Assessing the external net benefits of wind energy: the case of Iowa's wind farms[*]

T.J. Rakitan[†]

December 30, 2017

ABSTRACT:

Wind energy infrastructure is often associated with decreases in nearby property values and increases in local incomes. However, these impacts are measured at different geographic scales, prompting the question of how the external net benefits of wind infrastructure are distributed over space. Using restricted-access income microdata and address-level house value information from county assessor records, I estimate the impact of utility-scale wind energy infrastructure ("wind farms") on both incomes and property values at the same geographic scale in northwest Iowa. I use a difference-in-differences approach that exploits the staggered installation times of Iowa's major wind farms, estimating changes in incomes and house values as a function of wind energy infrastructure attributes following the analysis of Roback (1982), Rosen (1979) and others. I find that county-level income effects reported in the literature do not appear to hold at the household level, while house value growth is not significantly different based on proximity to wind farms. This suggests that county- or region-specific attributes correlated with wind energy placement are driving existing results.

JEL codes: Q42, R11

Keywords: wind energy, rural economic development

---

[*] This research was conducted with restricted access to proprietary and confidential data collected and maintained by the Iowa Department of Revenue (IDR), used on-site at IDR's facilities during an internship at IDR. The views expressed in this research do not necessarily reflect the views of IDR, its employees and affiliates or the State of Iowa.

[†] Visiting Assistant Professor, Department of Economics, Valparaiso University. 360 Arts & Sciences Building, 1400 Chapel Drive, Valparaiso, IN 46383. Author e-mail: tj.rakitan@valpo.edu. In addition, I am grateful to John Miranowski and Peter Orazem for their insight and guidance in developing this research, and to Amy R. Harris at IDR for excellent data guidance. I would also like to thank Georgeanne Artz, Otávio Bartalotti, Gray Calhoun, David Keiser, Brent Kreider, Ivan Rudik, and Wendong Zhang for excellent comments and suggestions. All errors are my own.

1 - Introduction

The placement of energy infrastructure has the potential to impact the well-being of nearby residents, which may partially offset the broader benefits of an expanding energy portfolio. In the economic literature, studies have considered the presence of oil and gas wells (e.g. Boxall, et al (2005); Gopalakrishnan and Klaiber (2012); Muehlenbachs, et al (2015)); natural gas pipelines (e.g. Hansen, et al (2006); Kask and Maani (1992)); and high-voltage transmission lines (e.g. Hamilton and Schwann (1995), Sims and Dent (2005)). These studies find evidence that house prices capitalize negative net welfare impacts from proximity to energy infrastructure.

Recently, hedonic and impact-evaluation methods have been applied to the case of wind energy generation installations, also called "wind farms." While several hedonic and contingent-valuation studies find zero or negative property value capitalization of wind farms' presence (e.g. Gibbons (2015), Hoen, et al (2010), Lutzeyer, et al (2016), Vyn and McCullough (2012)), other studies using input-output models find that construction of large-scale wind projects has positive effects on gross local product (e.g. Lantz and Tegen (2009), Slattery, et al (2011), Tegen, et al (2012)). Other econometric studies find that wind energy installation placement is associated with increases in per capita income and county-level employment (Brown, et al (2012), Weber, et al (2013)), as well as increases in tax bases and government revenue (De Silva, et al (2015), Kahn (2013)).

Taken together, this set of results—that rents often capitalize welfare losses while incomes and employment seem to rise in the presence of wind energy installations—prompts the question of whether the local external net benefits of wind energy infrastructure are positive or negative.[1] To this end, I estimate the impact of large-scale wind farms on house values and income using address-level data from Iowa. I take a reduced-form, difference-in-differences approach, comparing outcomes for "treated" households located near wind farms with those from "control" households located farther away. The

---

[1] In this context, "external net benefits" refers to the overall welfare change experienced by those not party to a transaction. The term encompasses both spillovers and externalities.

quasi-experimental research design “differences out” non-time-varying group effects, and both groups are composed of panels of households observed in 2002, 2008 and 2012.

To date, income studies have largely relied on aggregated data, while hedonic house price studies use data at the household level. By contrast, I observe both measures at the household level, which allows me to estimate both income and house value impacts at a consistent geographic scale and provides a more complete characterization of the local net benefits of wind power. The data come from separate sources; house values were obtained from county assessors throughout Iowa, while income observations come from restricted-access income tax records used on-site at the Iowa Department of Revenue (IDR).[2] Variation in “exposure” to wind farms is both temporal and spatial; I control for wind farm age as well as generation capacity, turbine count and distance from the household.

I find that the county-level wind farm-related welfare changes reported in the literature do not occur at the local level in rural Iowa. A conservative interpretation of my results is that there are no substantial spillovers from wind farm placement in rural areas. As a matter of policy, this suggests that regions with low population densities are best suited to host wind farms if negative welfare consequences are a principal concern.

The remainder of the paper is organized as follows: the next section discusses selected literature and details the institutional and technological background of Iowa’s wind energy landscape; Section 3 presents the economic theory underlying the study and the econometric methodology; Section 4 discusses data; Section 5 presents the results and Section 6 concludes.

2 - Literature

Since the mid-2000s, the state of Iowa has maintained the second-highest statewide wind energy generation capacity, and as of 2012 maintained the largest wind energy capacity share of any state in the

---

[2] Iowa’s state tax collection bureau.

U.S. at 30% (EIA 2012).[3] Iowa has more than 95 separate wind energy installations, with statewide nameplate generation capacity[4] of over 6.1 gigawatts. Most often turbines are sited on farmland or other exposed, relatively flat terrain with few buildings or trees to disrupt airflow. On average, the turbines in most of Iowa's wind farms are spread over 11,700 acres (about 18 square miles) per wind farm. This equates to approximately 103 acres per megawatt of nameplate capacity.[5] Areas of concentration are throughout the western half of the state, as well as along the northern tier. The spatial distribution of wind farms generally follows the geographic distribution of Iowa's greatest wind resource potential, visible in Figure 1. Average wind speeds at an altitude of 80 meters throughout Iowa's northwest fall between 7.5 and 9 meters per second.

The years between 2000 and 2014 saw a proliferation of wind farms throughout the state. Figure 2 describes statewide cumulative installed capacity starting in 1992. The large year-over-year capacity increases beginning in 2008 are clearly visible, with statewide capacity growing at approximately 125 megawatts per year from 2000 to 2007, accelerating to 650 megawatts per year between 2007 and 2013. During this time period, the state of Iowa also maintained two fully-transferable renewable energy production tax credits.[6] However, an analysis by the Iowa Department of Revenue finds that the policy has generated revenues for the state that partially offset its costs. Girardi (2014) estimates a projected

---

[3] At the time of writing, this fact is still true; wind power in Iowa boasted at 33% share of statewide generation capacity in 2016 and 2017 (U.S. EIA, "State Energy Profiles: Iowa." Available at https://www.eia.gov/state/print.php?sid=IA).

[4] "Nameplate capacity" refers to the theoretical maximum power output of a turbine generator under an ideal set of conditions.

[5] As a point of reference, Denholm, et al (2009) find that U.S. wind energy installations usually require between 30 and 140 acres per megawatt of capacity.

[6] In 2005, the state of Iowa adopted two tax credits to subsidize renewable energy production in the state, aimed predominantly at large wind energy installations. Iowa's Wind Energy Production Tax Credit (WEP) is available as a non-refundable tax credit for eligible projects completed between July 1 2005 and July 1 2012 and paid in continuity for 10 years from the date of installation, while the Renewable Energy Tax Credit (RE) is available for wind farms brought on line beginning July 1, 2005 (Iowa Public Utilities Board). As of the 2013 tax year, the claimed WEP and RE tax credits totaled approximately $5.2 million. Credits are fully transferrable for state tax return purposes; the State of Iowa has ascertained that credits often trade below their face value (Girardi (2014)). Despite the potentially large dollar value of these payouts, only 1.3% to 3% of Iowa's total wind energy production was awarded the tax credit. As such, it does not appear that state-level incentives greatly altered Iowa's utility-scale wind energy development.

property tax gain to the state of Iowa of approximately $958,000 between 2014 and 2015 due to these policies.

The property tax gains experienced by the state of Iowa are related directly to the land upon which wind farms are sited. Studies in the academic literature substantiate the positive contributions of wind farms to public coffers. For example, De Silva, et al (2016) find a 0.02% drop in property tax rates and a 0.014% increase in per-student school district revenues associated with a 1% increase in wind power capacity, while Kahn (2013) finds public schools in districts funded by green energy revenues spend approximately $1,300 more per student than comparable counties with no wind farms. Both studies use data from the Texas Panhandle region.

Other benefits documented in the literature include employment and wage gains in areas with greater wind penetration. In their Texas study, De Silva, et al (2016) estimate the per-capita income gains from an additional megawatt per capita of wind power capacity to be approximately $2,600, along with positive (but statistically insignificant) county-level employment increases in selected industries. Brown, et al (2012) also find evidence of per-capita income benefits, using county-average wind speed as an instrument for county-level wind power capacity. They estimate a per-capita income gain of $11,000 for each additional megawatt of capacity per capita, as well as employment gains of 0.5 jobs for each additional megawatt per capita. In addition, energy royalty payments and land rents can contribute to non-wage income growth in areas with large energy resources. Weber, et al (2013) document concentrated rural wealth creation from energy royalties paid to farm households. Their analysis includes mineral royalties from oil and gas rights ownership as well as energy rents paid to wind farm households; they note that rents are concentrated among relatively few landowners.

Wind farms can also generate negative local impacts. Public opposition to a large proposed wind farm in the waters of Cape Cod was driven in part by objections to the disruption of scenery (Eileen McNamara, "What really toppled Cape Wind's plans for Nantucket Sound," *Boston Globe*, Jan 30th, 2015). Wind farms have also been responsible for migratory bird kills and disruption of local ecosystems (Barclay, et al (2007)). Additionally, long-term exposure to low-frequency sounds attributed to wind turbine operation has been claimed to cause "wind turbine syndrome," a condition associated with developmental difficulties in children and mental anguish in adults (Pierpont (2006); Farboud, et al (2013)), although there are competing hypotheses regarding the underlying basis for these conditions (Rubin, et al (2014)). Less-severe annoyances may include interruptions to wireless communication technologies, including radio, television and cellular signals (Ángulo, et al (2013)). Despite these claims, the environmental economics literature contains mixed evidence of adverse impacts on consumers. Vyn and McCoullogh (2014), Hoen (2006), Hoen (2010) and Hoen, et al. (2014) have found no statistically or economically significant differences in residential house prices in the vicinity of wind power generation facilities in the U.S. and Canada. On the other hand, some evidence indicates that the negative impact of wind infrastructure may be more closely associated with visibility than health risk. Gibbons (2015), for example, finds evidence of a 4% drop in house values in the U.K. associated with proximity and visibility of wind turbines. Dröes and Koster (2014) find similar results, observing a 1.4% to 2.3% decreases in hedonic sales value for houses sited within 2 kilometers of a wind turbine in Denmark. Heitzelman and Tuttle (2012) also find a negative effect, and Jensen, et al (2014) are able to attribute a 3% residential house price drop to wind farms' visual disamenity, while "soundshed" disruption accounts for a property value decrease between 3% and 7%.

Other recent literature has used stated-preference methods to understand local sentiment about existing wind farms rather than using hedonic methods to characterize a willingness-to-pay to avoid the negative effects or gain access to amenities. In one such paper, Lutzeyer, et al (2016) utilize a choice experiment to gauge willingness-to-pay for off-shore wind energy in vacation-rental viewsheds, finding evidence that recreational renters would never pay more for a beach view interrupted by wind turbines. Walker, et al. (2014) point out that hedonic methods, which rely on observed sales of a fixed asset (e.g. a house, a plot of agricultural land), tend to over-sample high-population-density areas relative to low-population-density areas–however, the spacing requirements of wind energy production, along with other subjects the hedonic literature, often translates to turbines being located in low-density areas with large areas of available land. Walker, et al. (2014) turn instead to surveys and interviews to assess local perceptions about the property-value changes associated with wind farms in two communities on Lake Erie in Ontario, Canada, finding that local residents perceive a loss in property value regardless of the available data. Similarly, Firestone, et al (2015) use a survey instrument to evaluate perceptions about the amenities and disamenities of a single turbine installed along the Delaware coast. However, they find that locals report positive attitudes toward the turbine's placement.

3 – Theory and Empirical Strategy

I assume a spatial equilibrium where wages and rents adjust to local characteristics, following Roback (1982) and Rosen (1978). Locational fixed factors—including wind energy infrastructure—affect the utility of nearby households, and workers' choices of where to live bids rents and wages up or down accordingly. Workers are assumed to be freely mobile between regions and face competitive labor markets. Labor is supplied inelastically and paid a wage w. Workers live in households indexed by h. Each household maximizes utility U by consuming a numeraire x at a price of 1 and renting land K at price r subject to the budget constraint $w \geq x + rK$. The above implies that indirect utility will depend on both wages and rents. Since households control their exposure to local characteristics by their choice of where to live, wages and rents will be implicit functions of local characteristics.

Figure 3 illustrates this mechanism in action. Consider two regions indexed by the variable ω that are identical but for wind farm exposure. Region $\omega = 0$ lacks a wind farm, while region $\omega = 1$ has one. Worker mobility implies that indirect utilities will equalize across markets, i.e. $V(w,r,0) = V(w,r,1) = \bar{V}$. If wind farms are a nuisance, utility in region 1 will be lower at all values of r and w than utility in region 0, i.e. $V(w,r,1)$ will lie strictly to the southeast of $V(w,r,0)$. Equilibrium occurs where $V(w,r,\omega)$ intersects the unit iso-cost line corresponding to numeraire production, given by $C(w,r) = 1$ in wage-rent space. Although utility is identical between regions, rents decline and wages rise in region 1 relative to region 0, implying an expanded budget set for region 0 consumers. That is, if wind farms are a disamenity, real incomes must rise to compensate workers located nearby them.

I operationalize the analysis above by examining the cross-sectional growth in wage and rent measures as functions of the wind farm exposure variable ω. Let y be the outcome of interest (either wages or rents) and define time period $t=0$ as the time period during which no houses were exposed to wind farms and $t=1$ as the time period in which $\omega=1$ for some but not all households. The real income differential can then be estimated by comparing the cross-sectional rates of growth of wages and rents.

The outcome of interest (i.e. incomes or house values; here denoted by y) will be a function of local characteristics at time t as well as household characteristics. This suggests the reduced-form relation

$$\ln(y_{hct}) = \beta \cdot \omega_{ht} + \gamma \cdot z_h \cdot \omega_{ht} + \mu_h + \theta_{ct} + \epsilon_{hct} \tag{1}$$

where ω_{ht} is the wind farm exposure dummy, z_h is a measure of the intensity of house h's exposure to a wind farm, μ_h is a household fixed effect, θ_{ct} is a county-year effect and ϵ_{hct} is a normally-distributed i.i.d. error term with a mean of zero and constant variance conditional on county or household attributes. At $t=0$, $\omega_{ht}=0$, while $\omega_{ht}=1$ for some households at $t=1$. The logarithmic treatment of y follows Roback's (1982) formulation and allows the right-hand side coefficients to be interpreted as percent changes.

The house fixed-effect captures both house characteristics and characteristics of household occupants (such as human capital). Necessarily, wage and rent growth will be correlated with these characteristics, as well as with county-specific and time-specific factors. I account for this by differencing across time periods. Following the time-period definitions above, $\omega_{h(t=0)} = 0$ for all households, implying

$$\ln(y_{hc(t=0)}) = \mu_h + \theta_{c(t=0)} + \epsilon_{hc(t=0)} \tag{2}$$

Similarly, the outcome at $t = 1$ can be written

$$\ln(y_{hc(t=1)}) = \beta \cdot \omega_{h(t=1)} + \gamma \cdot z_h \cdot \omega_{h(t=1)} + \mu_h + \theta_{c(t=1)} + \epsilon_{hc(t=1)} \tag{3}$$

Differencing between time periods yields the expression

$$\begin{aligned} \ln(y_{hc(t=1)}) - \ln(y_{hc(t=0)}) = {} & \beta \cdot \omega_{h(t=1)} + \gamma \cdot z_h \cdot \omega_{h(t=1)} \\ & + \mu_h + \theta_{c(t=1)} + \epsilon_{hc(t=1)} - (\mu_h + \theta_{c(t=0)} + \epsilon_{hc(t=0)}) \end{aligned} \tag{4}$$

Collecting terms yields the growth equation

$$\begin{aligned} \Delta_t \ln(y_{hc}) & \equiv \ln(y_{hc(t=1)}) - \ln(y_{hc(t=0)}) \\ & = \beta \cdot \omega_{h(t=1)} + \gamma \cdot z_h \cdot \omega_{h(t=1)} + \zeta_c + v_{hct} \end{aligned} \tag{5}$$

where $\zeta_c = (\theta_{c(t=1)} - \theta_{c(t=0)})$ and $v_{hct} = (\mu_h - \mu_h) + (\epsilon_{hc(t=1)} - \epsilon_{hc(t=0)})$. The specification in (5) differences out the household effect μ_h, while a county control ζ_c accounts for the influence of changes in local characteristics that can affect regional growth.

The wind farm exposure parameters β and γ are identified if wind farm placement is uncorrelated with the error term $\epsilon_{hc(t=1)} - \epsilon_{hc(t=0)}$. That is, if unobserved shocks to household h's wage or rent growth also affect the probability of the existence of a wind farm of size z_h, then estimates of β and γ will be biased. However, this would also require that such shocks be uncorrelated with the county growth effect ζ_c as well as with the household effect μ_h, which has been differenced out in computing the growth rate of Equation (5).

To estimate Equation (5) econometrically, I specify:

$$\Delta_t \ln(y_{hc}) = \beta \cdot Treatment_h + \gamma \cdot Treatment_h \cdot Intenisty_h + \zeta_c \cdot County_{hc} + \epsilon_{hc} \tag{6}$$

where y is income or house value; $Treatment_h$ is a dummy equal to 1 if house h is within 5 miles of a wind turbine, ζ_c is a fixed-effect that is nonzero if household h is in county c, and ϵ_h is the error term. The county fixed-effect ζ_c accounts for county-level factors that can affect the growth in wages or property values. The $Intensity_h$ measure decomposes the treatment effect across several measures of exposure intensity. These include the household's years of exposure to a wind farm ($Duration_h$), distance away from a wind farm ($Distance_h$), wind farm power capacity in units of 100 MW ($Capacity_h$) and total number of turbines that make up the wind farm (in 100-count units) ($Turbines_h$). The coefficients have the interpretation of changes in the rate of growth of house values and incomes. If wind farm exposure is a disamenity, then increasing exposure intensity should be associated with lower house values and higher incomes.[7]

The econometric specification in Equation (6) has the form of a difference-in-differences estimation. Differencing the outcome of interest between time-periods provides the first difference, accounting for house-level fixed effects, while wind farm exposure constitutes the second difference. By removing the influence of non-time-varying household-specific effects and controlling for county-specific time-varying factors, I minimize the potential for bias in the estimate of the effect of wind farm placement.

4 – Data

I construct two datasets from three separate sources. Wind turbine data come from the U.S. Geological Survey Data Series 817 (Diffendorfer, et al 2014), while household data are

---

[7] Note that, in the case of distance, larger distances constitute lower intensity—therefore, if wind farm exposure is a disamenity, the expected sign of distance is positive.

taken from the records of county assessors and proprietary data maintained by the State of Iowa. The wind farm dataset contains geo-coded location and attribute information for individual wind towers throughout the United States, including date of installation, generation capacity per turbine and total number of turbine towers within a given wind farm. Utility-scale wind farms in Iowa typically have 40 to 100 individual turbines, with a mean turbine count of 69.71. Average capacity per turbine has also increased over the years; the largest installation in Iowa as of 2012 was constructed in 1999 and contains 257 individual towers, although each one is only rated at 0.75 MW capacity. On the other hand, the wind farm having the greatest capacity (443.9 MW) was built in 2011 and has 193 individual turbines. Mean generation capacity for wind farms in Iowa is 112.55 megawatts. Iowa's wind farms are concentrated in the western and north portions of the state; Figure 4 shows this distribution visually, displaying county-level total turbine counts as of 2014.

Income data come from records maintained by the Iowa Department of Revenue (IDR), the state's tax-collection bureau. These data are confidential and unavailable to the public, and the income analysis was conducted on-site at IDR. The records capture information from all Iowa state income tax returns filed electronically ("e-file"), as well as limited data captured from all paper returns filed in a timely fashion,[8] beginning in 2002.[9] Income data is aggregated to the household level and reflects the earnings of non-dependent taxpayers filing on the same tax return at the same address.[10] I observe household Adjusted Gross Income (AGI) for all households in the dataset, although I do not observe the particular sources of income by

---

[8] Here, "timely" refers to January of the year following the year for which the return is filed. For example, a paper return for tax year 2007 filed by January of 2009 would be captured in IDR's files.

[9] Electronically filed tax returns have accounted for an increasing share of all returns filed in Iowa; internal data from IDR indicate an e-file share of 62.2% in 2004, increasing to 86.6% in 2011.

[10] The income of children or other residents who do not file as independent taxpayers is not considered.

household, i.e. I cannot distinguish between wage and non-wage income. As a result, some of the income changes I observe may be due to changing returns on capital owned by the household, possibly including land leased to agriculture or energy, but the area-frame sampling and the difference in differences approach mitigate these issues somewhat. Observations excluded from the final dataset include taxpayers with out-of-sate home addresses and those who did not file tax returns for tax years 2002, 2008 and 2012. Finally, to control for human capital and worker characteristics in each household, I restrict the income sample to households with the same principle tax filers in all years under study.

House values were obtained directly from county assessors' offices. House values are composed of the total assessed value of the land, dwelling and any improvements to buildings on a given parcel. Data in the sample reflect residential parcels containing single-family residences or rural dwellings. Assessed values have certain advantages over transaction-based observations: they provide a complete time series of values for individual properties regardless of whether the property is sold, and they are not subject to thin and selected samples. The local effects of nearby sales influence the assessor's valuation of non-transacted properties, meaning that the information contained in the price of transacted houses should be reflected in the assessor's valuation.[11]

Using the wind turbine location data to determine turbine positions, houses were selected using area-frame sampling based on proximity to turbines and observed similarities of the parcels on which they were located. This initial dataset was refined to include only addresses with dwellings for the duration of the study period. Houses with unclear location information

---

[11] Ma and Swinton (2012) examine the differences in amenity valuations from transaction prices and assessed-value data, concluding that assessed values do not accurately capture marginal willingness-to-pay for natural amenities, especially in a dynamic context. However, this also implies that assessed values will not capitalize energy royalties, meaning that royalties paid should appear as income gains.

were geo-located by address using ArcGIS software. The resulting dataset was used to determine exposure to wind energy at each household location. Once measures of wind farm size were associated with each house, the data were merged with value and income data by physical address. Households in the "control" group are located more than 5 miles away[12] from a wind turbine but with otherwise similar wind and topography characteristics comparable to wind farm locations.

One caveat is necessary: while most Iowa counties use electronic databases to record property values, many only began keeping electronic records after 2005. Additionally, many assessors who began maintaining electronic records in years after 2002 do not have complete records for years prior to the start of the electronic recordkeeping. Of the Iowa counties hosting utility-scale wind energy, only 5 were able to provide electronic house-value records dating back to 2002. Also, not all tax filers report a physical home address. As a result, the full sets of income observations and house value observations do not perfectly overlap. I estimate Equation (6) separately for each data set rather than condition on a household belonging to both datasets. From each dataset I obtain a panel of observations, i.e. households that appear in 2002, 2008 and 2012.

Tables 1 and 2 report summary statistics for treatment and control households. Households in the "Treated by 2012" group are located within five miles of a wind farm that began operation after 2002 and prior to 2012. Table 1 reports statistics for the income dataset,[13] including household distance away from the nearest wind turbine regardless of treatment group

---

[12] The 5-mile cutoff follows Gibbons' (2015) result that negative visual disamenity effects dissipate at approximately 5 miles away from a wind turbine.

[13] Percentile cutoffs are censored in Table 1 to preserve the confidentiality of income data.

status, contemporaneous years of exposure and treatment-intensity measures of capacity and turbine count. Table 2 reports statistics for house values and includes the same covariates.[14]

In 2002, incomes and house values in the control group are lower than households in the treatment group. However, control incomes grow quickly, ending higher than the treated group in 2012. The realized covariate measures differ somewhat between both data sets, but the summary statistics are similar. On average, "Treated by 2012" households in the income dataset are exposed to older wind farms of higher capacity and lower turbine counts than their counterparts in the house value dataset.

5 – Results

Tables 3 and 4 present the results of estimating the log-differenced specifications. All the estimations follow Equation (6) and include county fixed effects (ζ_c). The average treatment effect β is presented in column 1, while subsequent columns examine the effect of the treatment-intensity parameter γ. Superscripts denote the outcome of interest as wages (incomes) and rents (house values). The presence of wind farms does not significantly affect incomes or house values, although the signs of the treatment intensity coefficients (γ) suggest negative impacts. *Distance* is an exception—it is negative for house values and positive for income. Though the estimate is not significantly different from zero, the pattern of signs is consistent with higher house values and lower incomes at close distances to a wind farm.

In addition, the joint effect of exposure and intensity (i.e. $\hat{\beta}+\widehat{\gamma_s}\cdot\overline{s}$, where $\overline{s}$ is the average intensity and intensity is $s\in\{Distance, Duration, Capacity, Turbines\}$) is also negative

---

[14] The samples were matched separately, which accounts for differences in covariate measurements.

for incomes and house values. F-tests of the joint significance of β and γ_s cannot reject the null of no effect in Tables 3 and 4, although some of the specifications in the Appendix do yield joint significance. Changing the treatment radius does little for the significance of the income results. In contrast to the previous literature, house value effects remain insignificant across the differing radii.[15]

The general lack of significance is confirmed in the alternative specifications presented in the Appendix. While some of the coefficients in Tables A.1 and A.2 are significant, their signs are not intuitive (e.g. in model 8 in Tables A.1 and A.2, the turbine count coefficients are positive and significant while the capacity coefficients are negative and significant). Varying the start and end dates generally does not affect the significance of the intensity coefficient estimates. However, an additional mile of distance away from a wind farm between 2002 and 2008 is associated with a 1.6% increase in incomes (Table A.3). Additionally, the average effect on rents (β^r) is 0.065 and significant at the 5% level between 2004 and 2012 (Table A.6). The marginal effect of an additional mile away from a wind farm is negative and significant, suggesting that proximity to a wind farm is associated with increased house values.

In the context of the theory outlined in Section 3, this implies that wind farms do not comprise a disamenity for households within five miles of the wind farm.[16] That is, if the disamenity effect is significant, then either rents must fall or wages must rise, as depicted in Figure 3. As an alternative, the same theory predicts that gains to local productivity due to wind

---

[15] Estimates with different treatment group radii are not reported due to confidentiality requirements. However, the marginal effects of capacity and turbine count become positive and significant for houses within 1 mile of a wind farm. While it is possible that larger wind farms bid up local rents through the capitalization of energy royalties, the lack of significant income effects suggests over the same area suggests that this could be due to sampling variation.

[16] This does not rule out the possibility that households located immediately adjacent to (or within the boundaries of) wind farms are compensated for exposure, but the effect size may be too small to matter over a wider area.

farm placement will shift the iso-cost curve to the right in Figure 3, leading to increased wages and rents. If the disamenity effect is great enough to counter the productivity effect, workers will bid rents down as firms bid them up, and wages still rise.[17]

The income increases documented in the literature at wider geographic scales (e.g. at the county level) do not appear here. For example, Brown, et al (2012) examine data at the county level, finding an implied benefit of approximately $11,000 per additional megawatt per capita over an eight-year span (i.e. $1,375 per year) attributable to wind energy throughout the United States.[18] This prompts the question of how county-level gains have occurred when households located nearby large wind farms do not appear to benefit directly over a similar timeframe. One possibility is that few energy royalty recipients reside close to the source of their royalties, or that royalty payments are concentrated among a small number of landowners (as reported in Weber, et al (2013)). Alternatively, economic development in wind-heavy regions may be tied to agricultural indicators; the study period considered by Brown, et al (2012) includes years in which agricultural commodity prices were unusually high. While I also include data from these years, my data are at the household level, so I am able to observe within-county income variation. It is possible that regions with higher wind resource potential also host productive farmland, making incomes susceptible to agricultural commodity price changes. If there is unobserved heterogeneity that is correlated with county-level wind resource potential, I have accounted for it with the county fixed effect ζ_c.

---

[17] Even in the case that wind farms are a negative local productivity shock, the wage effect is ambiguous, but rents must fall.

[18] This finding would require an additional megawatt per resident; at the mean county population of 45,200 in the data used by Brown, et al (2012), this implies that the $11,000 per megawatt per capita translates to $11,000 for 45,200 additional megawatts of installed capacity, or approximately $0.24 over eight years per individual megawatt.

6 – Conclusion

I estimate the external net benefits of wind farm location by examining income and house value growth in rural Iowa. I use data at the address level, allowing me to difference out unobserved household-specific characteristics that may affect growth in both outcomes, and I account for local market activity with county fixed effects. My data are more detailed than others in the literature, and my estimation strategy allows me to distinguish the effect of wind farm placement from other local drivers of economic activity.

My results indicate that the external net benefits of wind farm placement are not different from zero. Neither incomes nor house values vary significantly with wind farm exposure. This result stands in contrast to results documented in the existing literature, which has found negative house value impacts and positive effects on income. I attribute this to the difference in geographic scales between the present study and others. For example, house value impacts have been shown to occur only within short distances of individual wind towers. At the same time, income gains may be distributed over so wide an area that their influence is too small to measure without precise information regarding land ownership.

Future work will address several of the gaps in the present analysis. For example, it remains unknown whether agricultural land capitalizes the disamenities of wind farm exposure as part of an option value. That is, if agricultural land were converted to residential use, would the disamenities of life near a wind farm be capitalized? Given the sparse population densities in areas with large wind farms, research into this question might provide an alternative to assessors' data in measuring cost-of-living as outlined in the theoretical framework. Additionally, assessed house values may reflect long-run trends in real estate prices, but do not necessarily represent an exact mutual valuation of a house and all its attributes as assumed in the traditional hedonic framework; this can possibly bias the marginal effect estimates toward zero. Expansions of this research will use parcel-level transactions for residential, rural and agricultural land to address both of these shortcomings.

References

Ángulo, I., D. de la Vega, I. Cascón, J. Cañizo, Y. Wu, D. Guerra, and P. Angueira. “Impact Analysis of Wind Farms on Telecommunication Services.” *Renewable and Sustainable Energy Reviews* 32 (April 2014): 84–99. doi:10.1016/j.rser.2013.12.055.

Barclay, Robert MR, E. F. Baerwald, and J. C. Gruver. "Variation in bat and bird fatalities at wind energy facilities: assessing the effects of rotor size and tower height." *Canadian Journal of Zoology* 85, no. 3 (2007): 381-387.

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. "Migration and hedonic valuation: The case of air quality." *Journal of Environmental Economics and Management* 58, no. 1 (2009): 1-14.

Boxall, Peter C., Wing H. Chan, and Melville L. McMillan. "The impact of oil and natural gas facilities on rural residential property values: a spatial hedonic analysis." *Resource and energy economics* 27, no. 3 (2005): 248-269.

Brown, Jason P., John Pender, Ryan Wiser, Eric Lantz, and Ben Hoen. “Ex Post Analysis of Economic Impacts from Wind Power Development in US Counties.” *Energy Economics* 34, no. 6 (2012): 1743–1754.

Denholm, Paul, M. Hand, M. Jackson, and S. Ong. *Land-use requirements of modern wind power plants in the United States. National Renewable Energy Laboratory (NREL) Technical Report NREL*. TP-6A2-45834, 2009.

De Silva, Dakshina G., Robert P. McComb, and Anita R. Schiller. “What Blows in with the Wind?” *Southern Economic Journal* 82, no. 3 (2016): 826–858.

Diffendorfer, Jay E., Louisa A. Kramer, Zach H. Ancona, and Christopher P. Garrity. “Onshore Industrial Wind Turbine Locations for the United States up to March 2014.” *Scientific Data* 2 (2015). http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4658569/.

Dröes, Martijn I., and Hans RA Koster. "Renewable energy and negative externalities: The effect of wind turbines on house prices." *Journal of Urban Economics* 96 (2016): 121-141.

Farboud, Amir, Rosa Crunkhorn and Aaron Trinidade. “Wind turbine syndrome: Factor fiction?” Accessed June 26, 2016. https://www.researchgate.net/profile/Amir_Farboud/publication/234695847_’Wind_turbine_syndrome’_fact_or_fiction/links/54ac4f870cf2479c2ee7b62e.pdf.

Firestone, Jeremy, Alison Bates, and Lauren A. Knapp. “See Me, Feel Me, Touch Me, Heal Me: Wind Turbines, Culture, Landscapes, and Sound Impressions.” *Land Use Policy* 46 (2015): 241–249.

Gibbons, Stephen. “Gone with the Wind: Valuing the Visual Impacts of Wind Turbines through House Prices.” *Journal of Environmental Economics and Management*, 2015. http://www.sciencedirect.com/science/article/pii/S0095069615000418.

Girardi, Anthony G. “Wind Energy Production Tax Credit and Renewable Energy Tax Credit Tax Credits Program Evaluation Study,” 2014. https://tax.iowa.gov/sites/files/idr/WEP%20and%20RE%20Tax%20Credit%20Evaluation%20Study.pdf.

Gopalakrishnan, Sathya, and H. Allen Klaiber. "Is the shale energy boom a bust for nearby residents? Evidence from housing values in Pennsylvania." *American Journal of Agricultural Economics* 96, no. 1 (2013): 43-66.

Hamilton, Stanley W., and Gregory M. Schwann. "Do high voltage electric transmission lines affect property value?." *Land Economics* (1995): 436-444.

Hansen, Julia L., Earl D. Benson, and Daniel A. Hagen. "Environmental hazards and residential property values: Evidence from a major pipeline event." *Land Economics* 82, no. 4 (2006): 529-541.

Heintzelman, Martin D., and Carrie M. Tuttle. "Values in the wind: a hedonic analysis of wind power facilities." *Land Economics* 88, no. 3 (2012): 571-588.

Hoen, Ben. “Impacts of Windmill Visibility on Property Values in Madison County, New York.” Bard College, 2006. http://amherstislandwindinfo.com/aiw-docs/hoen-fenner-2006.pdf.

———. “The Impact of Wind Power Projects on Residential Property Values in the United States: A Multi-Site Hedonic Analysis.” *Lawrence Berkeley National Laboratory*, 2010. http://escholarship.org/uc/item/0gk965bg.pdf.

Hoen, Ben, Jason P. Brown, Thomas Jackson, Mark A. Thayer, Ryan Wiser, and Peter Cappers. “Spatial Hedonic Analysis of the Effects of US Wind Energy Facilities on Surrounding Property Values.” *The Journal of Real Estate Finance and Economics*, 2014, 1–30.

Iowa Public Utilities Board. “Renewable Energy Tax Credits.” https://iub.iowa.gov/renewable-energy-tax-credits. Accessed October 5, 2016.

Kahn, Matthew E. “Local Non-Market Quality of Life Dynamics in New Wind Farms Communities.” *Energy Policy* 59 (August 2013): 800–807. doi:10.1016/j.enpol.2013.04.037.

Kask, Susan B., and Sholeh A. Maani. "Uncertainty, information, and hedonic pricing." *Land Economics* (1992): 170-184.

Lantz, E., and S. Tegen. “Economic Development Impacts NREL/CP-500-45555 of Community Wind Projects: A Review and Empirical Evaluation,” 2009. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.447.4533&rep=rep1&type=pdf.

Lutzayer, Sanja, Daniel J. Phaneuf and Laura O. Taylor. “The Amenity Costs of Offshore Wind Farms: Evidence from a Choice Experiment.” Working paper, North Carolina State University Center for Environmental and Resource Economic Policy. Available at https://cenrep.ncsu.edu/cenrep/wp-content/uploads/2016/03/LPT_Offshore-Wind-1.pdf, accessed 1/25/2017

Moretti, Enrico. "Workers' education, spillovers, and productivity: evidence from plant-level production functions." *The American Economic Review* 94, no. 3 (2004): 656-690.

Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins. "The housing market impacts of shale gas development." *The American Economic Review* 105, no. 12 (2015): 3633-3659.

Ma, Shan, and Scott M. Swinton. "Hedonic valuation of farmland using sale prices versus appraised values." *Land Economics* 88.1 (2012): 1-15.

Pierpont, Nina. "Wind Turbine Syndrome." *Testimony before the New York Legislature Energy Committee*, 2006. http://waubrafoundation.org.au/wp-content/uploads/2013/06/Pierpont-Dr-Nina-Wind-Turbine-Syndrome-the-Brain1.pdf.

Roback, Jennifer. "Wages, Rents, and the Quality of Life." *The Journal of Political Economy*, 1982, 1257–1278.

Rubin, G. James, Miriam Burns, Simon Wessely, and others. "Possible Psychological Mechanisms For 'Wind Turbine Syndrome'. On the Windmills of Your Mind." *Noise and Health* 16, no. 69 (2014): 116.

Sims, Sally, and Peter Dent. "High-voltage overhead power lines and property values: a residential study in the UK." *Urban Studies* 42, no. 4 (2005): 665-694.

Slattery, Michael C., Eric Lantz, and Becky L. Johnson. "State and Local Economic Impacts from Wind Energy Projects: Texas Case Study." *Energy Policy*, Clean Cooking Fuels and Technologies in Developing Economies, 39, no. 12 (December 2011): 7930–40. doi:10.1016/j.enpol.2011.09.047.

Tegen, S., M. Hand, B. Maples, E. Lantz, P. Schwabe, and A. Smith. "2010 Cost of Wind Energy." *Contract* 303 (2012): 275–3000.

U.S. Bureau of Labor Statistics. Table 1800. Region of residence: Average annual expenditures and characteristics, Consumer Expenditure Survey, 2011-2012. U.S. Department of Labor. Available at: https://www.bls.gov/cex/2012/region/region.pdf

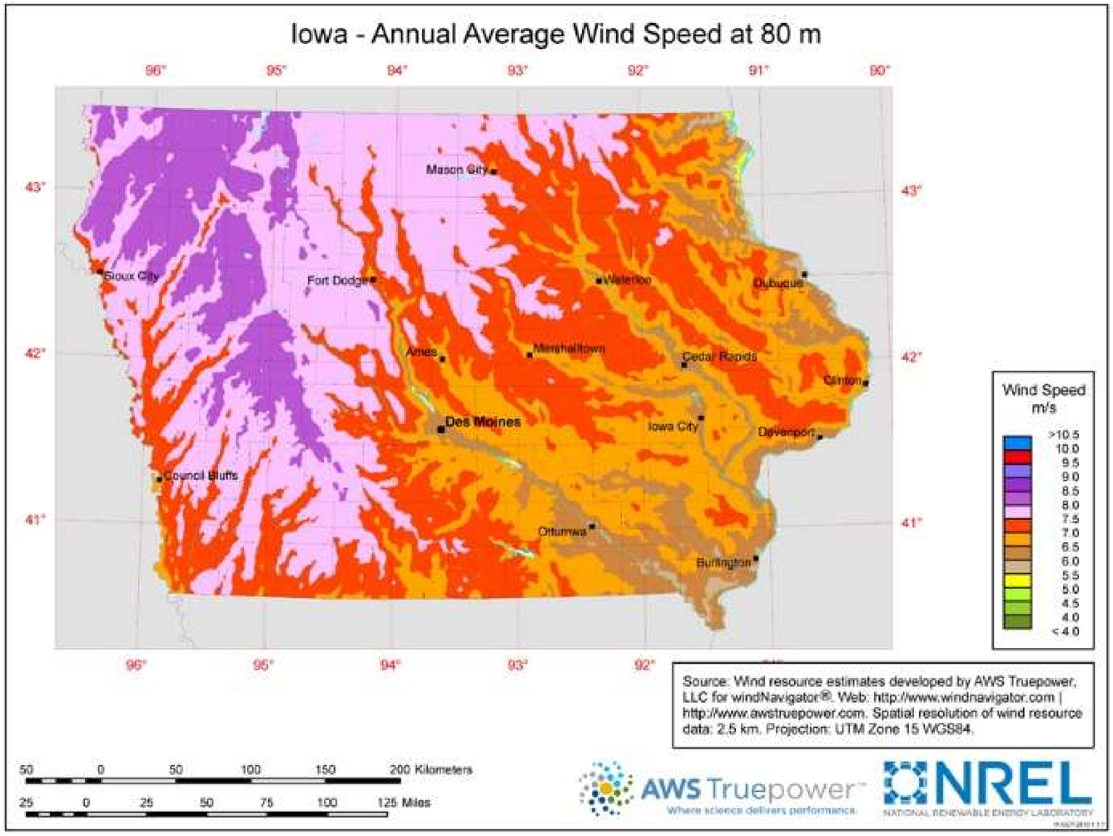
U.S. Energy Information Administration. “State Energy Profile: Iowa.” Available at https://www.eia.gov/state/analysis.cfm?sid=IA. Updated March 17th 2016, accessed 1/25/2017.

Vyn, Richard J., and Ryan M. McCullough. “The Effects of Wind Turbines on Property Values in Ontario: Does Public Perception Match Empirical Evidence?” *Canadian Journal of Agricultural Economics/Revue Canadienne D’agroeconomie* 62, no. 3 (2014): 365–392.

Walker, Chad, Jamie Baxter, Sarah Mason, Isaac Luginaah, and Danielle Ouellette. “Wind Energy Development and Perceived Real Estate Values in Ontario, Canada.” *AIMS Energy* 2, no. 4 (2014): 424–442.

Weber, Jeremy G., Jason P. Brown, and John Pender. "Rural wealth creation and emerging energy industries: lease and royalty payments to farm households and businesses." *Federal Reserve Bank of Kansas City Working Paper* 13-07 (2013).

Figures and Tables



Source: Wind resource estimates developed by AWS Truepower, LLC for windNavigator®. Web: http://www.windnavigator.com | http://www.awstruepower.com. Spatial resolution of wind resource data: 2.5 km. Projection: UTM Zone 15 WGS84.

Figure 1: a map of Iowa's wind resource potential

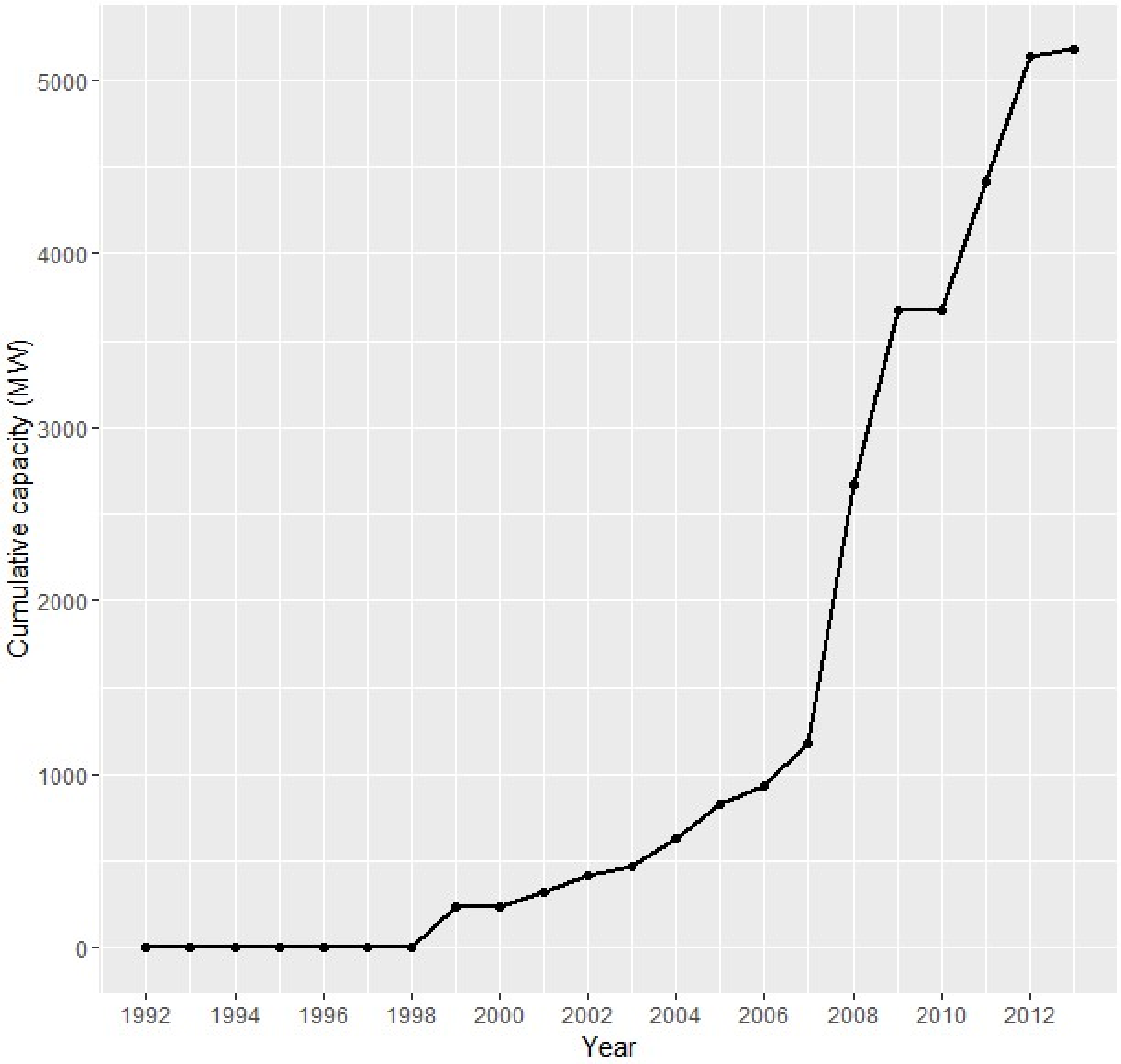


Figure 2: Cumulative wind power capacity installed in Iowa, 1992 to 2012

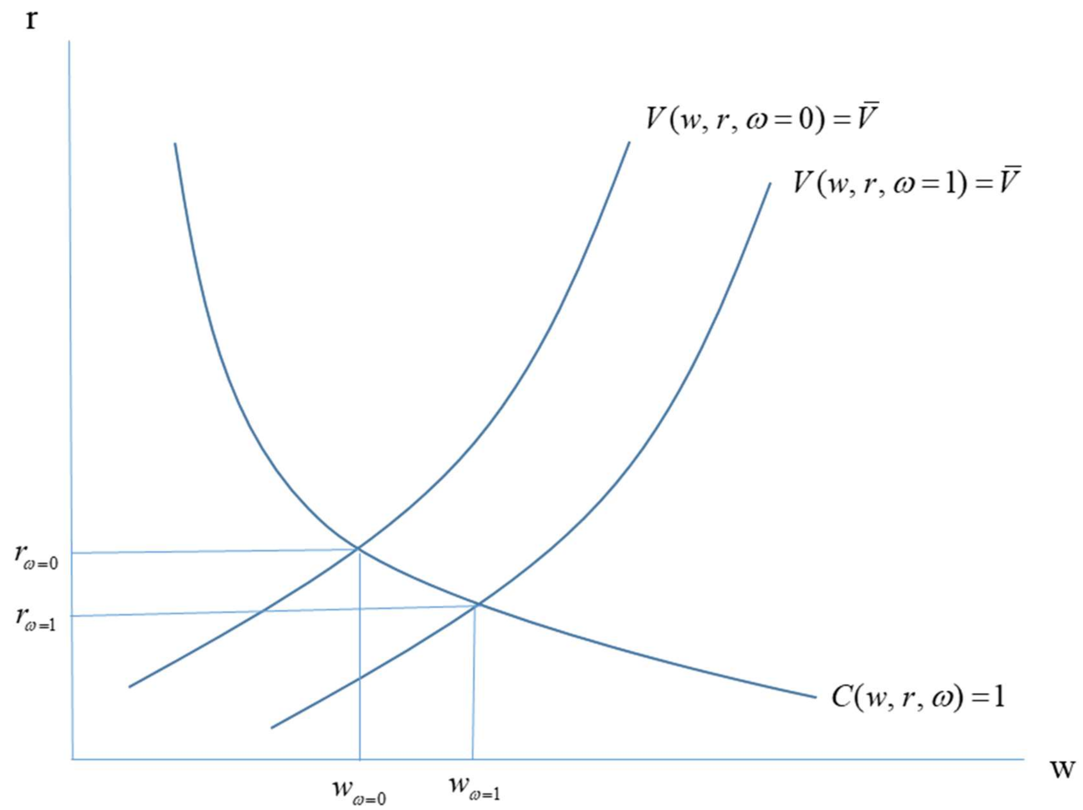
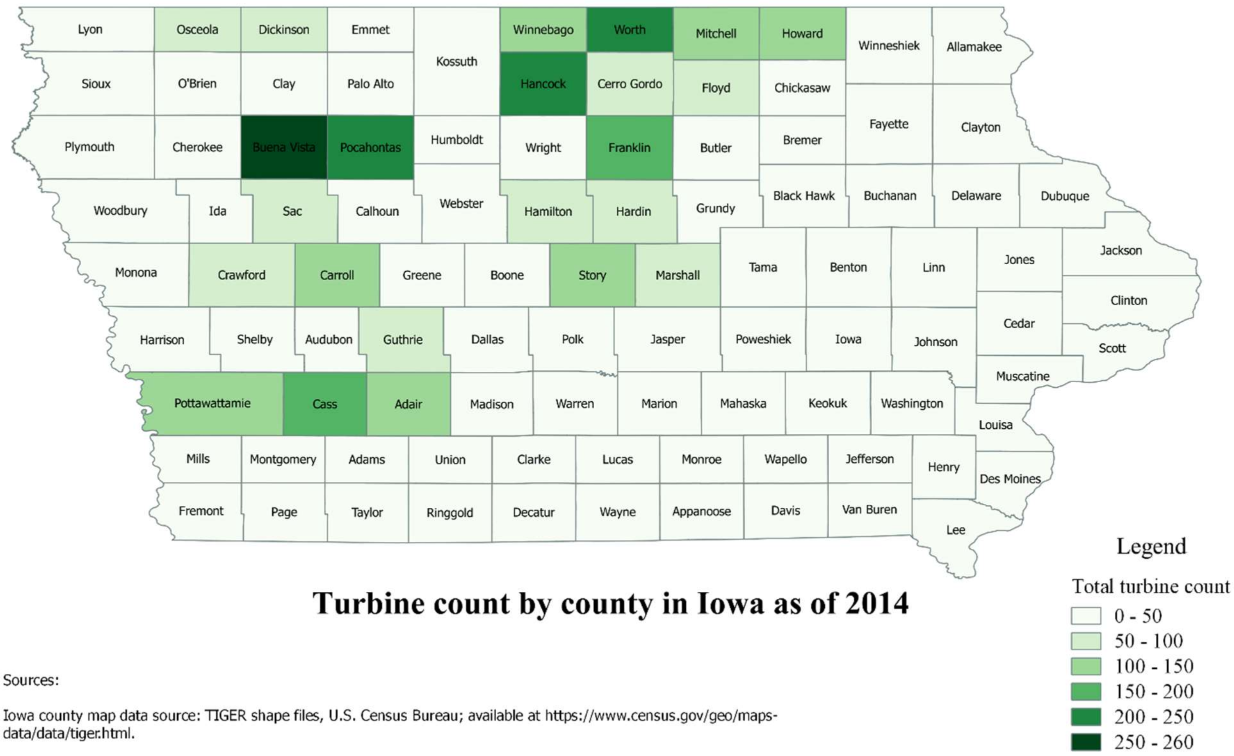


Figure 3: Local wage and rent differential when wind farm exposure is a disamenity



Turbine count by county in Iowa as of 2014

Sources:

Iowa county map data source: TIGER shape files, U.S. Census Bureau; available at https://www.census.gov/geo/maps-data/data/tiger.html.

Turbine count data source: author's calculations from USGS Data Series 817.

Figure 4: Iowa wind turbine counts by county

Table 1: Summary statistics – Income dataset

Year	Treatment group	Variable	Mean	Std Dev	10th Pctl†	90th Pctl†	Observations
2002:							
	Control	Household Income	\$42,471.73	33844.3	\$12,800.00	\$75,800.00	152
		Distance (miles)	10.477	4.138	5.653	16.491	152
		Duration (Years)	0	0	0	0	152
		Capacity (100 MW)	0	0	0	0	152
		Turbines (100 count)	0	0	0	0	152
	Treated by 2012	Household Income	\$49,804.51	33995.77	\$17,800.00	\$79,200.00	267
		Distance (miles)	2.418	1.447	0.405	4.156	267
		Duration (Years)	0	0	0	0	267
		Capacity (100 MW)	0	0	0	0	267
		Turbines (100 count)	0	0	0	0	267
2012:							
	Control	Household Income	\$123,158.68	348059.87	\$16,600.00	\$220,800.00	152
		Distance (miles)	10.480	4.144	5.653	16.491	152
		Duration (Years)	0	0	0	0	152
		Capacity (100 MW)	0	0	0	0	152
		Turbines (100 count)	0	0	0	0	152
	Treated by 2012	Household Income	\$94,352.11	196041.74	\$19,243.00	\$169,775.00	267
		Distance (miles)	2.418	1.447	0.405	4.156	267
		Duration (Years)	3.873	2.607	0	7	267
		Capacity (100 MW)	0.915	0.624	0.016	1.5	267
		Turbines (100 count)	0.592	0.431	0	1	267

†Observations censored by rounding

Table 2: Summary statistics – House values dataset

Year	Treatment group	Variable	Mean	Std Dev	10th Pctl	90th Pctl	Observations
2002:							
	Control	House value	$58,508.02	40,249.27	$12,840.00	$111,780.00	91
		Distance (miles)	8.068	5.904	5.526	10.24	91
		Duration (years)	0	0	0	0	91
		Capacity (100 MW)	0	0	0	0	91
		Turbines (100 count)	0	0	0	0	91
	Treated by 2012	House value	$98,246.57	44,649.23	$50,609.00	$155,115.00	968
		Distance (miles)	2.93	1.251	0.758	4.107	968
		Duration (years)	0	0	0	0	968
		Capacity (100 MW)	0	0	0	0	968
		Turbines (100 count)	0	0	0	0	968
2012:							
	Control	House value	$96,279.23	77,882.24	$26,110.00	$164,290.00	91
		Distance (miles)	8.068	5.904	5.526	10.24	91
		Duration (years)	0	0	0	0	91
		Capacity (100 MW)	0	0	0	0	91
		Turbines (100 count)	0	0	0	0	91
	Treated by 2012	House value	$121,480.24	56,624.22	$60,085.00	$193,650.00	968
		Distance (miles)	2.93	1.251	0.758	4.107	968
		Duration (years)	2.99	2.452	0	7	968
		Capacity (100 MW)	0.895	0.709	0.016	1.5	968
		Turbines (100 count)	0.603	0.468	0.01	1	968

Table 3: Income growth, 2002 to 2012

	Dependent variable: change in log income				
Parameter	(1)	(2)	(3)	(4)	(5)
Treated by 2012 (β^{w})	-0.084 (0.135)	-0.003 (0.175)	-0.025 (0.164)	0.03 (0.159)	-0.023 (0.157)
Distance (miles) (γ^{w}_{dist})		0.015 (0.022)			
Duration (years) (γ^{w}_{dur})			-0.017 (0.027)		
Capacity (100 MW) (γ^{w}_{cap})				-0.131 (0.086)	
Turbines (100 count) (γ^{w}_{turb})					-0.123 (0.131)
Joint effect:	-	0.033	-0.09	-0.089	-0.095
Joint significance:	No	No	No	No	No
County FE:	Yes	Yes	Yes	Yes	Yes
Observations	419	419	419	419	419
R^2	0.1041	0.1055	0.1049	0.1075	0.1055

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: House value regressions, 2002 2012

	Dependent variable: change in log house value				
Parameter	(1)	(2)	(3)	(4)	(5)
Treated by 2012 (β^r)	-0.066	-0.120*	-0.03	-0.056	-0.057
	(0.052)	(0.070)	(0.058)	(0.052)	(0.053)
Distance (miles) (γ^r_{dist})		-0.009			
		(0.007)			
Duration (years) (γ^r_{dur})			-0.005		
			(0.004)		
Capacity (100 MW) (γ^r_{cap})				-0.008	
				(0.010)	
Turbines (100 count) (γ^r_{turb})					-0.011
					(0.015)
Joint effect:	-	-0.146	-0.044	-0.063	-0.063
Joint significance:	No	No	No	No	No
County FE:	Yes	Yes	Yes	Yes	Yes
Observations	1,059	1,059	1,059	1,059	1,059
R^2	0.183	0.188	0.184	0.184	0.184

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

APPENDIX: ADDITIONAL TABLES

In additional specifications, capacity and turbine count become significant only when both are included (see model 8 in Tables A.1 and A.2). Effect sizes and signs are similar for both income growth and house value growth. Capacity coefficients are negative, implying a 1.4% income decrease and a 0.84% house value decrease per megawatt. Applying these growth rate differences to base-year control-group averages yields an income difference of $595 per megawatt and a house value difference of $491 per megawatt. Turbine results are similar. Using control-group incomes, the estimated 2.1% income gain reported in Table A.1 is approximately equivalent to $892 per additional turbine. House value differences are similar—using the base-year control-group house values, the 1.4% house value gain is equivalent to $819 per turbine. House values also grow more slowly within 5 miles of a wind farm, although the implied loss of 0.0034% (approximately $2, using control-group base-year house values) per year is not economically significant.

Use of alternative endpoint years also has little effect on growth rates (see Tables A.3 – A.6). While the 2002-2008 growth estimations reported in Tables A.3 and A.4 use the same data as the estimations presented in Chapter 2, the 2004-2012 growth estimations use an expanded dataset that overlaps substantially with the original data. In particular, a larger number of house value observations are available beginning in 2004, and sampling variation in tax filers led to a greater number of data points between 2004 and 2012. While treatment intensity measures are not significant in Table A.5, the treatment effect β^{w} is significant, implying a loss of 30% relative to control group income growth. House value growth over the same period is negatively related to distance, implying that treated houses lose 7% in house value growth per additional mile away from a wind farm. Duration of exposure is also negative and significant; growth of treated houses is 2% lower per additional year of exposure.

Table A.1: Income growth, 2002 to 2012 (additional specifications)

	Dependent variable: change in log income		
Parameter	(6)	(7)	(8)
Treated by 2012 (β^w)	0.023	-0.016	0.295
	(0.165)	(0.166)	(0.183)
Duration (years) (γ^w_{dur})	0.004	-0.004	-0.055
	(0.035)	(0.037)	(0.039)
Capacity (100 MW) (γ^w_{cap})	-0.14		-1.395***
	(0.114)		(0.452)
Turbines (100 count) (γ^w_{turb})		-0.109	2.091***
		(0.183)	(0.716)
Joint effect:	-0.089	-0.095	0.043
Joint significance:	No	No	10%
County FE:	Yes	Yes	Yes
Observations	419	419	419
R^2	0.1075	0.1055	0.1193

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.2: House value growth, 2002 to 2012 (additional specifications)

	Dependent variable: change in log house value		
Parameter	(6)	(7)	(8)
Treated by 2012 (β^{r})	-0.007	0.001	0.039
	(0.061)	(0.061)	(0.054)
Duration (years) (γ^{r}_{dur})	-0.011	-0.013	-0.034***
	(0.011)	(0.012)	(0.013)
Capacity (100 MW) (γ^{r}_{cap})	0.017		-0.896***
	(0.031)		(0.238)
Turbines (100 count) (γ^{r}_{turb})		0.036	1.465***
		(0.048)	(0.402)
Joint effect:	-0.024	-0.016	0.018
Joint significance:	No	No	5%
County FE:	Yes	Yes	Yes
Observations	1,059	1,059	1,059
R^2	0.185	0.185	0.191

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.3: Income growth, 2002 to 2008

Parameter	*Dependent variable: change in log income*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated by 2008 (β^w_{2008})	-0.08	-0.051	-0.02	0.039	-0.018	0.218	-0.015	12683***
	(0.081)	(0.083)	(0.088)	(0.19)	(0.083)	(0.222)	(0.089)	(0.425)
Distance (miles) (γ^w_{dist})		0.016*						
		(0.009)						
Duration (years) (γ^w_{dur})			-0.043			-0.065	-0.003	-0.037
			(0.037)			(0.041)	(0.045)	(0.098)
Capacity (100 MW) (γ^w_{cap})				-0.097		-0.171		-0.104
				(0.129)		(0.139)		(0.29)
Turbines (100 count) (γ^w_{turb})					-0.318		-0.309	-0.15
					(0.196)		(0.239)	(0.508)
Joint significance:	No	No	No	No	10%	No	No	No
County FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	419	419	419	419	419	419	419	419
R^2	0.1103	0.1152	0.1128	0.1117	0.1165	0.1167	0.1165	0.1169

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.4: House value growth, 2002 to 2008

	Dependent variable: change in log house value							
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated by 2008 (β^{r}_{2008})	0.021	0.016	0.028	0.058	0.06	0.085**	0.089**	0.053
	(0.022)	(0.021)	(0.024)	(0.041)	(0.049)	(0.041)	(0.045)	(0.081)
Distance (miles) (γ^{r}_{dist})		-0.005						
		(0.005)						
Duration (years) (γ^{r}_{dur})			-0.013			-0.016	-0.016	-0.016
			(0.012)			(0.010)	(0.010)	(0.010)
Capacity (100 MW) (γ^{r}_{cap})				-0.026		-0.038*		-0.205
				(0.025)		(0.023)		(0.301)
Turbines (100 count) (γ^{r}_{turb})					-0.041		-0.062	0.282
					(0.046)		(0.040)	(0.523)
Joint significance:	10%	No	10%	No	No	10%	10%	No
County FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,059	1,059	1,059	1,059	1,059	1,059	1,059	1,059
R^2	0.066	0.068	0.067	0.066	0.066	0.069	0.069	0.069

Note: $^{*}p<0.1$;$^{**}p<0.05$;$^{***}p<0.01$

Table A.5: Income growth, 2004 to 2012

	Dependent variable: change in log income							
Parameter:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated by 2008 (β^{w})	-0.308**	-0.209	-0.321*	-0.313*	-0.331**	-0.321*	-0.3*	0.088
	(0.156)	(0.18796)	(0.17813)	(0.16877)	(0.16523)	(0.17806)	(0.18088)	(0.2132)
Distance (miles) (γ^{w}_{dist})		0.017						
		(0.01974)						
Duration (years) (γ^{w}_{dur})			0.004			0.005	-0.018	-0.11*
			(0.03193)			(0.04911)	(0.05606)	(0.06657)
Capacity (100 MW) (γ^{w}_{cap})				0.007		-0.002		-1.441***
				(0.08157)		(0.1287)		(0.46927)
Turbines (100 count) (γ^{w}_{turb})					0.066		0.126	2.542***
					(0.12245)		(0.21846)	(0.83056)
Joint significance:	5%	No	10%	10%	No	10%	No	10%
County FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	448	448	448	448	448	448	448	448
R^2	0.0624	0.0644	0.0625	0.0624	0.0629	0.0625	0.0631	0.0764

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.6: House value growth, 2004 2012

Parameter	*Dependent variable: change in log house value*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated by 2008 (β^r)	0.065** (0.026)	0.159*** (0.047)	0.157*** (0.054)	0.106* (0.056)	0.115** (0.057)	0.187*** (0.066)	0.187*** (0.067)	0.183*** (0.067)
Distance (miles) (γ^r_{dist})		-0.071*** (0.027)						
Duration (years) (γ^r_{dur})			-0.023** (0.011)			-0.022* (0.012)	-0.022* (0.012)	-0.023 (0.017)
Capacity (100 MW) (γ^r_{cap})				-0.03 (0.040)		-0.023 (0.034)		-0.086 (0.569)
Turbines (100 count) (γ^r_{turb})					-0.054 (0.061)		-0.036 (0.056)	0.102 (0.933)
Joint significance:	5%	1%	5%	5%	5%	10%	10%	10%
County FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,824	1,824	1,824	1,824	1,824	1,824	1,824	1,824
R^2	0.098	0.104	0.1	0.098	0.098	0.1	0.1	0.1

Note: *p<0.1; **p<0.05; ***p<0.01. Table A.6 presents estimates of the house value specifications of Equation (6) using data from 2004 to 2012. Due to variation in electronic recordkeeping by county assessors, additional observations are available during this time period—the estimates in Table A.6 use this expanded data set. Marginal results are similar when the data set is restricted to the set of overlapping addresses from the 2002 base year, but joint significance is lost for most of the specifications under this restriction.