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

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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 home 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, disamenities
JEL: D62, Q42, R30

*This project benefited from the suggestions of Lint Barrage, Emily Oster, Neil Thakral, Matthew Turner, and from audience comments at the Brown Microeconomics Seminar. I thank Jesse Shapiro for his knowledgeable guidance on the techniques used in this paper during my time as a research assistant. 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 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. In particular, the lowest levels of support are expressed by people living closest to wind farms, a phenomenon known as Not-In-My-Backyard (Swofford & Slattery 2010). From an international perspective, 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. For Australia, Hall et al. (2013) bring qualitative evidence of a "social gap" between publicly stated support and individual local acceptance, partly explained by the trade-off between global environmental gains and local bearing of the costs of visual changes to a place or landscape. According to Toke (2005), these are among the reasons

[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).

that explain why only less than half of the onshore wind farm applications in England and Wales are successful through the normal planning process.

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 in the US 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 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 a 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 0.25%. This is a remarkable negative effect considering that, on average, 17 new turbines are 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 a 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

[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.

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 improved version 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 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 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 approach 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 Wind turbines

I use data on all wind energy projects in the US through December 2017, made available by the Federal Aviation Administration (FAA).[5] Wind turbines observations are divided into four categories:

- Determined with Built Date: records returned to the FAA with a Built Date; generally represent completed constructions.
- Determined without Built Date: records that are in some state of construction (and might be completed) but no Built Date has been returned to the FAA yet.
- Determined as Hazard: records that have been determined to be a hazard to air navigation and in general are not under construction.
- Not yet Determined: records in the early phase of the permitting process for which no determination of whether they are a hazard or not has been made.

In the main analysis, I use the sample of wind turbines that are Determined with Built Date. I drop observations that I am not able to match to any ZIP code or census tract (mainly because they are located in Alaska or offshore) or that are not classified as wind turbines.[6] I also remove observations below the first percentile of the height distribution to keep only turbines that have a significant impact on the local landscape. After imposing these restrictions, the sample of wind turbines for the analysis at the ZIP code level is comprised of 41,108 turbines, with a median height of 418 feet.[7;8]

I rely on the group of turbines Determined as Hazard for a falsification test. The categories Determined without Built Date and Not yet Determined are not used in this paper because of the higher difficulty in classifying each project as completed or not.

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

[6]The data also include records for meteorological towers and other towers unrelated to wind energy.

[7]Similarly, the sample of turbines for the analysis at the census tract level counts 43,575 turbines, with a median height of 416 feet.

[8]According to the NationalWindWatch (2006), two diffused turbines model are the 1.8-megawatt Vestas V90 from Denmark, with a total height of 410 feet, and the 2-megawatt Gamesa G87 from Spain, totaling 399 feet.

2.2 Potential wind capacity

Potential annual average gross capacity factors for the US are computed by Lopez et al. (2012) using data from the National Renewable Energy Laboratory (NREL). The authors use wind power at 80 meters height above surface to produce estimates of wind resources at a 200-meters horizontal spatial resolution. Next, they eliminate areas that cannot host wind plants (such as urban areas, federally protected lands, and onshore water features) and estimate average annual energy production assuming a power density of 5 MW/km^2 and 15% energy loss.[9] Finally, they divide the US map into cells with areas of approximately 400km^2 and compute the percentage of each cell having potential capacity greater than 30%.

Figure 2 shows that wind turbines (represented by red triangles) are mainly placed in locations with a higher proportion of their area with potential capacity of at least 30% (shaded in dark blue). High potential capacity factors tend to be concentrated in the so called "wind corridor", a region stretching from North Dakota and Montana southward to western Texas, and characterized by high average annual wind speeds.[10]

2.3 House prices

Data on house prices come from two distinct sources.

First, Zillow provides monthly prices on all single-family, condominium and co-operative homes for selected US ZIP codes.[11] I use two measures of house prices from Zillow: (i) median listing prices per square foot, and (ii) Zillow Home Value Index (ZHVI). Median listing prices are available from January 2010 through January 2018 for more than 10,000 distinct ZIP codes. On the other hand, ZHVI data span the period April 1996–January 2018 for more than 15,000 ZIP codes. The larger time and geographic coverage of the ZHVI makes it my preferred Zillow metric.

In order to take into account the changing composition of properties sold in different points in time, the Zillow Home Value Index is created from estimated sale prices (called Zestimates) on *every* home in Zillow's database, instead of using prices from the subset of houses actually on

[9] These are common features of a typical wind technology available in 2008 (DOEEERE 2008).

[10] Average wind speed at 80 meters height in the wind corridor ranges from 6 to 9 m/s (see map at `https://windexchange.energy.gov/maps-data/319`).

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

sale.[12] Appendix figure 1 shows the distribution of monthly log ZHVI, for prices below \$1 million.

Second, I use the house price index (HPI) constructed by Bogin et al. (2016) (BDL henceforth) at the ZIP code and census tract level. The index is based on the repeat-sales methodology, which makes the assumption that the characteristics of a given house remain unchanged over the period of the analysis. Holding this true, the price index for a given location can be computed by regressing differences in sale prices of the *same* house on a vector of location$\times$time dummies.[13] BDL use this methodology on a sample of 97 million home transactions with nearly 54 million transaction pairs from the Federal Housing Finance Agency (FHFA). A specific feature of BDL's index is the low level of geographic aggregation (ZIP code and census tract), obtained by aggregating sales occurring over a one-year time horizon. In summary, BDL's index is available for approximately 18,000 ZIP codes and 55,000 census tracts from 1975 through 2017. Appendix figure 2 provides an overview of the ZIP codes for which the HPI exists in both 2000 and 2005. After joining BDL house prices at the ZIP code level with wind turbines and wind power capacity data, the resulting sample consists of about 16,800 distinct ZIP codes, or more than 44,000 ZIP code-years. On the other hand, the number of wind turbines matched is just above 35%.

Figure 3 shows that, on average, the four price measures trace similar patterns for the US housing market.

Obviously, locations included in the BDL or Zillow samples are not randomly selected and they likely correspond to more populated geographic areas where home transactions occur more frequently. However, in most cases, covered locations represent a relevant fraction of the complete set of each state's territory.

2.4 Additional variables

Home prices, turbines location and potential wind capacity are the central variables for the analysis that follows. I supplement this data with geographic and demographic controls, mainly at the ZIP

[12] Zestimates are calculated daily for more than 100 million homes, using automated valuation models that are re-trained three times a week using updated data. Zestimates are then seasonally adjusted, and the ZHVI is defined as the median of all Zestimates in a given location (see `https://www.zillow.com/research/zhvi-methodology-6032/` for more details on ZHVI methodology and `https://www.zillow.com/zestimate/#acc` for an overview of Zestimates accuracy).

[13] Refer to Case et al. (1991) for a comparison of the repeat-sales methodology with other price index approaches. Notice moreover that Clapp et al. (1991) find that repeat-sales homes are systematically different than single sales homes.

code level.

First, I compute each ZIP code's distance from the coastline and elevation.[14] Second, average income is computed as the ratio between adjusted gross income and number of returns in the 2010 tax year according to the IRS Statistics of Income series.[15] A location specific indicator of rurality is obtained from the Population Studies Center of the University of Michigan.[16] It is based on the Rural-Urban Continuum Codes computed by the United States Department of Agriculture (USDA), which classifies each county into nine groups according to its level of urbanization. The mapping from counties to ZIP codes assumes that if a ZIP code falls into more than one county, the characteristic of the county with the largest share of the ZIP code will be used. The remaining demographic controls – total population, male ratio, and different ethnicity ratios – come from the 2010 Census.[17]

3 Sample characteristics

Wind energy projects are usually targeted towards less developed areas. Figure 4 shows that, on average, ZIP codes that are allocated a wind farm (defined as a cumulative number of at least ten turbines at some point in time) have lower house prices than ZIP codes where a wind farm is never built. The difference between the two sub-samples is small (about $1,500) but remarkably stable over time.

Table 1 presents a summary of means and standard deviations of a battery of demographic and geographic variables. Column (1) displays descriptive statistics for the full sample, while columns (2) and (3) distinguish between ZIP codes characterized by the presence of a wind farm or not, respectively. Areas with wind farms are on average more distant from the coastline, have a higher elevation, and are less populated. They have a lower average income, a higher fraction of white inhabitants, and lower fractions of blacks and asians. They also tend to have a higher

[14] 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 ArcGIS catalog. Distance from the coast and elevation are calculated from the ZIP code centroid.

[15] Income data is publicly available from the IRS at `https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi`.

[16] Accessible at `https://dsdr-kb.psc.isr.umich.edu/answer/1102`.

[17] All variables are mapped to ZIP codes and made available by Jean Roth at `http://www.nber.org/data/census-2010-zip-code-data.html`.

fraction of male residents. The last row shows that locations that are not allocated a wind farm are characterized by a lower percentage of the area of the ZIP code with potential wind capacity in 2008 greater than 30%.

Column (4) of table 1 shows the results of t-tests on the equality of means in the two sub-samples, assuming unequal variances. ZIP codes with and without a wind farm are significantly different in terms of all variables considered. Since the following analysis relies on the percentage of the area of the ZIP code with potential wind capacity greater than 30% as excluded instrument, I further investigate if the covariates are balanced conditional on this variable. This can be seen as a partial test of the independence assumption of the instrumental variable design. Column (5) shows the coefficients estimated regressing each exogenous control on the percentage of the ZIP code area having potential wind capacity greater than 30%, while column (6) adds to the regression all the other covariates as controls, together with state fixed effects. The differences between the two sub-samples remain statistically significant, although the coefficients on the excluded instrument are relatively small. Overall however, the instrument does not seem to achieve a perfect balance of the geographic and demographic covariates considered. This informs the subsequent analysis, where models in first differences are preferred over similar specifications in levels.

4 Identification strategy

4.1 Instrumental variable approach

If wind turbines were as good as randomly assigned to ZIP codes, conditional on covariates, I could estimate the effect that they have on house prices using the following model

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

where $ln\left(p_{lt}\right)$ measures the log-transformed home price in location l (ZIP code or census tract), and time t (year or month), while $turbines_{lt}$ describes the number of wind turbines built in that location and time. 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, 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 the analysis – i.e. $\mathbf{X}_{lt} = \mathbf{X}_l$ – we can rewrite equation 1 in first differences as

$$\Delta ln\left(p_{lt}\right) = \beta \Delta turbines_{lt} + \tau_t + \Delta \varepsilon_{lt} \tag{2}$$

Conditional on the validity of the time independence assumption, this would help dealing with the fact that covariates are not balanced between locations with and without a wind turbine, as observed in section 3. However, the coefficients estimated running simple OLS on equation 2 are likely to be biased by the existence of omitted or unobservable variables that are correlated with both the change in house prices and wind turbine presence. For instance, if poorer geographic areas are more likely to be assigned a wind turbine, and the price of houses in these areas is lower, then this would generate a negative relationship between turbines and home prices.

In the attempt to reduce this problem and try to identify the true causal impact of wind turbines on house prices, I rely on an instrumental variable (IV) approach. My instrument is based on the percentage of the area of a ZIP code or census tract with potential wind capacity in 2008 greater than 30%. This variable is computed as follows: I first take the cells defined by Lopez et al. (2012), which detail what percentage of each cell has potential wind capacity in 2008 of at least 30%. I intersect these cells with ZIP code or census tract geographies. Next, assuming that the potential wind capacity estimated for each cell is equally distributed on the cell's area, I compute a weighted average for the wind variable using as weights the proportion of the ZIP code or census tract territory covered by each cell. Appendix figure 3 provides an example and more details on the construction of the instrument. Finally, I choose to interact my instrument with a dummy set to one in the years after the first wind turbine was installed in the US (i.e. 1998), since wind should have an effect on house prices only through the presence of wind turbines.

The hypothesis underlying this instrument is that locations having a larger area with potential wind capacity above the 30% threshold are more likely to be allocated a wind farm. This will likely hold since potential wind capacity factor is a metric used by engineers to evaluate the profitability of a site (Kalmikov & Dykes 2010).

It follows that I can rewrite the estimation problem using the two IV equations

$$\text{First stage:} \quad \Delta turbines_{lt} = \pi Z_{lt} + \delta_t + \nu_{lt} \tag{3}$$

$$\text{Second stage:} \quad \Delta ln\left(p_{lt}\right) = \beta_{IV} \Delta \widehat{turbines}_{lt} + \tau_t + \Delta\varepsilon_{lt} \tag{4}$$

where Z_{lt} is the excluded instrument described above. Conditional on the instrument validity, the coefficient β_{IV} measures the local average treatment effect (LATE) of wind turbines presence on house prices.

4.1.1 Alternative instruments

My instrumental variable approach is based on potential wind capacity factor with technology available in 2008. Lopez et al. (2012) also estimate potential wind capacity factors based on "current" technology, and on predicted technology in the "near future". Appendix figure 4 shows that there exists a high correlation between the three estimates of potential wind capacity.

An alternative instrument can be constructed using wind power class. The NREL records wind speeds for the US at a 50-meter height above the ground. Using annual average wind raster data with a resolution from 200-meters to 1000-meters cell sizes, wind resources are then grouped into classes that range from poor (class 1) to superb (class 7).[18] Appendix figure 5 shows a map of wind power class for the US. It unveils a similar pattern as the one seen in figure 2. In order to construct an instrumental variable that is relevant to the allocation decision of a wind turbine, I can then rely on the fact that, as noted by Elliott et al. (1987), "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".

Preliminary analysis (not reported) shows that the results of section 5 remain virtually unchanged if I use a different specifications of the instrument.

[18] Wind power data can be downloaded from `https://www.nrel.gov/gis/data-wind.html`.

4.2 Event study analysis

As an alternative approach to the IV estimation, I perform an event study of the effect of wind farms on house prices. This is mainly based on the framework originally developed by Jacobson et al. (1993) to study displaced workers' earnings losses, which is well suited to analyze multiple events occurring at different timings. I adopt the notation used in Sandler & Sandler (2012), who offer an overview of the recent literature on event studies. In particular, let e^l denote the date when a wind farm is built in location l. As before, a wind farm is defined as an aggregate number of at least ten wind turbines present in the same location. The event study regression can be written as

$$ln\left(p_{lt}\right) = \sum_{\tau=-T, \tau\neq-1}^{T} \mathbb{1}(t-e^l=\tau)\beta_\tau + \alpha_t + \gamma_l + \varepsilon_{lt} \tag{5}$$

where α_t denotes time fixed effects, γ_l captures location fixed effects, and the set of β_τ's are the coefficients of interest. Assuming that the timing of construction of the wind farm is exogenous with respect to other variables potentially correlated with house prices, I can argue that any significant mean shift at the time of the event can be interpreted as the causal effect of wind farm presence on house prices. I can test this indirectly looking at pre- and post-trends in the event study plot, which should be flat around the event if the assumptions of the model are satisfied.

5 Results

5.1 IV results

I now present the main results of the OLS and IV approaches outlined in section 4.1. Table 2 shows the coefficients obtained from an OLS regression of change in house prices on change in number of turbines present in each location. The estimated effect is, across all samples and specifications, either statistically insignificant or positive and non economically relevant. As discussed in section 4.1 however, these relations are likely to 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 assignment to locations, I thus instrument wind turbine presence with the percentage of the area of each 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. Table 3 reports the estimates from the first stage regressions summarized in equation 3. Higher values of the excluded instrument predict a larger change in the number of turbines assigned to a given location across all samples. For my preferred specification (BDL ZIP code sample with state fixed effects) reported in column (4), a 10% increase in the percentage area of a ZIP code with potential wind capacity larger than 30% is, on average, associated with 0.06 additional turbines per year. Panel A of figure 5 shows a graphic representation of the first stage, where I fit a local quadratic regression on the BDL ZIP code sample using the rule-of-thumb bandwidth suggested by Fan & Gijbels (1996).[19] Consistent with the earlier estimates, the number of additional wind turbines in a given ZIP code is increasing in the excluded instrument.

Table 4 reports the coefficients estimated from the IV regression described in equation 4. For all samples and specifications, we confirm the hypothesis that wind turbine presence has a negative and statistically significant effect on home prices. Focusing on column (4), which again is based on the BDL ZIP code sample with state fixed effects, the yearly negative impact of an additional turbine on house prices is found to be about 0.25%. It is important to notice that 17 new turbines are installed in the average ZIP code-year, conditional on non-zero construction. The negative effect of wind plants on home prices is thus particularly large. Panel B of figure 5 reports a graphic representation of the reduced form between potential wind capacity and HPI change. The relationship outlined in the plot is mainly negative, bringing further evidence supporting the previous conclusion.

5.2 Monotonicity test and threats to IV validity

Monotonicity is one of the key assumptions of the IV design. It is not directly testable since it requires, for each individual, that a higher value of the instrument corresponds to a higher value of the endogenous regressor (the treatment). In the specific case of this paper, it implies that potential wind capacity increases each ZIP code's probability of being allocated a wind farm. Following

[19]I also create a version of figure 5 using residualized variables to take into account time and state fixed effects. This is constructed as follows. I first regress the instrument and the change in number of turbines on the vector of time and state fixed effects. Next, I take the residuals obtained from this regression and plot them against each other fitting a local quadratic regression with the rule-of-thumb bandwidth suggested by Fan & Gijbels (1996).

Cook et al. (2015) I can test this assumption indirectly, by performing sub-group analysis of the first stage. “Two way flows”, i.e. groups with different signs in the first stage coefficient, might indicate a violation of monotonicity. Table 5 shows coefficients obtained regressing the change in number of wind turbines on the instrument, for sub-groups from the sample of ZIP codes with BDL house price index data. ZIP codes are grouped according to a measure of rurality ranging from 1 (metro areas of 1 million population or more) to 9 (completely rural or less than 2,500 urban population, not adjacent to a metro area). The first stage coefficient is positive in each sub-group, and it tends to be larger in more rural ZIP codes. Appendix table 1 and 2 find comparable results for the sample of census tracts with BDL HPI and the sample of ZIP codes with ZHVI, respectively.

I discuss now a potential threat to the IV design validity. House prices may evolve differently in locations with different levels of potential wind capacity even in the absence of wind turbines. An imperfect falsification test relies on the idea that there should be no reduced form between the instrument and changes in house prices in the years before the first wind turbine was installed in the US (i.e. prior to 1998). Table 6 shows that, contrary to the expectations, there seems to be a significant effect of wind potential on house prices even in the years before 1998. This result casts some doubts on the validity of the IV design. However, for both samples constructed using BDL data (panel A and B), the sign of this relationship goes in the opposite direction of that found in the IV regression (reported in table 4). On the other hand, the reduced form for the Zillow Home Value Index sample is negative and significant. This result might be driven by the fact that ZHVI data, starting in April 1996, contain only a few observations for each location for the period before the diffusion of wind energy plants in the US.[20]

5.3 Event study results

Figure 6 displays the coefficients β_τ from equation 5 for the set of ZIP codes in the BDL sample that are allocated a wind farm.[21] The plot shows some evidence of a decline in the years following

[20] I do not perform a similar falsification test for the sample of ZIP codes with Zillow median listing prices per square foot since the time coverage of these data does not include any period before the installation of the first US wind turbine.

[21] Event study plots for the BDL sample at the census tract level are more noisy and are thus not reported. On the other hand, the higher frequency and shorter overall time span of Zillow monthly data make them less ideal for an event study design, as it will become clearer later in this section.

the event. However, there is no discrete jump in the dependent variable at the time of the event. On the contrary, house prices start trending down already three years before the construction of the wind farm, and continue being on a downward trend even six years after the event.

There are several reasons that can help explaining this pattern. One clear threat to the event study design is that it takes a relative long time between the start and completion of the work related to a wind farm project.[22] House prices might well start trending down before the wind farm is ultimated. Moreover, local communities may anticipate the negative externality exerted by wind energy projects on environmental amenities. This could lead to an over-supply of houses even before wind turbines construction begins, depressing home prices in the area.

Figure 7 presents a falsification test for the event study design. I consider here the sample of wind turbines that are determined as hazard, and define the event as the year in which a wind farm project is received by the FAA for examination.[23] According to the definition in section 2.1, wind farms determined as hazard should not be under construction. The figure shows some sign of a decline in house prices in the years preceding hazard determination. However, after the FAA verdict – when the wind farm project is supposedly abandoned – the HPI trend turns positive offsetting the initial drop.

6 Conclusions and future work

This paper investigates the relation between wind turbine presence at the ZIP code and census tract level and home prices. To address problems related to the endogenous placement of wind turbines and other confounding trends, it uses the percentage of the area of a ZIP code or census tract having potential wind capacity in 2008 equal to 30% or more, interacted with a dummy set to one in the years after the first wind turbine was installed in the US. Results from the preferred 2SLS specification suggest that home prices in places that are allocated a wind turbine are on average 0.25% lower for each additional wind turbine assigned to that location. An event study analysis brings additional evidence supporting the IV conclusions.

[22] For the sub-sample of wind turbines reporting official beginning and ending dates of the construction work, the average duration of the project is longer than 12 months (with a standard deviation of 31.6 month). The completion of large wind farms is likely to take even longer since not all wind turbines are built at the same time.

[23] I exclude from this sample the set of ZIP codes that have both a wind farm project determined as hazard and another wind energy plant that is instead successfully approved.

Despite the findings discussed in this paper are suggestive of a negative relation between wind turbines presence and home prices, this evidence if far from being conclusive. The main limitation of this analysis is the trade-off between (i) house prices coverage of the US geography, and (ii) sufficient sensitivity of aggregate home price indices to changes in the local environment.

I have currently applied to Zillow individual transaction level data. Although not perfectly representative of the universe of real estate transactions in the US, the level of detail of these data will considerably improve the estimates accuracy.

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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	47.5509	56.5857	-9.0347	-0.1097	-0.1116
	(34.3034)	(10.7874)	(34.5236)	(0.7299)	(0.0168)	(0.0168)
Total population	15055.1253	8941.6601	15149.6384	-6207.9783	-178.1270	-99.0650
	(14777.3287)	(10314.7706)	(14816.2206)	(658.7455)	(7.1227)	(6.4686)
Elevation	294.6454	503.6166	291.4148	212.2018	1.2884	-0.4558
	(383.4397)	(403.9627)	(382.2311)	(25.5721)	(0.1880)	(0.1023)
Distance to the coast	228.1892	379.1010	225.8561	153.2449	3.1656	0.3865
	(267.0270)	(320.8699)	(265.4482)	(20.2794)	(0.1288)	(0.0494)
Male ratio	0.4950	0.5019	0.4949	0.0069	0.0001	0.0000
	(0.0220)	(0.0233)	(0.0219)	(0.0015)	(0.0000)	(0.0000)
White ratio	0.8286	0.9082	0.8274	0.0809	0.0017	0.0001
	(0.1869)	(0.1021)	(0.1877)	(0.0066)	(0.0001)	(0.0000)
Black ratio	0.0833	0.0180	0.0843	-0.0663	-0.0011	0.0001
	(0.1520)	(0.0397)	(0.1528)	(0.0028)	(0.0001)	(0.0000)
Asian ratio	0.0242	0.0087	0.0244	-0.0157	-0.0003	0.0001
	(0.0514)	(0.0282)	(0.0516)	(0.0018)	(0.0000)	(0.0000)
Percentage ZIP code area with	3.5990	21.5823	3.3210	18.2613		
potential wind capacity > 30%	(15.8003)	(36.1620)	(15.1093)	(2.2766)		
Number of ZIP codes	16618	253	16365	16618	16618	16618

Notes: The sample is the set of ZIP codes having information on BDL's house price index for at least one year and the full vector of control variables. See section 2 for each variable definition and source. 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 and state fixed effects.

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	0.00016	0.00010	0.00011	0.00009	0.00005	-0.00003	-0.00002
	(0.00006)	(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. The sample in panel A (B) is the set of ZIP codes (census tracts) having information on BDL's house price index. The sample in panel C is the set of ZIP codes with data on median listing prices per square foot from Zillow, while the sample in panel D is the set of ZIP codes for which the Zillow Home Value Index is available. 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)	0.0041 (0.0004)	0.0052 (0.0005)	0.0048 (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 sample in panel A (B) is the set of ZIP codes (census tracts) having information on BDL's house price index. The sample in panel C is the set of ZIP codes with data on median listing prices per square foot from Zillow, while the sample in panel D is the set of ZIP codes for which the Zillow Home Value Index is available. 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	-0.0220	-0.0109	-0.0091	-0.0025	-0.0059	-0.0149	-0.0197	-0.0025
	(0.0023)	(0.0013)	(0.0013)	(0.0008)	(0.0030)	(0.0041)	(0.0026)	(0.0009)
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 sample in panel A (B) is the set of ZIP codes (census tracts) having information on BDL's house price index. The sample in panel C is the set of ZIP codes with data on median listing prices per square foot from Zillow, while the sample in panel D is the set of ZIP codes for which the Zillow Home Value Index is available. 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 5: Monotonicity test, BDL ZIP code sample

	$\triangle$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	0.0036 (0.0010)	2233	56479
(4)	Urban population of 20,000 or more, adjacent to a metro area	0.0043 (0.0012)	1429	32263
(5)	Urban population of 20,000 or more, not adjacent to a metro area	0.0058 (0.0034)	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	0.0107 (0.0017)	843	16598
(8)	Completely rural or less than 2,500 urban population, adjacent to a metro area	0.0042 (0.0028)	344	5493
(9)	Completely rural or less than 2,500 urban population, not adjacent to a metro area	0.0013 (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 measure 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.

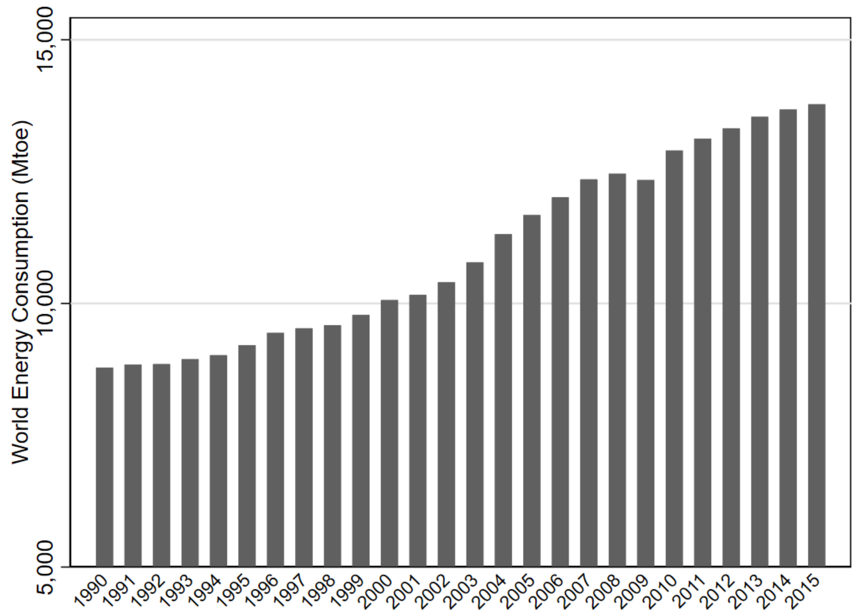
Table 6: Falsification test

	Panel A		*Panel B*		*Panel C*	
$\triangle ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)
Potential wind capacity	0.00008	0.00009	0.00000	0.00009	-0.00002	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)
State fixed effects	No	Yes	No	Yes	No	Yes
Number of locations	38202	38202	13322	13322	13958	13958
Number of location-time	364161	364161	157663	157663	791295	791295

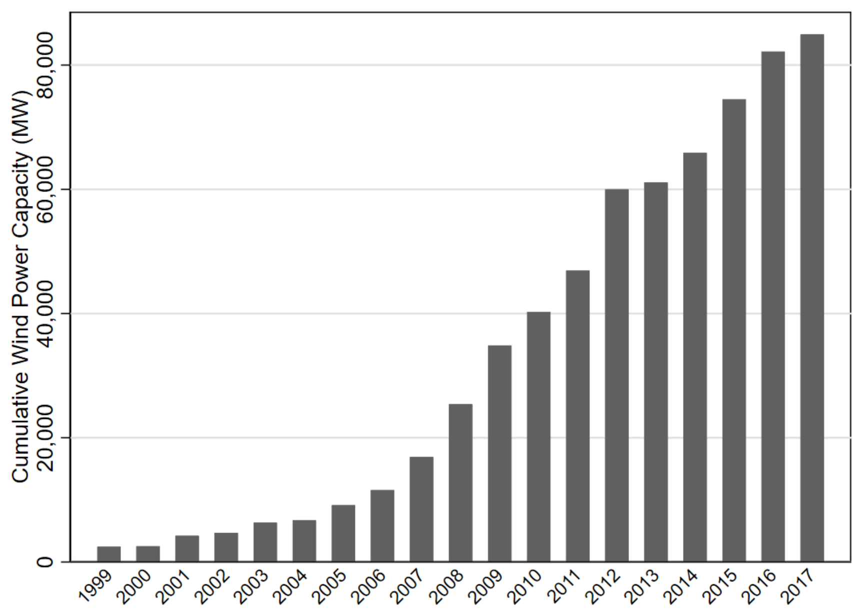
Notes: The sample is restricted to the period before the first wind turbine was installed in the US (i.e. 1998). In panel A, a time period is a year and the unit of analysis is the census tract-year. In panel B, a time period is a year and the unit of analysis is the ZIP code-year. In panel C, a time 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

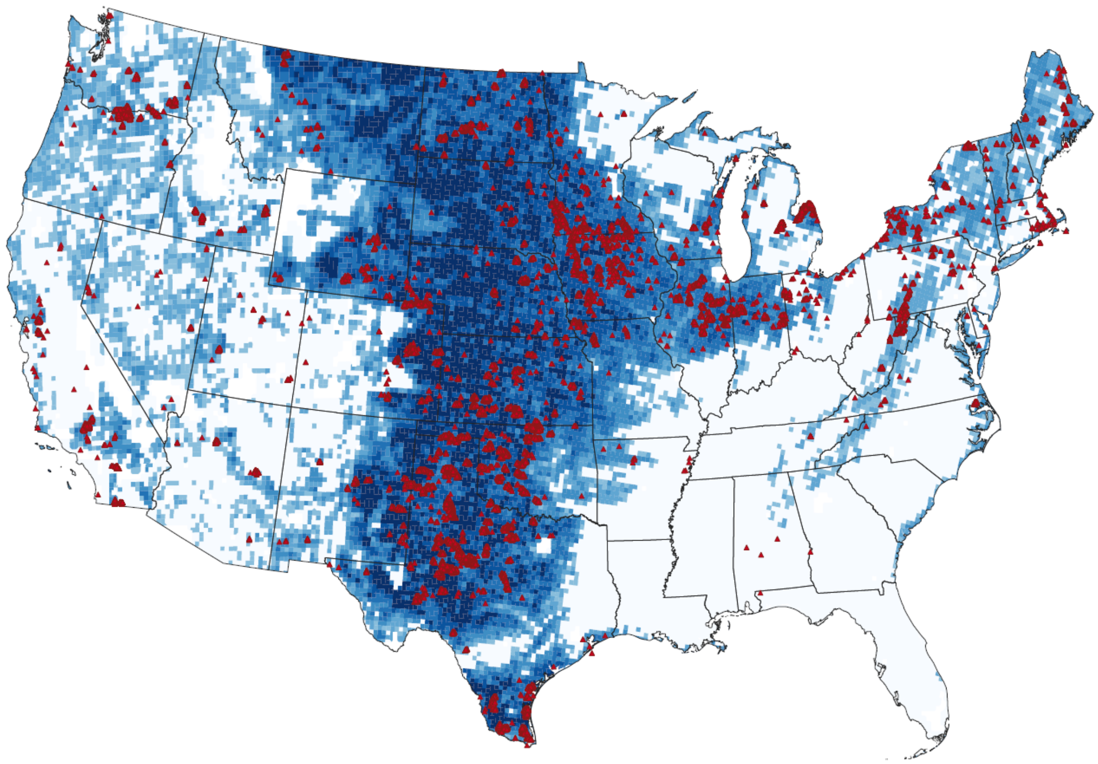


Panel B: US wind energy capacity



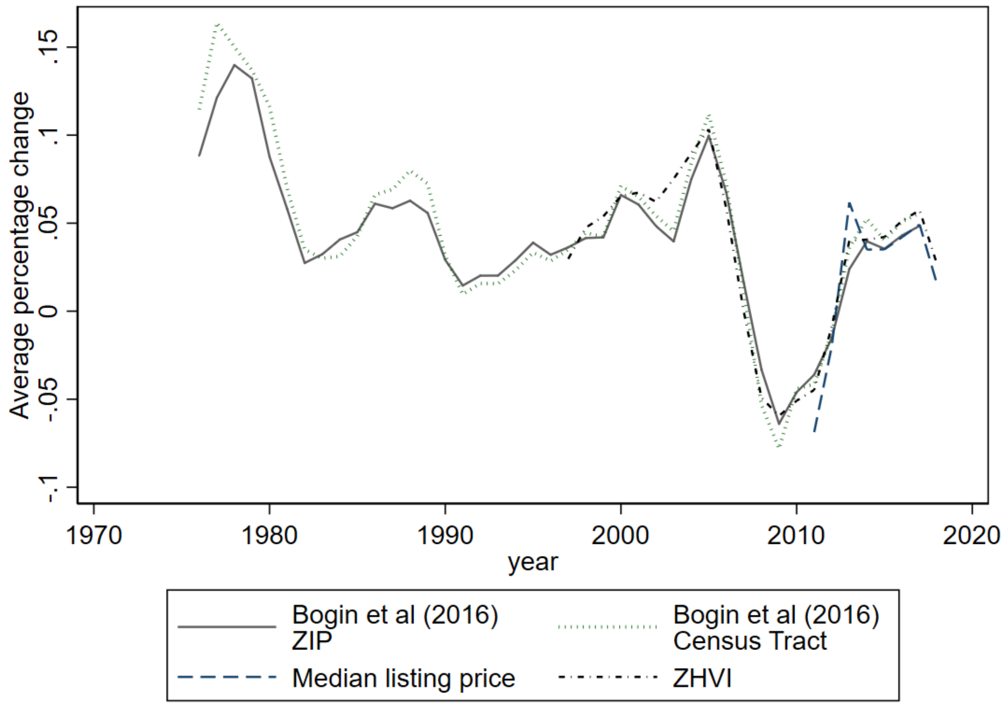
Notes: Data on world energy consumption comes from the 2016 Global Energy Statistical Yearbook (`https://yearbook.enerdata.net/`). Data on US wind energy capacity comes from the Office of Energy Efficiency & Renewable Energy (`https://windexchange.energy.gov/maps-data/321`).

Figure 2: Wind turbines location and potential wind capacity in 2008



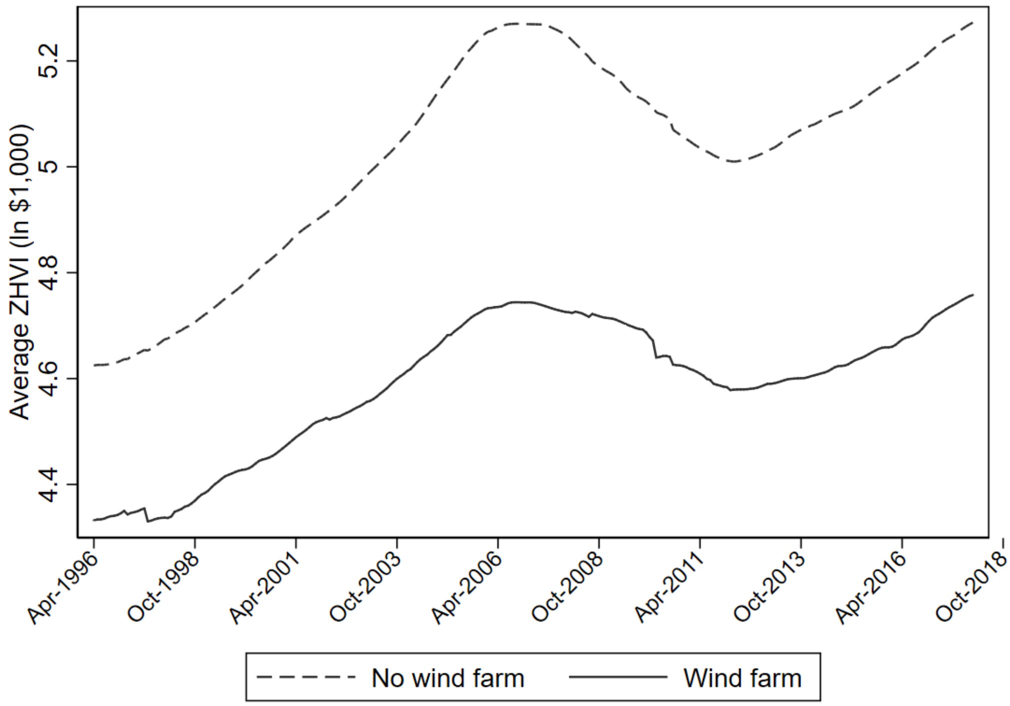
Notes: The figure shows data on potential wind capacity in 2008 estimated by Lopez et al. (2012) using data from the National Renewable Energy Laboratory (NREL). The US map (Alaska excluded) is divided into cells of approximately 400km^2. Blue cells correspond to locations having a non-zero fraction 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 3: Comparison of house prices measures



Notes: Data on home prices are either from Zillow or estimated by Bogin et al. (2016). Prices from Zillow are first averaged at the ZIP code-year level. Each series is then computed as the average percentage change between two consecutive years.

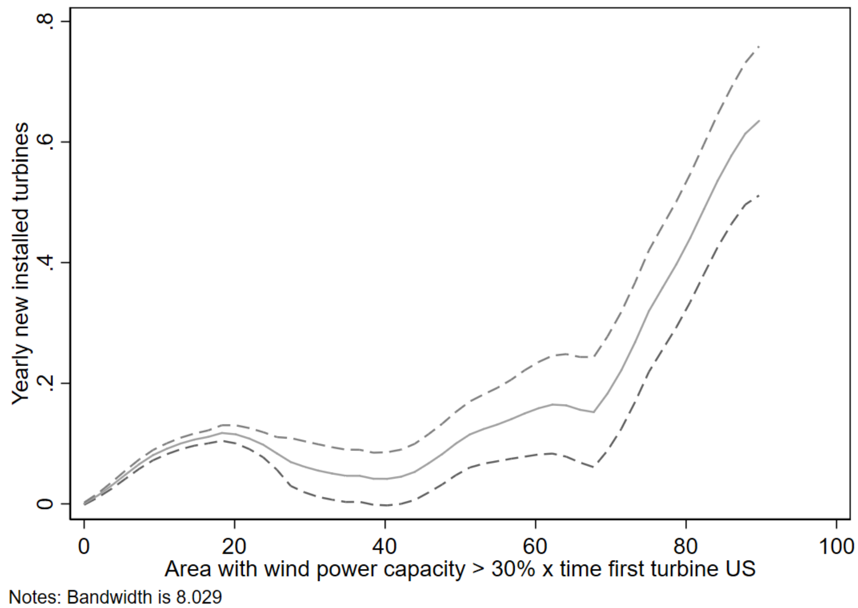
Figure 4: House prices time series



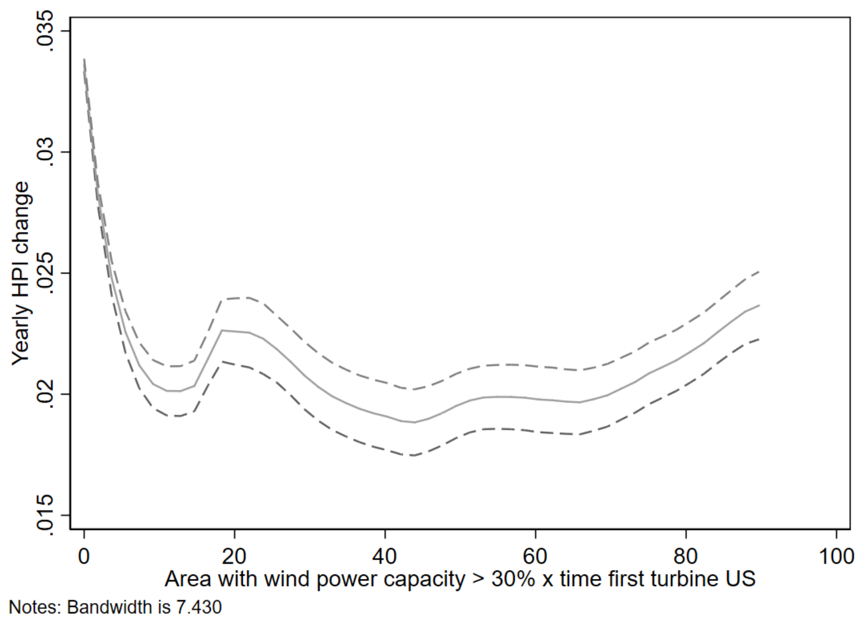
Notes: The figure reports data on average monthly log Zillow Home Value Index. The sample is divided into two sub-groups, according to whether a cumulative number of at least ten turbines is ever observed in a given ZIP code (solid line) or not (dashed line).

Figure 5: Graphic representation of instrumental variable approach

Panel A: First stage

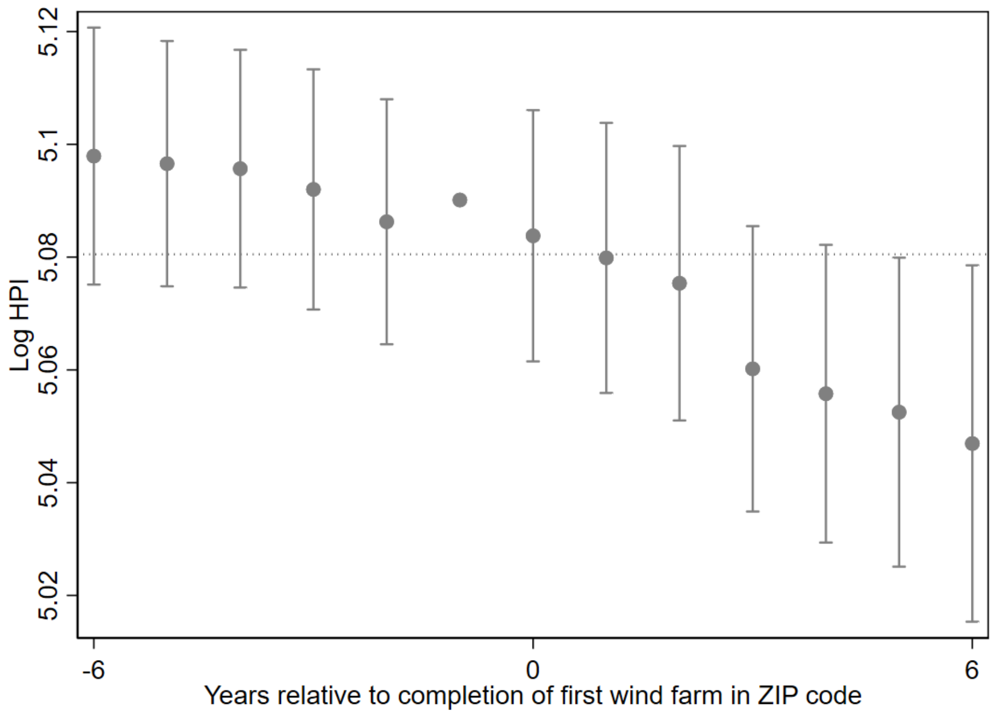


Panel B: Reduced form



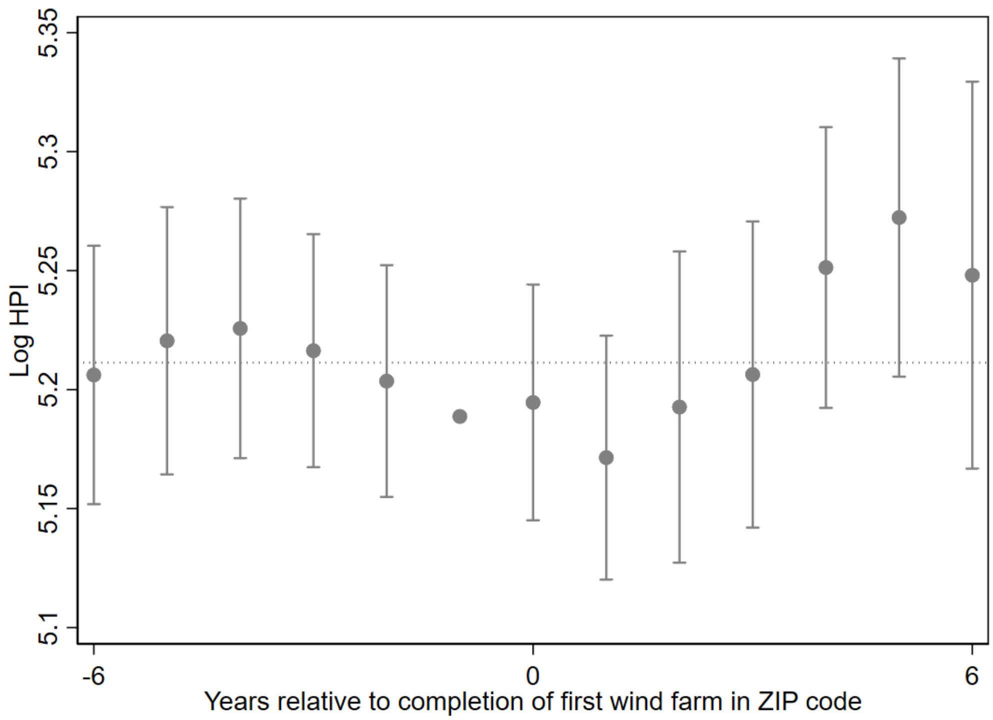
Notes: The sample is the set ZIP codes with data on the house price index (HPI) estimated by Bogin et al. (2016). Panel A shows a fit from a local quadratic regression of change in number of wind turbines in the ZIP code on the instrument, with the the rule-of-thumb bandwidth suggested by Fan and Gijbels (1996). Panel B similarly reports the fit from a local quadratic regression of the change in HPI on the instrument. Dashed lines depict ninety-five percentage confidence intervals.

Figure 6: House prices before and after wind farm construction



Notes: The sample is the set of ZIP codes having information on BDL house price index (HPI) and that are allocated a wind farm at some point in time. The figure plots coefficients from a regression of log HPI on a vector of lead and lagged indicators for years relative to the construction of the first ZIP code wind farm, with the year prior to the event ("-1") as the omitted category. The unit of observation is the ZIP code-year. Error bars are ± 2 coefficient standard errors (robust). The regression includes year fixed effects, ZIP code fixed effects, and two indicators for observations before and after six years of wind farm construction. The dotted lines show the sample mean of ZIP code log HPI across observations within six years of the event. Each coefficient series is shifted by a constant so that the observation-count-weighted mean of the regression coefficients is equal to the sample mean of the corresponding dependent variable.

Figure 7: House prices before and after hazard determinarion



Notes: The sample is the set of ZIP codes having information on BDL house price index (HPI) and where a wind farm project is determined as hazard. The figure plots coefficients from a regression of log HPI on a vector of lead and lagged indicators for years relative to the time of hazard determination, with the year prior to the event ("-1") as the omitted category. The unit of observation is the ZIP code-year. Error bars are ± 2 coefficient standard errors (robust). The regression includes year fixed effects, ZIP code fixed effects, and two indicators for observations before and after six years of hazard determination. The dotted lines show the sample mean of ZIP code log HPI across observations within six years of the event. Each coefficient series is shifted by a constant so that the observation-count-weighted mean of the regression coefficients is equal to the sample mean of the corresponding dependent variable.

Appendix Table 1: Monotonicity test, BDL census tract sample

	△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	0.0035 (0.0012)	10759	270462
(3)	Counties in metro areas of fewer than 250,000 population	0.0044 (0.0011)	5661	135328
(4)	Urban population of 20,000 or more, adjacent to a metro area	0.0031 (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	0.0039 (0.0009)	2647	49892
(7)	Urban population of 2,500 to 19,999, not adjacent to a metro area	0.0066 (0.0012)	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	0.0034 (0.0022)	351	5614

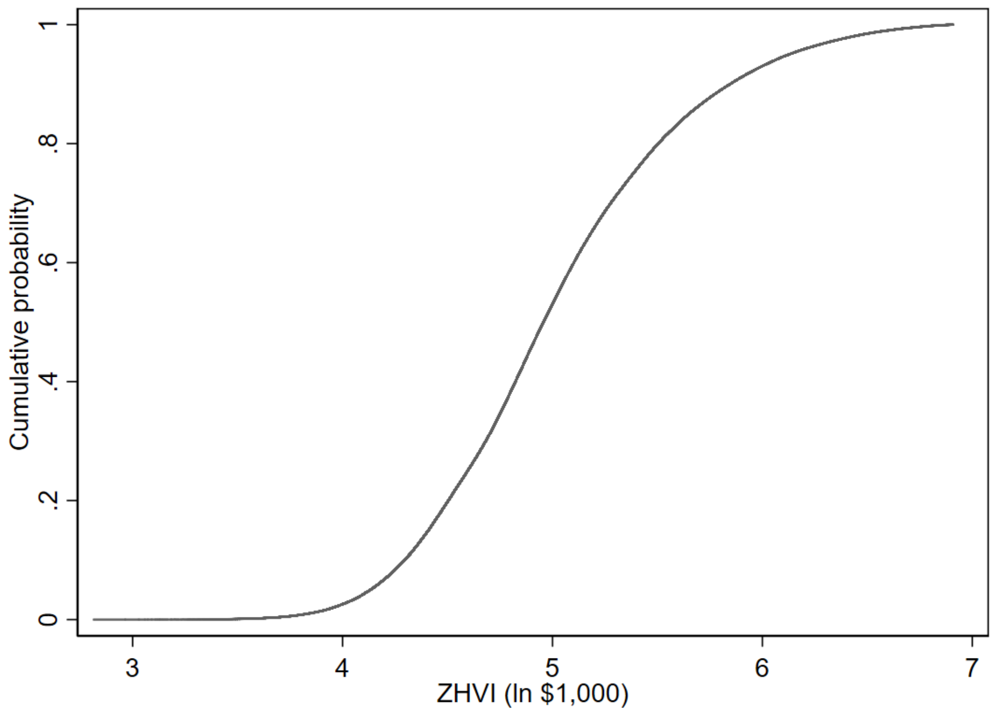
Notes: Each specification use a different sub-sample from the set of census tracts having information on house prices estimated by Bogin et al. (2016). Sub-samples are defined according to a measure of rurality at the county level ranging from 1 through 9 (see `https://dsdr-kb.psc.isr.umich.edu/answer/1102`). 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 ZIP code sample

	$\triangle$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

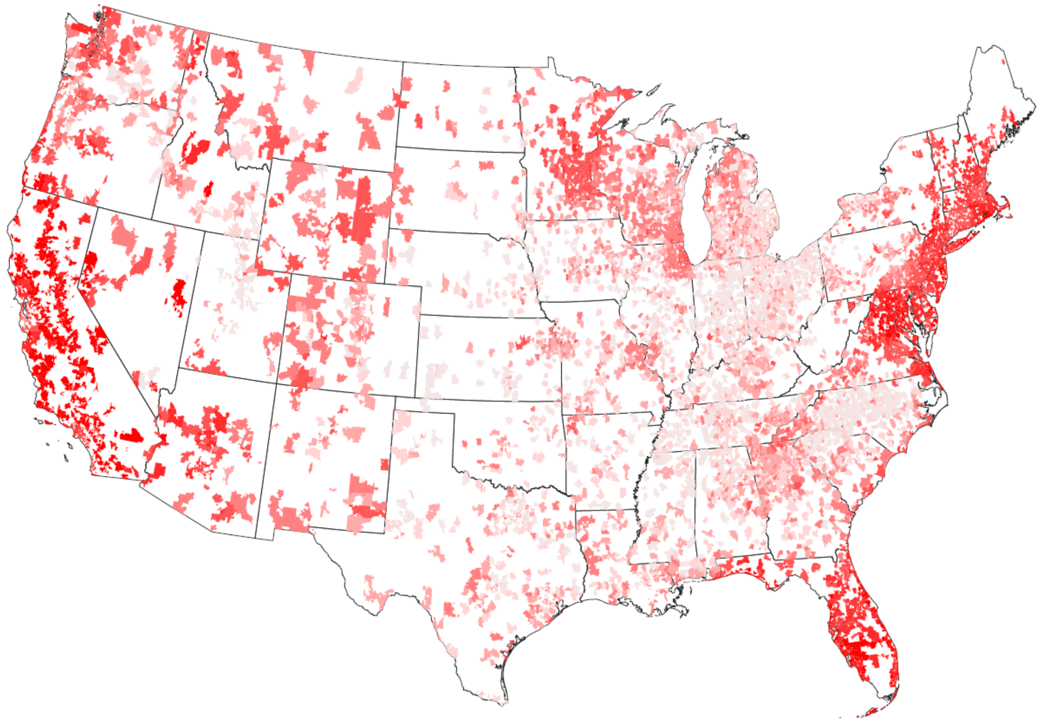
Notes: Each specification use a different sub-sample from the set of ZIP codes having Zillow Home Value Index data. Sub-samples are defined according to a measure of rurality at the county level ranging from 1 through 9 (see `https://dsdr-kb.psc.isr.umich.edu/answer/1102`). For each regression, the independent 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: Monthly house prices (ZHVI)



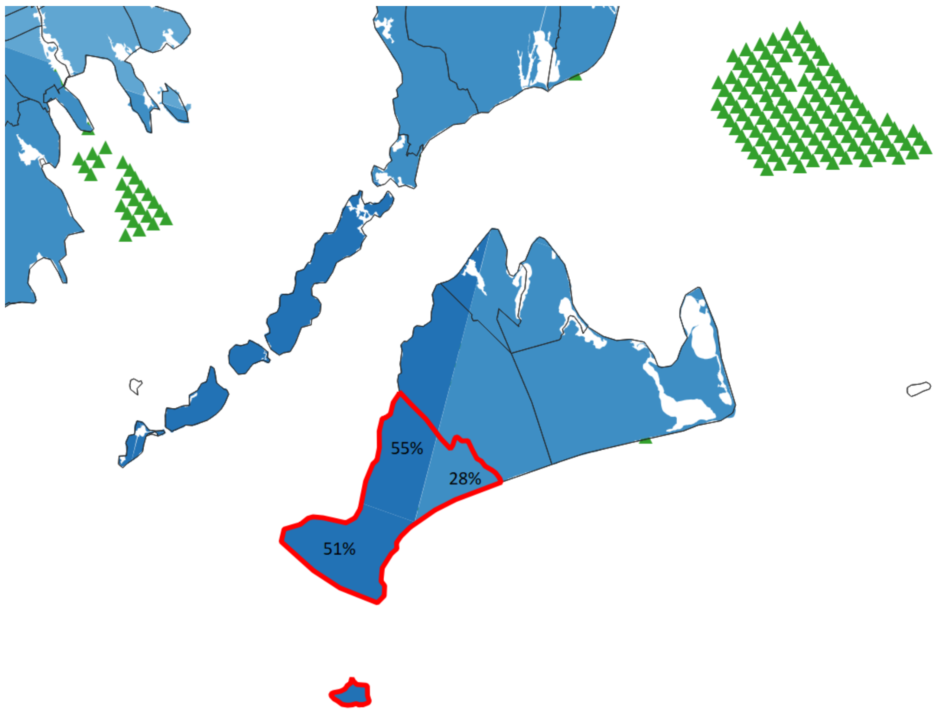
Notes: The sample is all ZIP code-months with data on the Zillow Home Value Index (ZHVI). The figure shows the cumulative distribution function for monthly log ZHVI truncated at $1 million.

Appendix Figure 2: Geographic coverage of BDL house price index



Notes: The sample is the set of ZIP codes having data on Bogin et al. (2016)'s house price index (HPI) in 2000 and 2005. Darker areas represent ZIP codes experiencing a larger increase in HPI between 2000 and 2005.

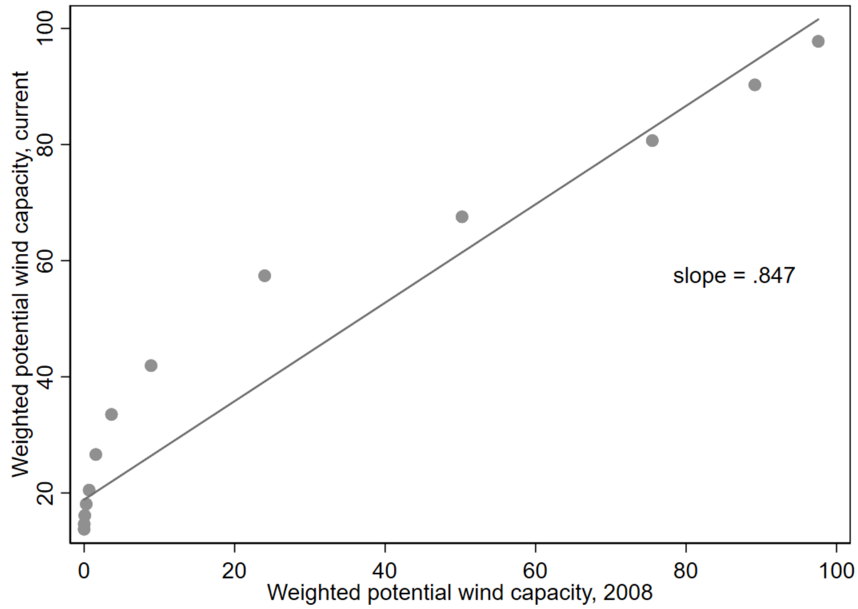
Appendix Figure 3: Construction of the instrument



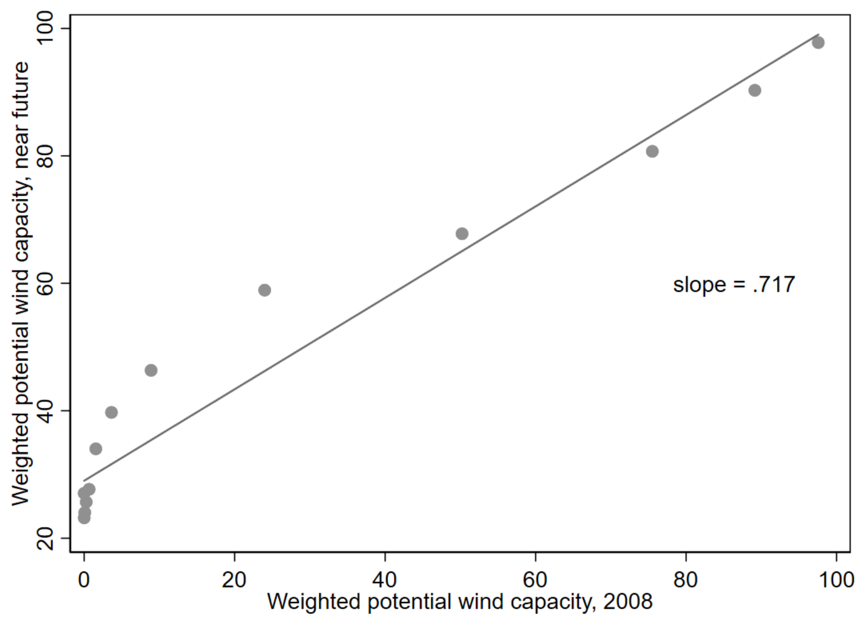
Notes: Green triangles represent offshore wind turbines (not included in the main analysis). The red bordered region is ZIP code 02535, Chilmark, MA (in Martha's Vineyard). Blue shaded areas represent potential wind capacity cells estimated by Lopez et al. (2012). Three of these cells intersect the geography of ZIP code 02535. The estimate of the area of the cell with potential wind capacity of at least 30% is different for each cell, and it is reported in percentages on the map. Assuming that potential wind capacity is equally distributed on the area of each cell, I compute a weighted average for the wind variable using as weights the proportion of the ZIP code territory covered by each cell. In this specific example, 47% of the area of ZIP code 02535 has potential wind capacity in 2008 of 30% or more.

Appendix Figure 4: Estimates of potential wind capacity with different technology

Panel A: Current estimate vs 2008

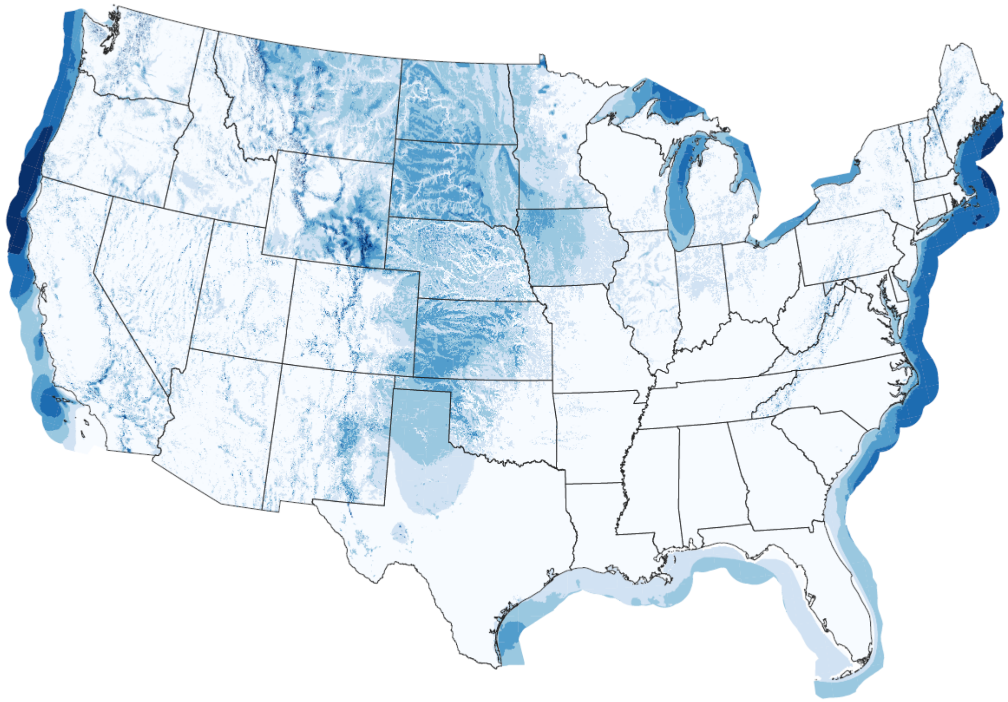


Panel B: Near future estimate vs 2008



Notes: Each panel reports the binned scatter plot between measures of wind capacity based on technology available in two distinct points in time. Potential wind capacity is estimated by Lopez et al. (2012). I divide ZIP codes into twenty equal-sized bins and plot, for each bin, the average potential wind capacity with the corresponding technology. The solid lines show a fit from an OLS regression on the underlying data. The slope of the estimated coefficients is reported in each plot.

Appendix Figure 5: Wind power class



Notes: The figure reports the annual average wind power class (no exclusions applied) used in the Renewable Electricity Futures Study and available for download at `https://www.nrel.gov/gis/data-wind.html`. Wind power class ranges from 1 (not shaded) to 7 (shaded in dark blue).