local property tax base and/or the revenue they generate through payments in lieu of taxes—revenue that can be then used to increase local public services, reduce property tax rates, or both.

In this paper, we examine the relationship between commercial wind energy installations and jurisdiction-wide housing values. Our analysis focuses on unified and elementary school districts, given that most school districts in the United States are independent local governments with the authority to levy property taxes and because they are one of the smallest units of local government, which makes it more likely that a commercial wind energy installation could have a meaningful impact on the local tax base. Further, it provides a convenient way to compare home prices that would be plausibly treated (within a school district with the wind) versus a control (a district in the same county without wind). We find that district-wide housing values increase by approximately 3 % after a wind energy installation becomes operational compared to homes in non-wind districts. We examine one likely mechanism for this increase and find the siting and operation of a commercial wind energy installation within a school district is correlated with relatively large increases in per pupil revenues and expenditures and smaller, but still significant, declines in the pupil-teacher ratio. We also find that the effect of wind energy installations on both school district resources and housing values are strongly correlated with project size, with the effects being significantly larger in districts with greater installed wind capacity per pupil. Finally, we find adverse impacts to property values after announcement and before construction for homes within 1.6 km (1 mile) of a turbine, but no statistically significant effects after that. These results correspond to the time when we are able to first measure positive capitalization effects.

Thus, we uncover a previously uninvestigated link between wind energy deployment and increased property values. Following economic theories, our findings imply that buyers of homes in wind-energy school districts are rationally finding that the benefits of owning homes in a school district with wind energy outweigh the costs (compared to homes outside the district in the same county). While we recognize that not all potential buyers would agree with this valuation, we expect many buyers submitting the winning (i.e., highest) offer for homes in districts with a wind energy installation perceive the potential benefits of owning a home in such a district as greater than the potential cost. But of course, we cannot surmise the specific benefits and costs being weighed. Instead, we can speculate that there are some positive aspects of school districts with wind that are being capitalized into home prices. These positive effects may be increases in school district revenue, expenditures, and reductions in class size, which we examined, or they also might be other aspects we did not examine, e.g., lower tax rates, increased employment opportunities, and housing scarcity. Or, some buyers might simply prefer to live in a community with wind energy nearby.

Furthermore, examinations of local community sentiment around existing wind energy projects have found, for the most part, a majority of positive (vs. negative) attitudes towards the local project [8,54–60], especially when looking beyond the immediate neighbors to those five to ten miles away. As well, individuals arriving in a community after it has been built, who would constitute the community of home buyers, have been found to be more positive than those who lived there before

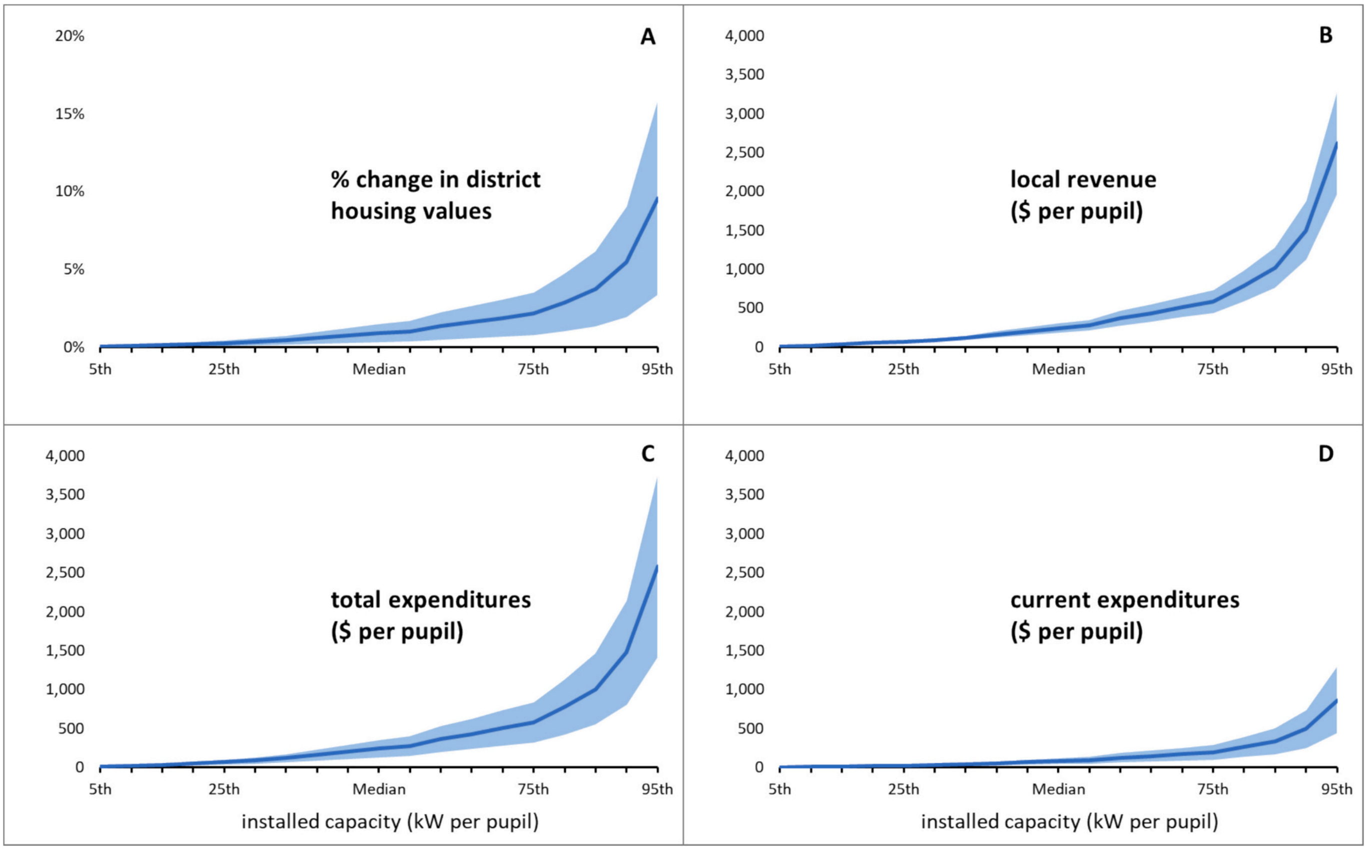

Fig. 3. School district outcomes by capacity per pupil. Figures show how A) school district housing values, B) local revenues, C) total expenditures, and D) current revenues vary with wind energy capacity per pupil. Estimates are based on eq. (2), with controls, using capacity per pupil in kilowatts as the treatment variable. Dark blue lines represent point estimates (treatment effects) at each ventile, and shaded areas represent 95 % confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Difference-in-differences estimates for school district outcomes and home prices above and below the median installed capacity per pupil. Estimates are shown for local revenues, total expenditures, current expenditures, and housing values. Models are estimated with controls, for any school district with at least 20 kW of installed capacity per pupil ("above median") or below that level ("below median") for any district with at least one 2 MW wind project ("Binary"). Revenue and expenditures results are in USD per pupil, and house values are approximately a percent change. *** p < 0.01, ** p < 0.05, * p < 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Local Revenue		Total Expenditures		Current Expenditures		Housing Values	
Treatment	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Binary	1713*** (287.6)	112.1 (110.6)	1500*** (348.8)	65.69 (280.0)	533.3*** (197.4)	−57.76 (144.4)	0.0695*** (0.0207)	0.0231 (0.0150)
Observations	1,686,072	1,686,469	1,686,123	1,686,520	1,686,106	1,686,503	1,810,923	1,811,299

construction [8]. It is well understood that some sorting on preferences does happen during the home-buying process. Specifically, Tiebout (1956) and others posit that buyers sort themselves in and out of communities based on personal preferences [18–20,61]. It seems reasonable to assume that the similar mechanisms that drive higher home prices after school district improvements, increased expenditures, and decreased tax rates are capturing the preferences for these changed community characteristics in a similar way as resident sentiment surveys have. Therefore, potential adverse impacts a wind project introduces do not appear to outweigh the positive impacts that exist. Of course, how conscious any particular buyer is of these considerations, especially those specifically related to the wind project, is unknown.

Admittedly, although increases in school district revenue, expenditures, and reductions in class size are likely some of the mechanisms behind the increases in housing values, they are not the only mechanism. As noted above, local economic activity related to the wind project could also drive up housing values, especially in the construction and early operation period as workers move into the area, some of which might stay to perform operations and maintenance on the turbines [50]. In addition, wind energy projects that increase the local tax base might result in overall lower tax rates, which, in turn, might be capitalized into housing values.

Accordingly, although we have examined a unique impact, we encourage additional research into capitalization effects that might be occurring because of other mechanisms, and, separately, among other units of government (e.g., municipalities, counties, etc.) that fiscally benefit from wind energy [33]. Moreover, although there is a large body of wind energy disamenity literature outside of the US, we only examine

Table 4
Difference-in-differences estimates for Homes within 1.6–3.2 km of a Turbine. Estimates shown for home prices within (1) 1.6 km (1 mile) (1), and (2) within 3.2 km (2 miles) of the nearest turbine, and in three mutually exclusive periods: after the announcement of the wind project, but before operations of the project begins; within the first four years following commencement of operations; and, five or more years after operations begin. Control sales are from school districts in the same county without wind energy. Models are estimated, with controls, for each additional kW of capacity per pupil. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
	Within 1.6 km of Turbines	Within 3.2 km of Turbines
	Treatment: Continuous kW of Capacity Per-Pupil	
Post Announcement Pre Operation	−0.000940**	−0.00001
	(0.000447)	(0.000331)
Within 4 Years of Post Operation	−0.00001	0.000485
	(0.000635)	(0.000452)
5 Years or More Post Operation	0.000838	0.000892
	(0.000576)	(0.000579)
Controls	Housing & District	Housing & District
Observations	1,805,907	1,807,259

positive amenity effects within the US. The developer practices and school district taxing mechanisms might or might not be unique to the US. Therefore, examining these effects outside the US would improve our understanding of the broader effects of wind energy development, especially if they included some analysis of broad economic impacts as has been conducted in the U.S. [32,33,37,42]. Additionally, although this study focused on wind energy, it seems likely that similar effects might exist for solar energy, or for that matter, other major industrial development projects that are located in a jurisdiction [62–64]. Finally, although we postulate as to the various community characteristics that might be considered by home buyers in school districts with wind energy, it is speculation, and therefore, additional research surveying the suite of home buyers and sellers in wind and non-wind areas would be fruitful.

CRediT authorship contribution statement

Ben Hoen: Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Eric Brunner:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **David Schwegman:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

Code availability

All of the code necessary to construct the datasets and replicate the results of this study are publicly available on Harvard Dataverse at: Brunner, Eric, 2025, Replication Data for: Uplifting Winds: The Surprisingly Positive Community-Wide Impact of Wind Energy Installations on Property Values, doi:https://doi.org/10.7910/DVN/HABJIG

Declaration of competing interest

Ben Hoen reports financial support was provided by US Department of Energy Wind Energy Technologies Office. Eric Brunner reports financial support was provided by US Department of Energy Wind Energy Technologies Office. David Schwegman reports financial support was provided by US Department of Energy Wind Energy Technologies Office. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table 1A
Summary statistics

	All School Districts		Districts with Turbines		Districts Without Turbines	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Outcomes						
Sale Price ($)	211,786	198,734	116,057	76,794	216,051	201,409
Total Expenditures Per-Pupil ($)	15,974	6109	15,195	5418	16,008	6136
Current Expenditures Per-Pupil ($)	13,426	4549	12,711	3289	13,458	4594
Pupil Teacher Ratio	14.89	3.71	13.21	3.03	14.96	3.72
Controls						
Living Area (sq. ft.)	1763	487	1703	513	1765	485
Number of Baths	1.77	0.38	1.66	0.44	1.78	0.38
Fraction BA or Higher (%)	0.20	0.12	0.14	0.05	0.20	0.13
Median Household Income ($)	43,491	15,610	35,414	7655	43,850	15,776
Fraction 55 or Older (%)	0.23	0.06	0.26	0.05	0.23	0.06
Fraction Nonwhite (%)	0.16	0.19	0.15	0.20	0.16	0.19
Rural Indicator (%)	0.62	0.48	0.84	0.36	0.61	0.49

(*continued on next page*)

Table 1A (*continued*)

	All School Districts		Districts with Turbines		Districts Without Turbines	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
District Statistics						
Number of Districts	8232		382		7850	
District by Year Observations	118,109		3821		114,288	
District Enrollment	3617	8811	1884	10,507	3674	8743
Number of Districts per County	10.97	10.50	8.63	8.48	11.30	10.62
Cumulative Capacity (KW)			13,835	18,936		
Share of Districts with Wind Energy per County (%)			0.37	0.30		
Within County Std. Dev. of KW/Pupil			3.70	20.73		

Notes: Sale price, revenue, and expenditure outcomes are measured in constant 2021 dollars. Cumulative capacity is measured in kilowatts. All control variables are from the 2000 Census. Column 1, 2 and 3, respectively present summary statistics for the full sample, the sample of districts with a wind energy installation that was operational any time within our sample time frame of 2005 to 2021, and control districts without a wind energy installation but within the same county as districts with wind.

Table 2A
Falsification tests.

	(1)	(2)	(3)	(4)	(5)
	3.2 km Donut Hole Continuous	Total Revenue	Total Expenditures	Current Expenditures	Pupil-Teacher Ratio
	Baseline Estimates from Tables 1 and 2				
	0.000738**	15.98***	19.94***	6.691***	−0.00182*
	(0.000318)	(3.990)	(5.488)	(1.992)	(0.00107)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,812,858	1,687,975	1,687,975	1,687,958	1763,020
	Moving Treatment Back 5 Years				
Treatment	−5.08e-05	0.427	3.181	−0.337	0.000521
	(0.000367)	(2.228)	(2.509)	(1.140)	(0.00106)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,811,167	1,686,500	1,686,500	1,686,483	1,761,376
	Moving Treatment Back 8 Years				
Treatment	−0.000343	−1.051	−2.795	2.807	−0.000366
	(0.000365)	(2.782)	(4.072)	(2.277)	(0.00108)
Controls	Yes	Yes	Yes	Yes	
Observations	1,810,606	1,685,944	1,685,944	1,685,927	1,760,820

Notes: Table presents estimates from falsification tests based on stacked DiD specifications. The top panel presents estimates from specifications where we move the actual year a wind energy installation becomes operational back 5 years and then drop all observations post the actual date the wind energy installation became operational. The bottom panel presents estimates from specifications where we move the actual year a wind energy installation becomes operational back 8 years and then drop all observations post the actual date the wind energy installation became operational. Specification in column 1 is weighted by the number of housing sale transactions in a given year and school district and include controls (average square footage of home, average number of baths, district median income, percent college educated, percent of population over 55, percent nonwhite and a rural location indicator) all interacted with linear time trend. Columns 2–5 include all the controls listed above, other than the housing characteristics. All specifications include school district-by-cohort fixed effects and county-by-year-cohort fixed effects. Robust standard errors, clustered at the district level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Additional discussion of instrumental variables and the implied impact of results.

One can view the results reported in Table 2 as the first-stage estimates from an instrumental variable (IV) model that examines the impact of school district spending on housing values. However, it is important to note that in order to causally identify the impact of spending on housing values using an IV framework, the exclusion restriction must be satisfied. In other words, it must be that the only way wind energy installations impact housing values is through their impact on school district spending. However, as we noted previously, that is likely not the case in the current context since the adoption of a wind energy installation can impact housing values through multiple channels other than just increases in spending, including reductions in local property tax rates and increases in employment brought about by the additional local economic development. Consequently, we have refrained from presenting the IV estimates. Nevertheless, note that it is possible to back out the IV estimates from the results reported in Tables 1 and 2 because, with a binary treatment, the IV estimator is the Wald estimator (i.e., the ratio of the reduced form estimate to the first stage estimate). From Table 2, for example, the impact of wind installations on total expenditures per pupil is 702.9. This is the first stage estimate. From Table 1, the impact of wind installations on housing values is 0.0294, which is the reduced form estimate. Thus, the IV estimate is 0.00004 (i.e., 0.0294 / 702.9). Multiplying this estimate by 1000, we find that a $1000 increase in total spending per pupil results in approximately a 4 % increase in housing values. Estimates from Bayer, Blair & Whaley [65] suggest that a 1 % increase in school spending increases home values by approximately 1.03 %. Given the average level of spending in our sample is $16,000, a $1000 increase is roughly a 6 % increase in spending, implying a capitalization effect of approximately 6 % based on Bayer, Blair & Whaley. Similarly, Dhar and Ross [66] find that a $1000 increase in school spending leads to approximately a 3.6 % increase in home value, which is quite similar to our estimate. Hence, our estimates are similar to those in the existing literature.

Data availability

With the exception of Cotality data, all the data necessary to replicate the results of this study are publicly available via Harvard Dataverse at: Brunner, Eric, 2025, Replication Data for: Uplifting Winds: The Surprisingly Positive Community-Wide Impact of Wind Energy Installations on Property Values, doi:https://doi.org/10.7910/DVN/HABJIG

The research relies on proprietary data from Cotality, which cannot be posted online or made freely available. Rather, an individual who wishes to replicate or extend this work would need to contact Cotality to obtain the housing transaction data used in the study.

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