Blowin’ in the Wind:
The impact of wind farms on house prices

Samuele Giambra*
Brown University

May 2018

Abstract

This paper estimates the impact of wind turbines presence at the ZIP code and census tract level on house prices. A naïve OLS specification shows no evidence of a relation between wind turbines and house prices. Using an instrumental variables strategy where the instrument is defined as the percentage of the area of the ZIP code or census tract with potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US, I find that the presence of a wind farm significantly reduces house prices. An event-study design brings additional evidence of this relation.

Keywords: wind turbines, home prices,
JEL: THREE JEL

*This project benefited from the suggestions of Lint Barrage, Emily Oster, Neil Thakral, Matthew Turner, and from audience comments at the Brown Microeconomics Seminar. E-mail: samuele_giambra@brown.edu.

1 Introduction

The world energy demand has grown exponentially over the last decades. In 2015 the overall energy consumption was about 575 quadrillion British thermal units (Btu) and the most recent projections from the 2017 International Energy Outlook forecast a new pick of 736 quadrillion Btu in 2040 (IEO 2017). Panel A of figure 1 shows that world energy use rose by 56.9% from 1990 through 2015.[1] In this framework, wind energy represents a key option for a sustainable future for two main reasons. First, wind is a clean and renewable energy source that produces virtually no toxic pollution or global warming emissions (Energy.gov 2017). Second, wind power production has very low operating and maintenance costs compared to traditional sources of energy, with nearly all the cost being related to wind turbines' construction and installation (Cullen 2013). In accordance with this view, the US wind energy sector has been characterized by a fast expansion during the last fifteen years, growing from a cumulative power capacity of less than 2,500 MW in 1999 to about 85,000 MW at the end of 2017 (see panel B of figure 1).

Even if the public opinion is typically in favor of wind power (Firestone & Kempton 2007), the construction of wind farms has often to overcome the opposition of local communities. A major concern is that the visual and aural impact of wind farms might decrease house values in the surrounding areas.[2] For instance, Slattery et al. (2012) conduct surveys in several communities near wind farms in Texas and Iowa and find that one third of the respondents consider wind turbines an unattractive feature of the landscape. Ladenburg & Dubgaard (2007) estimate for Denmark that households are willing to pay between 46 and 122 Euros per year for siting a future offshore wind farm further away from the coast.

The object of this paper is to analyze the impact of wind turbines presence on house prices. Using data on the location and building date of each turbine from the Federal Aviation Administration (FAA), and home prices from Zillow and the Federal Housing Finance Agency (FHFA), I am able to estimate changes in house prices for areas that are or are not allocated a wind farm. However, the presence of wind turbines in a given geographic area is clearly an endogenous outcome

[1] For a direct comparison with the previously reported fact, one million Btu is roughly equivalent to 25.1996 tonne of oil equivalent (toe).

[2] Another concern is that the noise and vibrations generated by wind farms could directly harm individuals living close to the plant. Although the traditional medical literature finds no evidence of a negative relationship between wind turbines and health (Knopper & Ollson 2011), a recent study claims that psychological factors might play a role in reports of sleep disturbance by people living in the proximity of wind plants (Jalali et al. 2016).

since infrastructure projects are usually targeted towards areas in specific economic conditions[3] or influenced by political variables. I thus rely on two empirical strategies to try to isolate the causal impact of wind turbines on house prices. First, I instrument for wind turbines presence using the percentage of the area of the ZIP code or census tract with potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. Gross potential wind capacity factors are estimated for the US by Lopez et al. (2012) taking into account the technology available in 2008 and local wind resources. The 30% threshold is often used by engineers to determine the profitability of a site (Kalmikov & Dykes 2010). The hypothesis underlying this instrument is that locations having a larger area above the threshold are more likely to be allocated a wind farm. Second, I perform an event study analysis to investigate how house prices change in the years before and after a wind farm is constructed. The event is defined as the time in which an aggregate of at least ten wind turbines becomes operative in a certain location.

The results from my preferred instrumental variable specification show that each additional wind turbine installed in a given year decreases home prices by about 0.3%. This is a remarkable negative effect considering that, on average, there are 17 new turbines installed in a ZIP code/year, conditional on non-zero construction.[4] On the other hand, the results of the event study are more noisy due to the intrinsic difficulty to identify an exact point in time in which the wind plant starts exerting a negative impact on house prices. Consequently, this approach appears to be less informative about the causal impact of wind turbines on home prices.

This paper mainly contributes to a recent literature that analyzes the detrimental effects of wind turbines on house transaction prices. Sims et al. (2008) are among the first to study this topic, using a sample of 201 house transactions within a mile of a wind farm in Cornwall, UK. The authors do not find any significant evidence of a causal effect of wind turbines on house prices, but this conclusion might be driven by the limitations of the data used. More recently, Hoen et al. (2009) analyze the impact of 24 wind farms in the US using data on 7,500 sales of houses within 10 miles. In an improvement of this study, Hoen et al. (2013) use a differences-in-differences (DD) approach on more than 50,000 house transactions between 1996 and 2011 from areas within 10

[3]Usually wind farms are built in rural areas and have the indirect aim of boosting the local economy (DOE/GO 2004).

[4]The standard deviation is about 27 new turbines in the average ZIP code/year.

miles of 67 wind farms in the US. Both of the aforementioned articles, however, are unable to uncover significant evidence of the impact of wind turbines on house prices. Focusing on Rhode Island, Lang et al. (2014) use data from 3,254 transactions of houses within a mile of a wind turbine, finding no significant effect. A fair amount of other studies employing DD techniques have instead reached conclusions in favor of the hypothesis of a negative impact on house value. For the Netherlands, Dröes & Koster (2014) use 2.2 million transaction prices and find that the construction of a wind turbine lowers the price of houses within 2km by 1.4 percentage points. Similarly, Sunak & Madlener (2016) find evidence of a negative impact of about 9-14% in two German cities. Gibbons (2015) develop a slightly more articulated digital elevation model to create a 200m grid that shows if a turbine is visible or not from each location. The author uses then a DD comparing price changes in locations where a new turbine is built and is visible with different comparison groups, such as price changes in places where the new turbine is hidden by the terrain or became visible in the past. The main conclusion of the study is that visible wind turbines decrease house prices by 5-6% within 2km, and by less than 1% within 14km.

In this paper, I contribute to this literature in two different ways. First, I enlarge the scope of the analysis using data on wind turbines in each state of the US through the end of 2017. Second, in the preferred specification, I address the endogeneity issue of the allocation of a wind turbine to a given geographic area using an instrumental variable approach similar to the one exploited by Dinkelman (2011), who instruments electrification projects in South Africa using land gradient. To my knowledge, this is the first attempt to use an IV approach to estimate the impact of wind turbines on house prices.

2 Data

2.1 Potential wind capacity and wind turbines

2.2 House prices

To analyze how the presence of wind turbines affects house values, I construct a panel that covers the period from 2000 to 2016, where variables are aggregated at the zip code level. Median home selling prices per square foot are collected from Zillow.[5] All types of homes are considered, that is, all single-family, condominium and co-operative homes with a county record. Zillow provides other measures of home values, as for instance the Zillow Home Value Index (ZHVI) that measures the median seasonally adjusted home value for a given area. However, these metrics are the output of statistical models that take already into account characteristics such as local amenities and are thus less indicated for the current analysis. To the house prices panel I add data on wind turbines made available by the Federal Aviation Administration (FAA), which contains monthly data through September 2016 on the exact position of each wind turbine in the US.[6] Records include undergoing projects, denied permissions, and locations under revision during the permission application process.

Figure 2 displays the time trend for median home selling prices in the US as it emerges from Zillow data. The dashed line shows the trend obtained averaging across all zip codes that are allocated a wind turbine during the period for which house price data is available or before. The solid line reports the corresponding trend for zip codes that do not receive a wind turbine in the period considered or before it.

Prices trend similarly over time in zip codes with and without a wind turbine, although they are somewhat noisy, reflecting the existence of a seasonal component. The empirical distribution of median home selling prices for the zip codes covered in the Zillow data is instead shown in Figure 3.

This distribution is computed after excluding some observations from the dataset according to the following procedure. I first identify 183 zip code-month units that are associated with a median house price higher than \$1000. If all other observations for the same zip code in different months have home prices below this cutoff, I treat the flagged value as a typo and I drop it from the dataset while leaving the other months. If instead there is more than one case of prices above the cutoff within the same zip code, I also drop all other observations related to that zip code. In total, I end up eliminating 21,567 zip code-month observations, or slightly more than 2.2% of the original dataset. As expected, the distribution of median home selling prices is highly right skewed. The mean value taken by this variable is about \$150.

[5] Zillow datasets are publicly available for download from `http://www.zillow.com/research/data/`.

[6] The actual GIS files are publicly available for download from `https://www.fws.gov/southwest/es/Energy_Wind_FAA.html`.

To the Zillow median home selling prices I add then geographic and census data. Annual average wind raster data with a resolution from 200-meter to 1000-meter cell sizes is made available by the National Renewable Energy Laboratory (NREL).[7] For instance, appendix figure 1 shows the map assembled by NREL detailing wind level in Rhode Island. Wind speeds are recorded at a 50-meter height above the ground. Wind power is then grouped into classes that range from poor (class 1) to superb (class 7). High resolution land-based wind data for Alabama, Florida, Louisiana or Mississippi is unfortunately not available; these states will thus be excluded from the analysis. Other geographic characteristics that are used as control variables are the distance from the coastline, elevation, and urbanized areas in year 2000.[8] In order to aggregate these variables at the zip code level, I first merge the related files in ArcGIS with the map detailing zip code boundaries. I then compute the percentage of the area of a given zip code that is recorded as urban according to the 2000 Census. Concerning the two other geographic controls, I instead find the centroid of each zip code and calculate the distance from the coastline and elevation related to these points.

The remaining demographic controls come from the 2000 Census.[9] These variables are collected at the census block group level, and I have thus to map them into the zip code polygons at which house prices are aggregated. To do this, I match each zip code with the block group that occupies the largest fraction of its area. This is certainly an imperfect mapping between zip codes and block groups, since it could happen that the same block group is matched to multiple zip codes. At the moment I am still working on the development of an algorithm that performs this operation in a more precise way.

3 Sample characteristics

Data related to wind turbine locations and other geographic and demographic variables is basically available for the entire US. On the other hand, I have information on median home selling prices only on a subsample of the full set of US zip codes. Appendix figure 2 makes this point more

[7]The data can be downloaded at http://www.nrel.gov/gis/data_wind.html.

[8]The US coastline can be accessed from https://earthworks.stanford.edu/catalog/stanford-xv279yj9196, while the shapefile containing elevation data can be accessed through the online catalogue of ArcGIS. Urbanized areas can be downloaded from the Census at https://www.census.gov/geo/maps-data/data/cbf/cbf_ua.html.

[9]All variables can be downloaded from https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

explicit. It shows in blue the zip codes for which information on home prices is available from Zillow. The red triangles represent wind turbines within these zip codes. Obviously, the zip codes included in the sample are not randomly selected and they likely correspond to highly populated geographic areas. However, at least for some of the US states, they represent a large fraction of the complete set of zip codes.

Considering only zip codes for which I have house prices, table 1 presents a summary of means and standard deviations of the key variables used in the analysis that follows. Column 1 displays descriptive statistics for the full sample, while column 2 and 3 distinguish between zip codes characterized by the presence of a wind turbine or not. Areas with wind turbines are on average more distant from the coastline, have a higher elevation, and are less populated. They have a lower income per capita, a higher fraction of white inhabitants, and a lower fraction of blacks and asians. Moreover, they tend to have a higher fraction of male residents and of individuals with lower education (high school degree or less). The last row shows that the zip codes that are not allocated a wind turbine are characterized by a lower fraction of the total geographic area having annual average wind with power class greater or equal than three. The correlation between average wind and wind turbines location can be visually inspected from Figure 4 (as well as appendix figure 3). The figure makes it evident that wind turbines (depicted as black triangles) tend to be placed in areas characterized by higher wind level (dark-shaded).

Column 4 of Table 1 shows that zip codes with and without a wind turbine are significantly different in terms of the variables considered. Since this paper uses the percentage of the area of a zip code having average wind of category three or more as instrument, I can investigate if the covariates are balanced conditional on this variable. Column 5 shows the coefficients estimated regressing each exogenous control on the percentage of zip code area having wind of power class larger than three, while column 6 adds to the regression all the other covariates as controls, together with state fixed effects. The differences in total population, percentage of black and asian population and level of education tend to disappear. The coefficients for the distance from the coastline, elevation and percentage of white and male population remain significant but considerably small. Income per capita is the only variable that remains statistically significant and with a large coefficient after regressing it on the wind variable and controlling for the other zip code characteristics. Overall however, the instrument seems to achieve a good balance of the covariates considered in the analysis.

4 Identification strategy

4.1 Instrumental variable approach

4.2 Event study analysis

If the presence of a wind turbine in a given zip code was determined randomly, I could in principle be able to estimate its effect on house values using the following model

$$ln(p_{lt}) = \alpha_l + \beta turbines_{lt} + \mathbf{X}_{lt}\theta + \tau_t + \varepsilon_{lt} \tag{1}$$

where $ln(p_{lt})$ measures the average house value in location l (zip code or census tract), and time t (year or month), while $turbines_{lt}$ describes the number of wind turbines active in that location. The other parameters in the model – α_l, and τ_t – capture fixed effects for location and time, respectively. Finally, $\mathbf{X}_{lt}$ represents a vector of time varying location characteristics, such as average household income, total population, high education rate, and minority prevalence.

If we are willing to assume that the vector of location specific control variables remains constant over the time period relevant for this analysis – i.e. $\mathbf{X}_{lt} = \mathbf{X}_l$ – we can rewrite equation 1 in first differences

$$\Delta ln(p_{lt}) = \beta \Delta turbines_{lt} + \tau_t + \Delta\varepsilon_{lt}$$

However, the coefficients estimated running simple OLS on equation 1 are likely to be biased by the existence of omitted variables that are correlated with both the change in house values and wind turbine presence. For instance, if poorer geographic areas are more likely to be allocated a wind turbine, and the price of houses in these areas is lower, then this would generate a negative relationship between turbines and house prices. In the attempt to reduce this problem, I control for a vector of zip code level covariates, $\mathbf{X}_{zs0}$, measured in 2000, the baseline period of the analysis. Among the control variables I include distance from the coastline; elevation; percentage of urbanized area; total population; fraction of whites, blacks and asians; income per capita; and educational attainment. Unfortunately, even after controlling for these zip code characteristics it is still likely that the estimate of α_2 will be biased due to omitted or unobservable variables and confounding trends. To identify the causal impact of wind turbines on house values I therefore rely on an instrumental variable approach. I use annual average 50-meter height above the ground wind data to construct a variable that measures the percentage of the area of a given zip code having wind of power category equal or higher than three. Since the productivity of wind turbines depends, among other geographic characteristics, on the location's wind power, this instrument is likely to be a good predictor for wind turbine presence. The two equations related to the IV approach are the following

$$\text{First stage:} \quad \Delta turbines_{lt} = \pi Z_{lt} + \tau_t + \nu_{lt} \tag{2}$$

$$\text{Second stage:} \quad \Delta ln\left(p_{lt}\right) = \beta \Delta \widehat{turbines}_{lt} + \tau_t + \Delta\varepsilon_{lt} \tag{3}$$

I will now discuss more in details why the instrument I construct is based on the cutoff of a power class equal to three. As mentioned above, wind data is reported by the NREL on the basis of seven wind power classes. In order to construct an instrumental variable that is relevant to the allocation decision of a wind turbine to a given location, I rely on the fact that, as noted in the Wind Energy Resource Atlas of the United States, "Areas designated class 3 or greater are suitable for most wind turbine applications, whereas class 2 areas are marginal. Class 1 areas are generally not suitable, although a few locations (e.g., exposed hilltops not shown on the maps) with adequate wind resource for wind turbine applications may exist in some class 1 areas."[10] Therefore, I choose to compute the percentage of the geographic area of each zip code that is characterized by average wind level of at least class three.[11] The results of the analysis that follows remain mainly unchanged if I choose slightly different specifications of the instrument, as for instance adding also areas with average wind of power class two.

[10]The Wind Energy Resource Atlas of the United States can be consulted at `http://rredc.nrel.gov/wind/pubs/atlas/chp1.html`.

[11]Practically, this step is implemented in ArcGIS intersecting the map containing wind level information with that reporting the US zip code boundaries.

5 Results

5.1 Threats to IV validity

I now present the main results of the IV approach outlined in the previous section. Table 2 reports the estimates obtained in the first stage. In all specifications standard errors are clustered at the date specific ($year \times month$) level. The dependent variable is an indicator that is equal to one whenever a wind turbine is present in a certain zip code and month. In column (1), the first row indicates that for a 10% increase in the area of the zip code having wind of at least category three, the probability of receiving a wind turbine increases by more than half percentage points. Column (2) adds to this baseline model the vector of control variables listed before. The size of the coefficient remains basically unchanged, as well as the F-statistic which is highly above the rule-of-thumb threshold of 10. Moving to column (3), I include state and date specific fixed effects. In this case, the coefficient of the first row shows that a 10% increase in the area of a zip code with average wind level of power class of at least three increases by 0.6% the probability that a wind turbine will be assigned to that zip code. The coefficients of the covariates included in column (2) and (3) have generally the expected signs: for instance, zip codes characterized by high elevation have on average a higher probability to be allocated a wind turbine. On the other hand, wind turbines are less frequently found in richer and more populated areas. A somehow less intuitive result comes from the negative coefficient of the variable measuring the percentage of the area of the zip code being urbanized in year 2000. We would in fact expect that wind turbines are more frequently allocated to highly rural zip codes. A possible explanation to reconcile this finding is that wind turbines are not directly placed in urban areas but next to them, in order to represent an alternative source of energy in locations where energy demand is particularly high. Moreover, this could also be a mechanic consequence of the fact that the zip codes for which Zillow collects data on home selling prices are not a random selection of the universe of US zip codes.

Figure 5 is a graphic representation of the first stage just discussed. I first regress the instrument on the vector of covariates together with state fixed effects. Next, I take the residuals obtained from this regression and plot them against the indicator for turbine presence in the zip code. As a last step I fit a local quadratic regression on this data using the rule-of-thumb bandwidth suggested by Fan & Gijbels (1996). Consistent with the earlier estimates the probability to find a turbine in a given zip code is increasing in the residualized percentage area of the zip code with average wind of category three or higher. Consistently with the monotonicity assumption, also the slope is increasing in the residualized instrumental variable.

We turn next to the analysis of the results from the OLS regression of median home selling price per square foot on turbine presence, reported in the first three columns of Table 3. Standard errors are clustered at the date specific level in all specifications. The coefficients related to the complete model -- shown in column (3) -- suggest that the presence of a turbine in a given zip code decreases the house prices by \$20, everything else kept constant. As intuitively expected, distance from the coastline and elevation have also a negative and significant effect on home selling prices, while an opposite relation exists for instance in the case of income per capita.

Despite the OLS coefficient on wind turbine presence shows already some evidence of a negative effect on house prices, this relationship could be biased by the presence of omitted variables and endogeneity in the choice of the area where wind turbines are built. To be able to isolate an exogenous source of variation in wind turbines allocation to zip codes I instrument wind turbine presence with annual average wind level as discussed in the previous section. The coefficients estimated using the IV approach are reported in column (4) to (6). Once again, standard errors in parenthesis are clustered at the date specific level. In all three columns we confirm the hypothesis that wind turbine presence has a negative and statistically significant effect on home values. Focusing on column (6), where I include all controls together with state and date fixed effects, the negative impact on house prices is found to be as large as \$122. It is important to notice that the 2SLS coefficients of wind turbine presence are way larger than the correspondent OLS estimates. This is likely due to the presence of measurement error in the price variable that is not completely eliminated by simply dropping outlier observations as discussed before.

6 Event study analysis

As an alternative approach to the instrumental variable estimation, I perform an event study of the effect of wind turbines on house values. In their study of displaced workers' earnings losses, Jacobson et al. (1993) develop a framework to analyze multiple events occurring at different timings. I adopt the notation presented in Sandler & Sandler (2012), who offer an overview of the recent literature of multiple event studies. Let y_{zst} denote the value of houses in zip code z, state s and time$t$, and call e^z the date of the event occurring in z. Then, I can estimate the following model

$$y_{zst} = \sum_{d=-D, d\neq -1}^{D} 1(t - e^z = d)\beta_d + \alpha_t + \gamma_s + \varepsilon_{zst}$$

where α_t denote time fixed effects and γ_s capture state fixed effects.

Figure 6 displays the coefficients β_d of the equation above for the median home selling prices per square foot collected by Zillow.

The time window considered is 3 years before and after a turbine is erected in a given zip code. Observations in the plot are the coefficients estimated from the sample of zip codes where wind turbines are actually built. This implicit restriction imposed by the event study framework limits the power of this analysis since the dataset I use contains only 269 cases of zip codes where a wind turbine is located and information on house prices is available. Moreover, requiring to observe at least three years before and after the turbine is built limits this sample set even further. The consequence of these restrictions is that no clear pattern emerges from the event study plot shown in Figure 6. More precisely, the figure shows that home selling prices decrease on average the year before a wind turbine is built, but this drop is not different in magnitude than the one measured two years after the event making the interpretation of any of those pattern less credible. Moreover, the standard errors related to the coefficients β_d (not depicted in the figure) are extremely large and eliminate any statistical difference between the observations plotted.

7 Conclusions and future work

This paper investigates the relation between wind turbine presence at the zip code level and home values. It uses the percentage of the area of a given zip code having annual average wind level of category three or more to address problems related to the endogenous placement of wind turbines and other confounding trends. Results from the 2SLS estimation suggest that home selling prices in places that are allocated a wind turbine are on average \$120 lower. On the other hand, the event study analysis does not convincingly show any particular trend before and after a wind turbine is constructed.

Despite the findings discussed in this paper clearly point towards the direction of an existing negative relation between wind turbines presence and home values, this evidence if far from being conclusive. However, Zillow will soon release a new version of its public available house price dataset that will cover the entire US at the census tract level. This will help reducing the issue of sample selection faced by this study and likely add more robustness to its results.

References

Cullen, J. (2013), 'Measuring the environmental benefits of wind-generated electricity', *American Economic Journal: Economic Policy* **5**(4), 107–33.

Dinkelman, T. (2011), 'The effects of rural electrification on employment: New evidence from south africa', *The American Economic Review* **101**(7), 3078–3108.

DOE/GO (2004), Wind energy for rural economic development, Technical report, U.S. Department of Energy.

Dröes, M. & Koster, H. (2014), 'Renewable energy and negative externalities: the effect of wind turbines on house prices'.

Energy.gov (2017), 'Advantages and challenges of wind energy'.
URL: *https://www.energy.gov/eere/wind/advantages-and-challenges-wind-energy*

Fan, J. & Gijbels, I. (1996), *Local polynomial modelling and its applications: monographs on statistics and applied probability 66*, Vol. 66, CRC Press.

Firestone, J. & Kempton, W. (2007), 'Public opinion about large offshore wind power: underlying factors', *Energy policy* **35**(3), 1584–1598.

Gibbons, S. (2015), 'Gone with the wind: Valuing the visual impacts of wind turbines through house prices', *Journal of Environmental Economics and Management* **72**, 177–196.

Hoen, B., Brown, J. P., Jackson, T., Wiser, R., Thayer, M. & Cappers, P. (2013), 'A spatial hedonic analysis of the effects of wind energy facilities on surrounding property values in the united states'.

Hoen, B., Wiser, R., Cappers, P., Thayer, M. & Sethi, G. (2009), 'The impact of wind power projects on residential property values in the united states: A multi-site hedonic analysis'.

IEO (2017), International energy outlook 2017, Technical report, U.S. Energy Information Administration.

Jacobson, L. S., LaLonde, R. J. & Sullivan, D. G. (1993), 'Earnings losses of displaced workers', *The American economic review* pp. 685–709.

Jalali, L., Nezhad-Ahmadi, M.-R., Gohari, M., Bigelow, P. & McColl, S. (2016), 'The impact of psychological factors on self-reported sleep disturbance among people living in the vicinity of wind turbines', *Environmental research* **148**, 401–410.

Kalmikov, A. & Dykes, K. (2010), 'Wind power wind power fundamentals', University Lecture.

Knopper, L. D. & Ollson, C. A. (2011), 'Health effects and wind turbines: A review of the literature', *Environmental Health* **10**(1), 78.

Ladenburg, J. & Dubgaard, A. (2007), 'Willingness to pay for reduced visual disamenities from offshore wind farms in denmark', *Energy Policy* **35**(8), 4059–4071.

Lang, C., Opaluch, J. J. & Sfinarolakis, G. (2014), 'The windy city: Property value impacts of wind turbines in an urban setting', *Energy Economics* **44**, 413–421.

Lopez, A., Roberts, B., Heimiller, D., Blair, N. & Porro, G. (2012), Us renewable energy technical potentials: a gis-based analysis, Technical report, NREL.

Sandler, D. H. & Sandler, R. (2012), 'Multiple event studies in public finance: a simulation study with applications', *Working Paper* **5**, 1–27.

Sims, S., Dent, P. & Oskrochi, G. R. (2008), 'Modelling the impact of wind farms on house prices in the uk', *International Journal of Strategic Property Management* **12**(4), 251–269.

Slattery, M. C., Johnson, B. L., Swofford, J. A. & Pasqualetti, M. J. (2012), 'The predominance of economic development in the support for large-scale wind farms in the us great plains', *Renewable and Sustainable Energy Reviews* **16**(6), 3690–3701.

Sunak, Y. & Madlener, R. (2016), 'The impact of wind farm visibility on property values: A spatial difference-in-differences analysis', *Energy Economics* **55**, 79–91.

A Repeat sales index methodology

This appendix investigates

Table 5: Monotonicity test, Bogin et al. (2016) prices at ZIP code level

	△turbines	Coefficient (Standard error)	Number of locations	Number of location-time
(1)	Counties in metro areas of 1 million population or more	0.0009 (0.0004)	5654	176352
(2)	Counties in metro areas of 250,000 to 1 million population	0.0029 (0.0008)	3514	98398
(3)	Counties in metro areas of fewer than 250,000 population	0.0035 (0.0009)	2233	56479
(4)	Urban population of 20,000 or more, adjacent to a metro area	0.0042 (0.0012)	1429	32263
(5)	Urban population of 20,000 or more, not adjacent to a metro area	0.0060 (0.0036)	410	9493
(6)	Urban population of 2,500 to 19,999, adjacent to a metro area	0.0056 (0.0015)	1734	33185
(7)	Urban population of 2,500 to 19,999, not adjacent to a metro area	0.0104 (0.0017)	843	16598
(8)	Completely rural or less than 2,500 urban population, adjacent to a metro area	0.0041 (0.0027)	344	5493
(9)	Completely rural or less than 2,500 urban population, not adjacent to a metro area	0.0014 (0.0007)	281	4555

Notes: Each specification use a different sub-sample from the set of ZIP codes having information on house prices estimated by Bogin et al. (2016). Sub-samples are defined according to a measures of rurality at the county level ranging from 1 through 9 (see `https://dsdr-kb.psc.isr.umich.edu/answer/1102`). For each regression, the independent variable is the percentage of the area of a given ZIP code having potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. All specifications include year fixed effects and standard errors are clustered at the ZIP code level.

Table 1: Covariates balance

	Means			Differences in means		
	Full sample	Wind farm	No wind farm	Columns (2)-(3)	By wind	
					No controls	Controls
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Average income	56.4481	47.6646	56.5888	-8.9242	-0.1049	-0.0823
	(34.3034)	(10.9847)	(34.5310)	(0.7304)	(0.0138)	(0.0138)
Total population	15055.1253	8975.5878	15152.5109	-6176.9231	-179.1140	-107.3981
	(14777.3287)	(10322.1167)	(14817.7508)	(648.1425)	(5.7944)	(5.1218)
Elevation	294.6454	501.8397	291.3265	210.5132	1.2916	-2.3481
	(383.4397)	(402.8016)	(382.2216)	(25.0640)	(0.1543)	(0.1174)
Distance to the coast	228.1892	373.4400	225.8625	147.5776	3.2832	2.7075
	(267.0270)	(320.6562)	(265.4457)	(19.9186)	(0.1046)	(0.0792)
Male ratio	0.4950	0.5016	0.4949	0.0067	0.0001	0.0001
	(0.0220)	(0.0231)	(0.0219)	(0.0014)	(0.0000)	(0.0000)
White ratio	0.8286	0.9098	0.8273	0.0825	0.0018	0.0001
	(0.1869)	(0.1008)	(0.1877)	(0.0064)	(0.0001)	(0.0000)
Black ratio	0.0833	0.0176	0.0843	-0.0667	-0.0011	-0.0000
	(0.1520)	(0.0391)	(0.1529)	(0.0027)	(0.0001)	(0.0000)
Asian ratio	0.0242	0.0085	0.0244	-0.0159	-0.0003	0.0001
	(0.0514)	(0.0278)	(0.0516)	(0.0018)	(0.0000)	(0.0000)
Percentage ZIP code area with	5.5365	32.0012	5.1126	26.8886		
potential wind capacity > 30%	(19.2390)	(39.6729)	(18.4270)	(2.4552)		
Number of ZIP codes	16618	262	16356	16618	16618	16618

Notes: The sample is the set of ZIP codes having information on house prices for at least one year and the full vector of control variables. Data on house prices comes from the Federal Housing Finance Agency (FHFA). Data on demographic controls comes from the 2010 Census. Income at the ZIP code level comes from the IRS, and potential wind capacity is estimated by Lopez et al. (2012) using data from the National Renewable Energy Laboratory (NREL). Standard errors are reported in parenthesis. Column (1) reports covariates averages for the full sample of ZIP codes. Columns (2) and (3) divide the sample into two sub-groups, according to whether a cumulative number of at least ten turbines is ever observed in a given ZIP code or not. Column (4) tests for differences between column (2) and (3) using a t-test with unequal variances. Column (5) reports the coefficient obtained regressing each covariate on the percentage of the ZIP code area with potential wind capacity greater than 30%. Column (6) additionally controls for the remaining covariates.

Table 2: OLS regressions

	Panel A		*Panel B*		*Panel C*		*Panel D*	
$\triangle ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\triangle$turbines	0.00016	0.00015	0.00010	0.00011	0.00008	0.00005	-0.00002	-0.00001
	(0.00005)	(0.00006)	(0.00007)	(0.00007)	(0.00015)	(0.00016)	(0.00003)	(0.00003)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of locations	46731	46731	16786	16786	9309	9309	14082	14082
Number of location-time	1147555	1147555	442092	442092	722194	722194	3309753	3309753

Notes: In panel A, a time period is a year and the unit of analysis is the census tract-year. In panel B, a time period is a year and the unit of analysis is the ZIP code-year. In panel C and D, a time period is a month and the unit of analysis is the ZIP code-month. House prices in panel A and B are estimated by Bogin et al. (2016). House prices in panel C are median listing prices per square foot from Zillow, while specifications in panel D use the Zillow Home Value Index. Each regression includes calendar time fixed effects. Standard errors in parenthesis are clustered by location.

Table 3: First stage regressions

	Panel A		*Panel B*		*Panel C*		*Panel D*	
$\triangle$turbines	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Percentage area with potential wind capacity > 30% x $\mathbb{1}$(year first turbine US)	0.0040 (0.0004)	0.0051 (0.0005)	0.0047 (0.0005)	0.0062 (0.0007)	0.0006 (0.0001)	0.0008 (0.0002)	0.0005 (0.0001)	0.0007 (0.0001)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of locations	46731	46731	16786	16786	9309	9309	14082	14082
Number of location-time	1147555	1147555	442092	442092	722194	722194	3309753	3309753

Notes: In panel A, a time period is a year and the unit of analysis is the census tract-year. In panel B, a time period is a year and the unit of analysis is the ZIP code-year. In panel C and D, a time period is a month and the unit of analysis is the ZIP code-month. The excluded instrument is defined as the percentage of the area of a given location having potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. Each regression includes calendar time fixed effects. Standard errors in parenthesis are clustered by location.

Table 4: IV regressions

	Panel A		*Panel B*		*Panel C*		*Panel D*	
$\triangle ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\triangle$turbines	-0.0232	-0.0116	-0.0096	-0.0029	-0.0057	-0.0144	-0.0226	-0.0053
	(0.0024)	(0.0014)	(0.0013)	(0.0008)	(0.0029)	(0.0039)	(0.0030)	(0.0011)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of locations	46731	46731	16786	16786	9309	9309	14082	14082
Number of location-time	1147555	1147555	442092	442092	722194	722194	3309753	3309753

Notes: In panel A, a time period is a year and the unit of analysis is the census tract-year. In panel B, a time period is a year and the unit of analysis is the ZIP code-year. In panel C and D, a time period is a month and the unit of analysis is the ZIP code-month. House prices in panel A and B are estimated by Bogin et al. (2016). House prices in panel C are median listing prices per square foot from Zillow, while specifications in panel D use the Zillow Home Value Index. The excluded instrument is defined as the percentage of the area of a given location having potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. Each regression includes calendar time fixed effects. Standard errors in parenthesis are clustered by location.

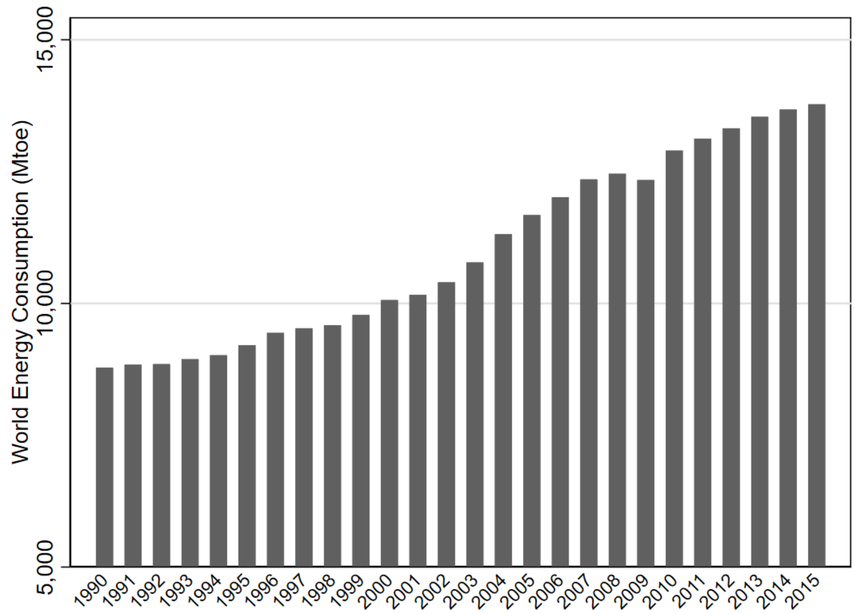
Table 6: Falsification test

$\triangle ln(p)$	*Panel A* (1)	(2)	*Panel B* (3)	(4)	*Panel C* (5)	(6)
Potential wind capacity	0.0002	0.0001	0.0000	0.0001	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State fixed effects	No	Yes	No	Yes	No	Yes
Number of locations	33766	33766	11536	11536	12052	12052
Number of location-time	292123	292123	132696	132696	493846	493846

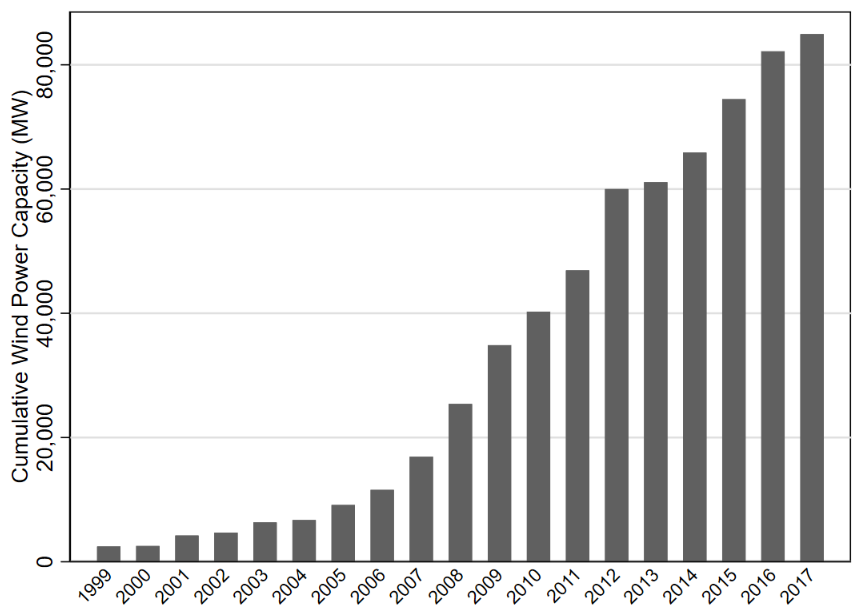
Notes: The sample is restricted to the period before the first wind turbine was installed in the US. In panel A, a time period is a year and the unit of analysis is the census tract-year. In panel B, a time period is a year and the unit of analysis is the ZIP code-year. In panel C, a time period is a month and the unit of analysis is the ZIP code-month. House prices in panel A and B are estimated by Bogin et al. (2016). The specifications in panel C use the Zillow Home Value Index. The independent variable is defined as the percentage of the area of a given location having potential wind capacity in 2008 greater than 30%. Each regression includes calendar time fixed effects. Standard errors in parenthesis are clustered by location.

Figure 1: Energy trends

Panel A: World energy consumption

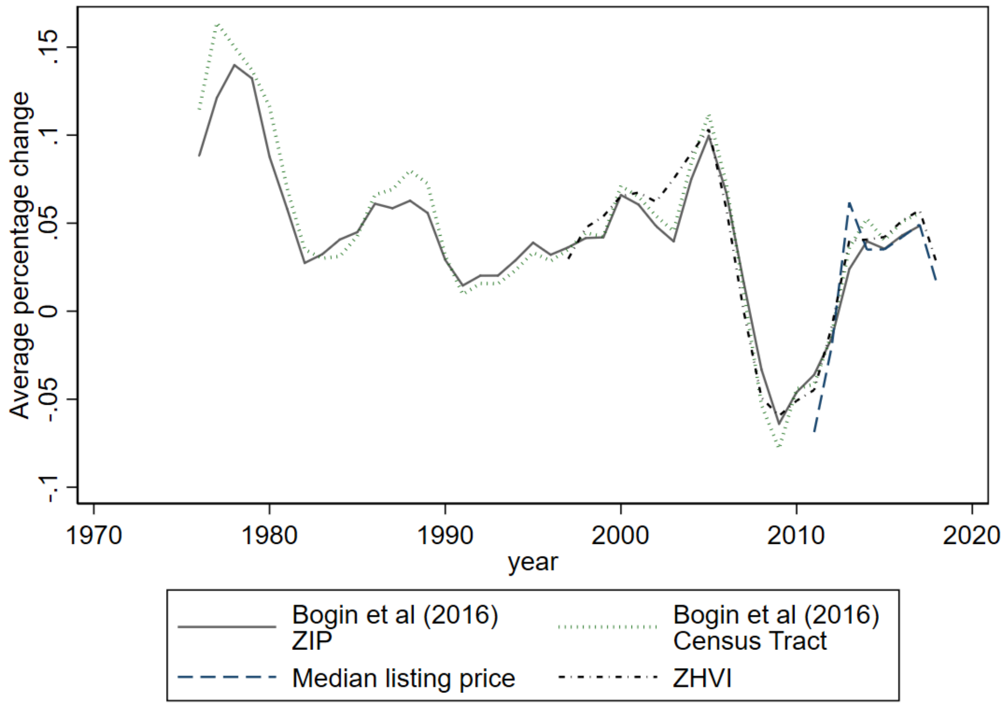


Panel B: US wind energy capacity



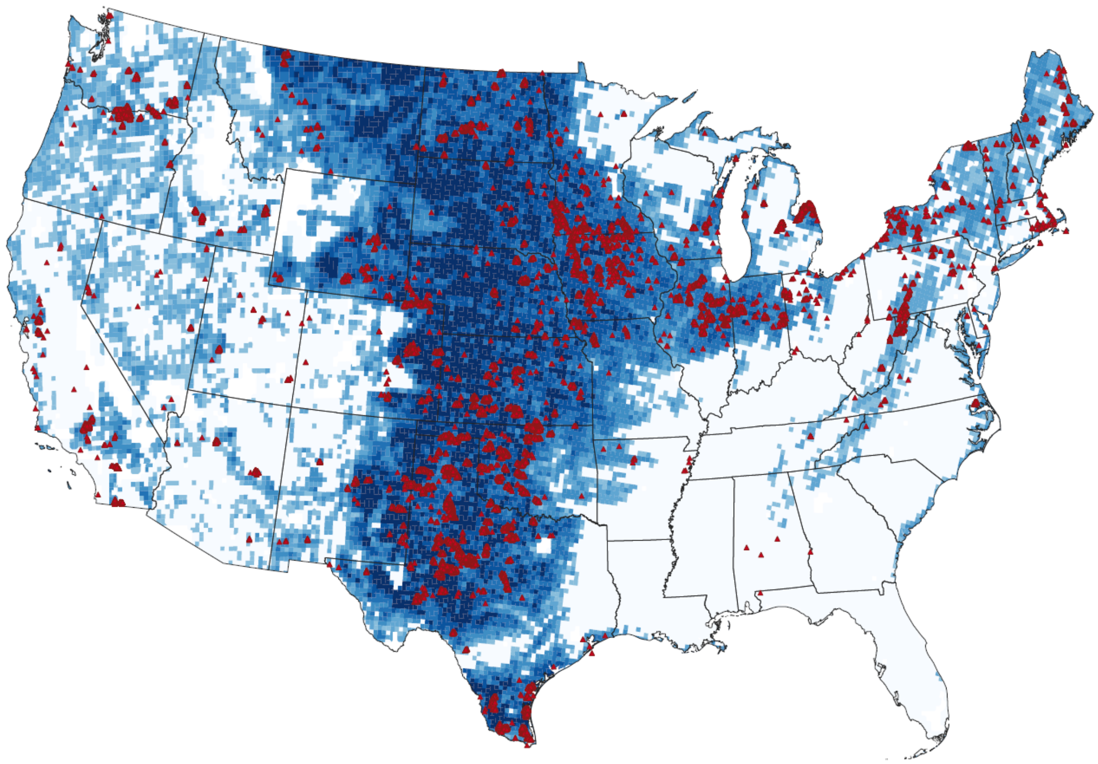
Notes: Data on world energy consumption comes from the 2016 Global Energy Statistical Yearbook (`https://yearbook.enerdata.net/`). Data on US wind energy capacity comes from the Office of Energy Efficiency & Renewable Energy (`https://windexchange.energy.gov/maps-data/321`).

Figure 2: Number of currently active executives



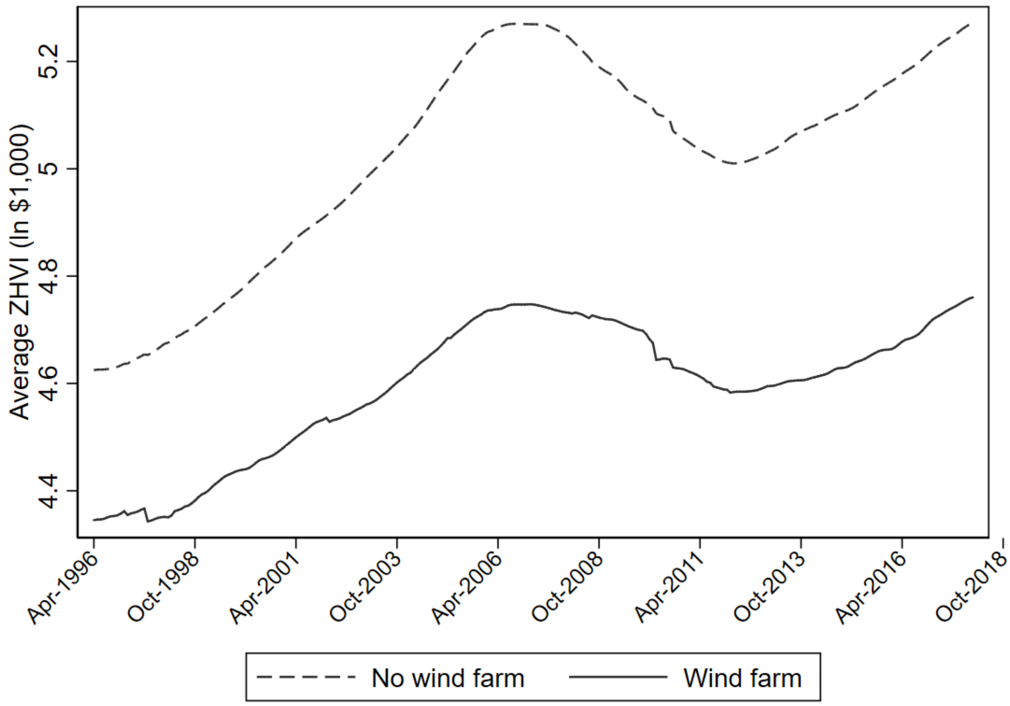
Notes:

Figure 3: Wind turbines location and potential wind capacity in 2008



Notes: The figure shows data on potential wind capacity in 2008 estimated by Lopez et al. (2012) using data from the National Renewable Energy Laboratory (NREL). The US map (Alaska excluded) is divided into cells of approximately equal size. Blue cells correspond to locations having a non-zero fraction of their area with potential wind capacity larger than 30%. The intensity of the color represents the proportion of the area with wind capacity above the threshold. Red triangles symbolize wind turbines installed by December 2017. Data on wind turbines comes from the Federal Aviation Administration (FAA).

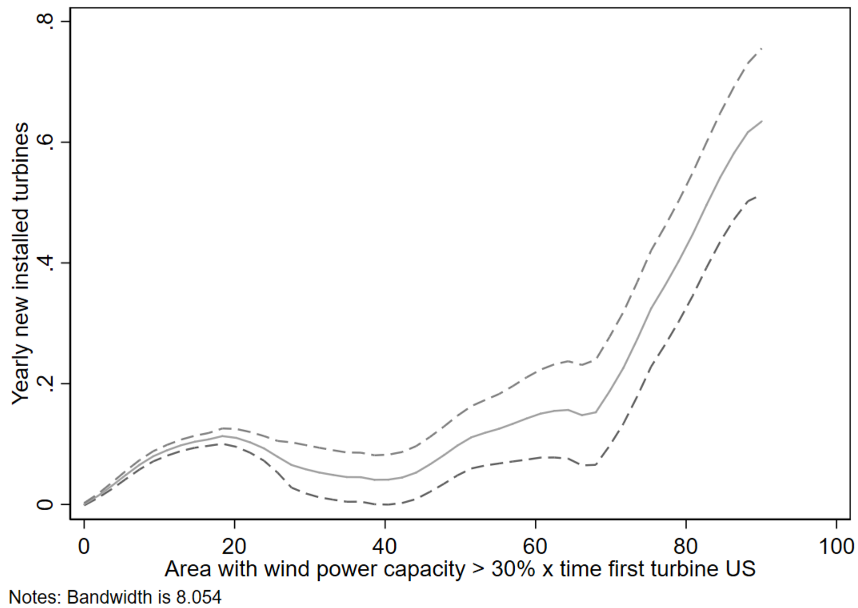
Figure 4: House prices time series



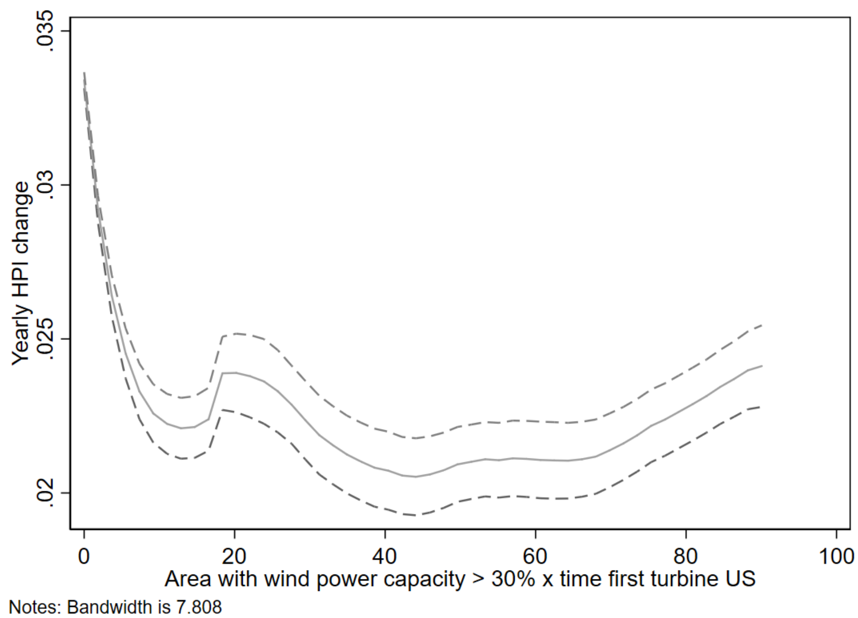
Notes: The figure reports data on average monthly log Zillow Home Value Index. The sample is divided into two sub-groups, according to whether a cumulative number of at least ten turbines is ever observed in a given ZIP code (solid line) or not (dashed line).

Figure 5: Graphic representation of instrumental variable approach

Panel A: First stage

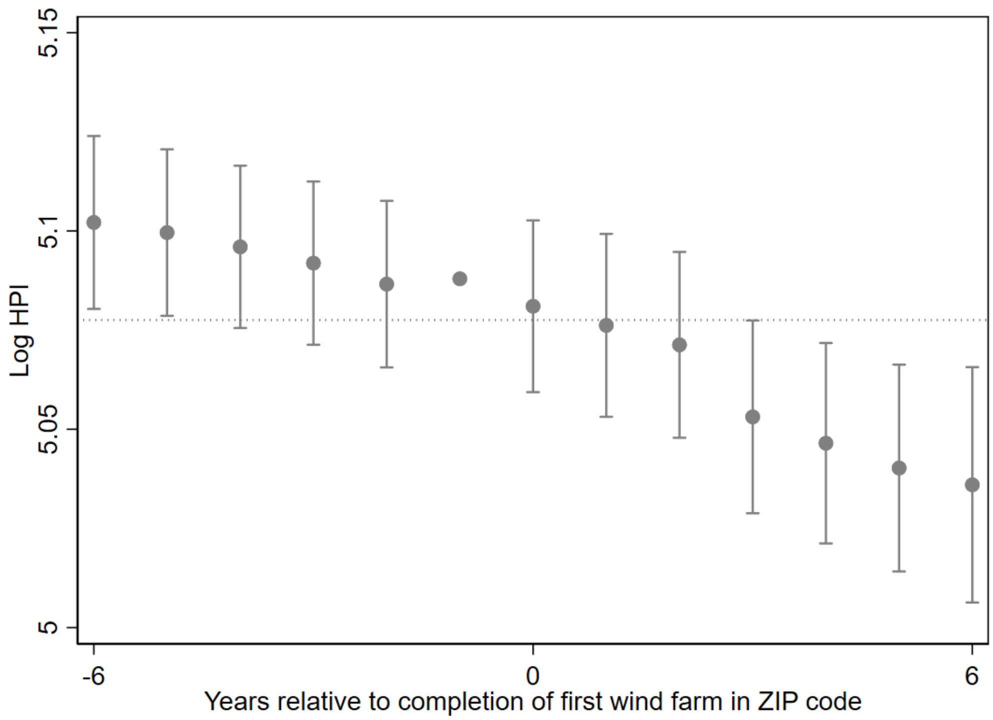


Panel B: Reduced form



Notes:

Figure 6: Yearly house price



Notes:

Appendix Table 1: Monotonicity test, Bogin et al. (2016) prices at census tract level

	$\triangle$turbines	Coefficient (Standard error)	Number of locations	Number of location-time
(1)	Counties in metro areas of 1 million population or more	0.0013 (0.0005)	21645	568137
(2)	Counties in metro areas of 250,000 to 1 million population	0.0034 (0.0011)	10759	270462
(3)	Counties in metro areas of fewer than 250,000 population	0.0042 (0.0010)	5661	135328
(4)	Urban population of 20,000 or more, adjacent to a metro area	0.0030 (0.0010)	2819	62017
(5)	Urban population of 20,000 or more, not adjacent to a metro area	0.0054 (0.0021)	984	21888
(6)	Urban population of 2,500 to 19,999, adjacent to a metro area	0.0038 (0.0009)	2647	49892
(7)	Urban population of 2,500 to 19,999, not adjacent to a metro area	0.0065 (0.0011)	1452	27345
(8)	Completely rural or less than 2,500 urban population, adjacent to a metro area	0.0019 (0.0015)	397	6549
(9)	Completely rural or less than 2,500 urban population, not adjacent to a metro area	0.0033 (0.0023)	351	5614

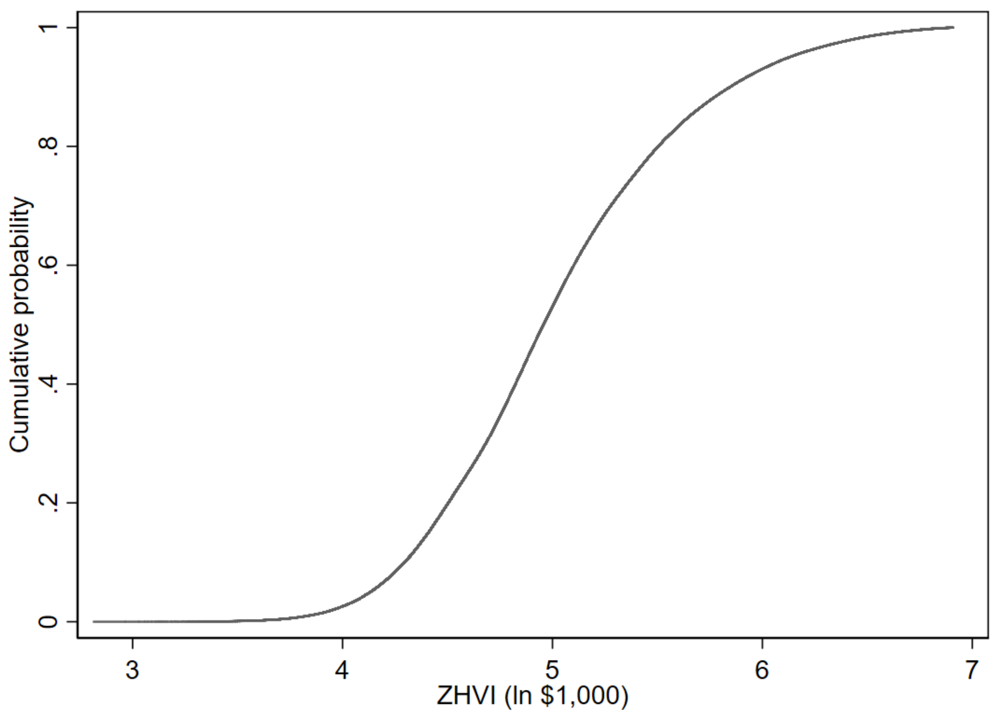
Notes: Each specification use a different sub-sample from the set of census tracts having information on house prices estimated by Bogin et al. (2016). Sub-samples are defined according to a measures of rurality at the county level ranging from 1 through 9 (see `https://dsdr-kb.psc.isr.umich.edu/answer/1102`). For each regression, the independent variable is the percentage of the area of a given census tract having potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. All specifications include year fixed effects and standard errors are clustered at the census tract level.

Appendix Table 2: Monotonicity test, Zillow Home Value Index

	△turbines	Coefficient (Standard error)	Number of locations	Number of location-time
(1)	Counties in metro areas of 1 million population or more	0.0002 (0.0001)	5322	1300018
(2)	Counties in metro areas of 250,000 to 1 million population	0.0003 (0.0001)	3234	773909
(3)	Counties in metro areas of fewer than 250,000 population	0.0004 (0.0001)	1870	440196
(4)	Urban population of 20,000 or more, adjacent to a metro area	0.0003 (0.0001)	1240	287556
(5)	Urban population of 20,000 or more, not adjacent to a metro area	0.0005 (0.0002)	295	61341
(6)	Urban population of 2,500 to 19,999, adjacent to a metro area	0.0010 (0.0003)	1098	234722
(7)	Urban population of 2,500 to 19,999, not adjacent to a metro area	0.0009 (0.0002)	448	86698
(8)	Completely rural or less than 2,500 urban population, adjacent to a metro area	0.0009 (0.0009)	160	31564
(9)	Completely rural or less than 2,500 urban population, not adjacent to a metro area	0.0007 (0.0005)	90	13829

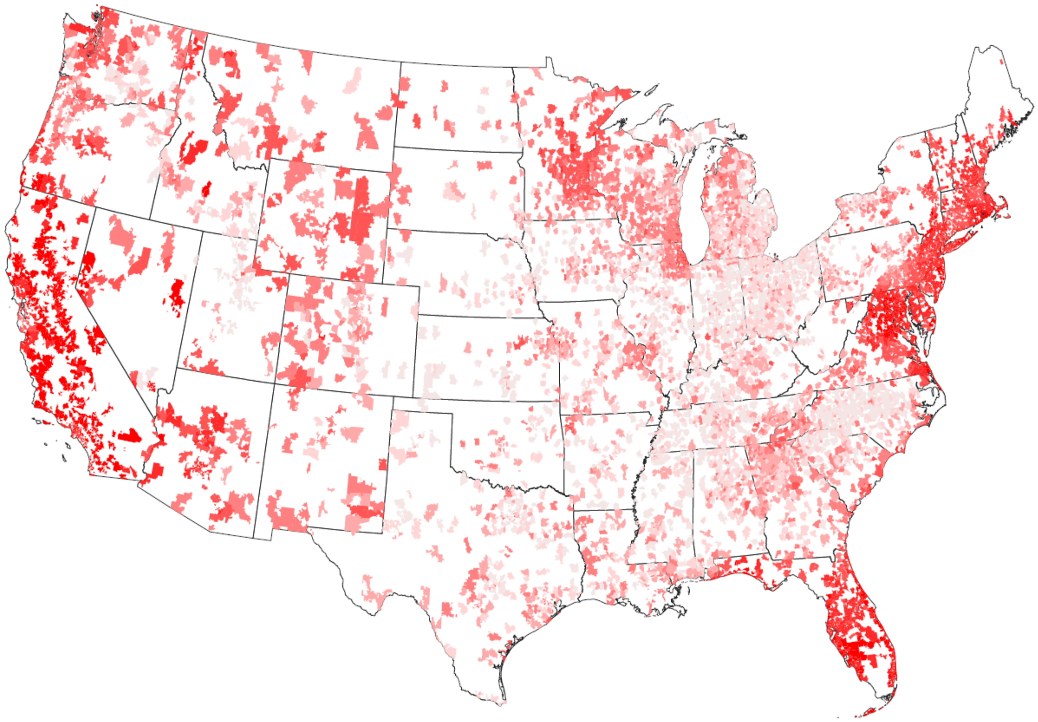
Notes: Each specification use a different sub-sample from the set of ZIP codes having Zillow Home Value Index data. Sub-samples are defined according to a measures of rurality at the county level ranging from 1 through 9 (see `https://dsdr-kb.psc.isr.umich.edu/answer/1102`). For each regression, the independent variable is the percentage of the area of a given ZIP code having potential wind capacity in 2008 greater than 30%, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. All specifications include calendar month fixed effects and standard errors are clustered at the ZIP code level.

Appendix Figure 1: Number of currently active executives



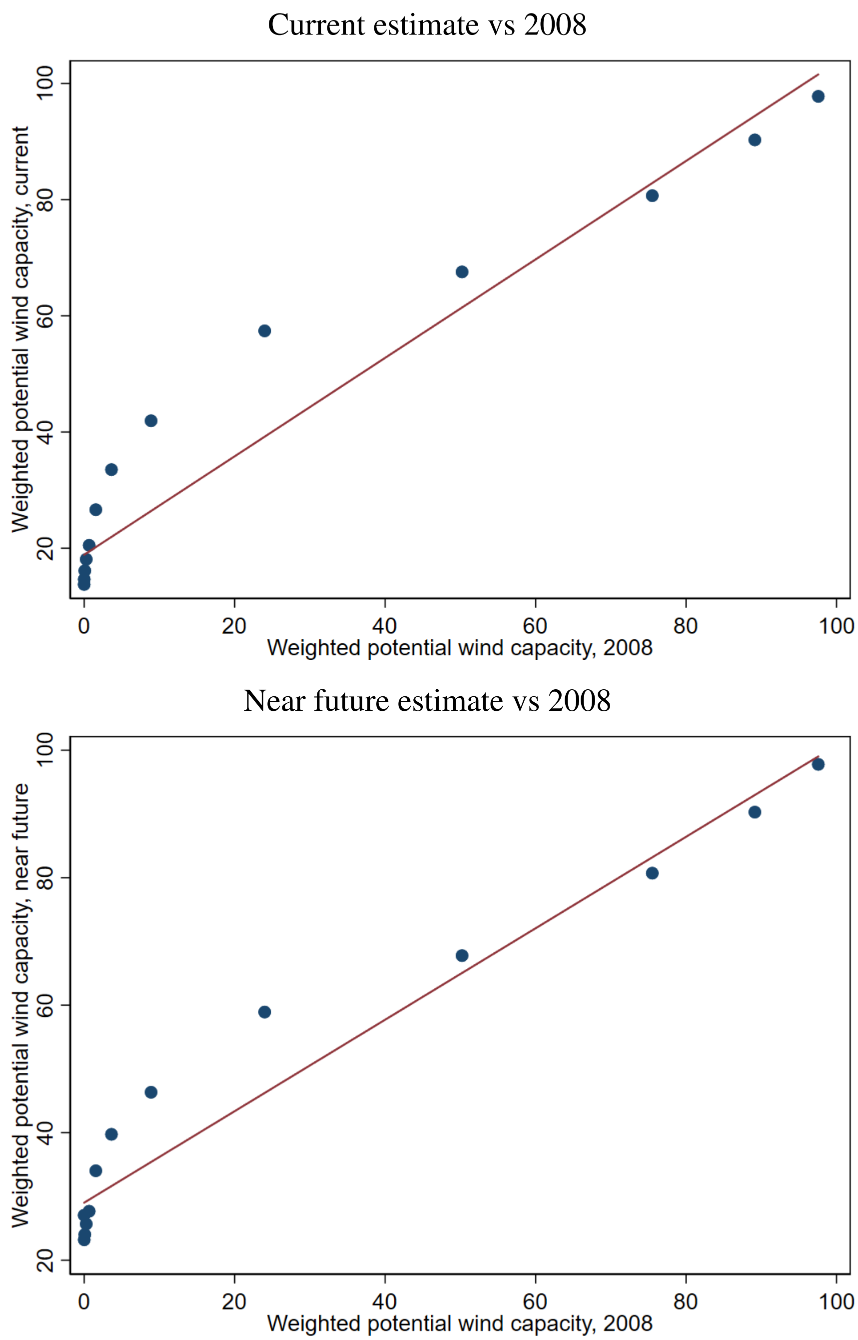
Notes:

Appendix Figure 2: Number of currently active executives



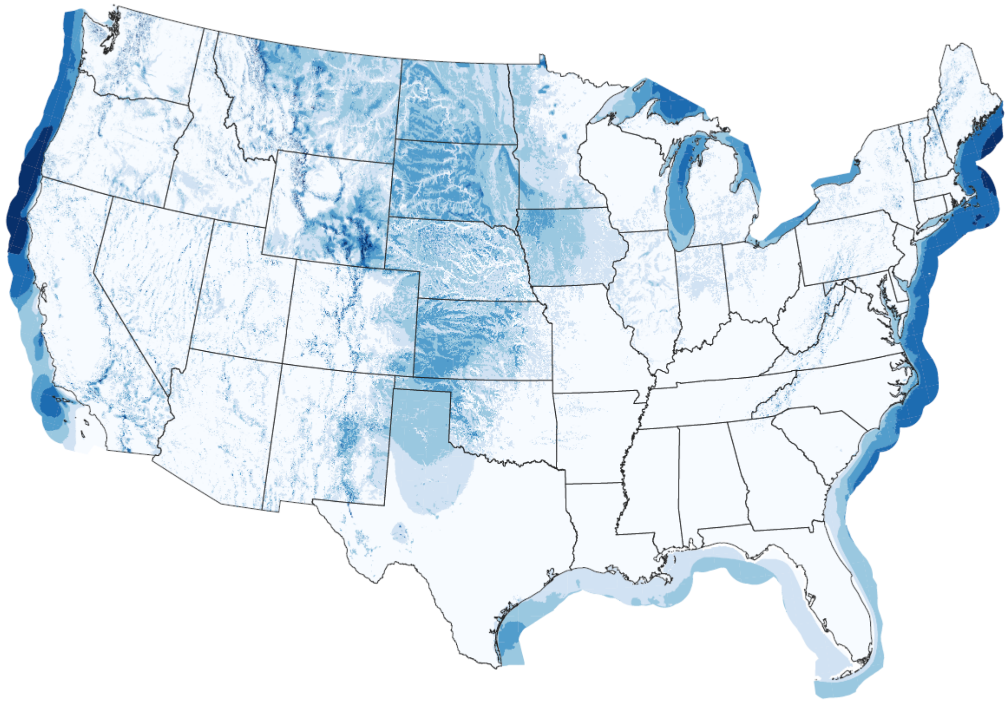
Notes:

Appendix Figure 3: Number of currently active executives



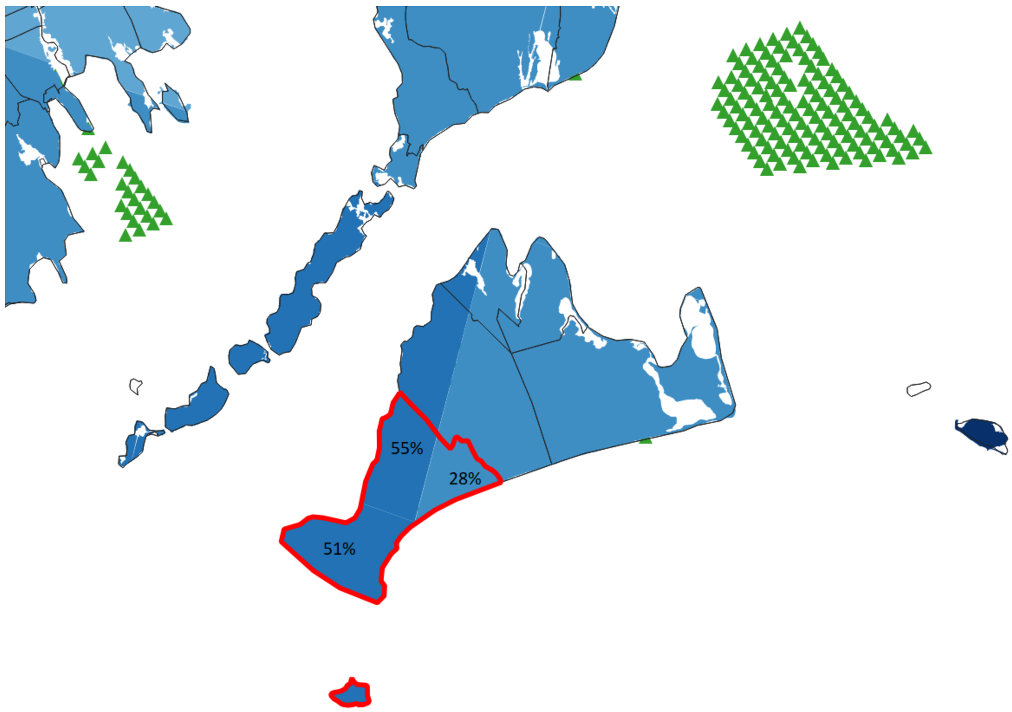
Notes:

Appendix Figure 4: Number of currently active executives



Notes:

Appendix Figure 5: Number of currently active executives



Notes: